An Intelligent Sensor Management Framework for Pervasive Surveillance

by

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I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

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Abstract

The nature and complexity of the security threats faced by our society in recent years have made it clear that a smart pervasive surveillance system constitutes the most effective cure, as it presents a conducive framework for seamless interaction between preventative capabilities and investigative protocols. Applications such as wild-life preserve monitoring, natural disaster warnings, and facility surveillance tend to be characterized by large and remote geographic areas, requiring large numbers of unattended sensor nodes to cover the volume-of-interest. Such large unattended sensor networks add new challenges as well as complicate the system management problem. Such challenges can be in the form of distributed operation with collaborative decision making, adaptive performance, and energy-aware strategies, to name a few. To meet the challenges of these mission-critical applications, the sensor system must exhibit capabilities such as heterogeneous and self-organized behaviour, data and information fusion, and collaborative resources control and management.

Sensor Management (SM) refers to the process that plans and controls the use of the sensor nodes in a manner that synergistically maximizes the success rate of the whole system in achieving the goals of its mission in assessing the situation in a timely, reliable, and accurate fashion. Managing heterogeneous sensors involves making decisions and compromises regarding alternate sensing strategies under time and resource availability constraints. As a result, the performance of the collective sensors dictates the performance of the entire system. Consequently, there is a need for an intelligent Sensor Management Framework (SMF) to drive the system performance. SMF provides a control system to manage and coordinate the use of sensing resources in a manner that maximizes the system success rate in achieving its goals. An SMF must handle an overwhelming amount of information collected, and adapt to the highly dynamic environments, in addition to network and system limitations.

This thesis proposes a resource-aware and intelligent SMF for managing pervasive sensor systems in surveillance context. The proposed SMF considerably improves the process of information acquisition by coordinating the sensing resources in order to gather the most reliable data from a dynamic scene while operating under energy constraints. The proposed SMF addresses both the operation of the coordination paradigm, as well as, the local and collaborative decision making strategies. A conceptual analysis of the SM problem in a layered structure is discussed to introduce an open and flexible design framework based on the service-oriented architecture to provide a modular, reusable, and extendable framework for the proposed SMF solution. A novel sensor management architecture, called Extended Hybrid Architecture for Sensor Management (E-HASM), is proposed. E-HASM combines the operation of the holonic, federated, and market-based architectures in a complementary manner.

Moreover, a team-theoretic formulation of Belief-Desire-Intention (BDI), that represent the E-HASM components, is proposed as a mechanism for effective energy-aware decision making to address the local sensor utility. Also, intelligent schemes that provide adaptive sensor operation to the changes in environment dynamics and sensor energy levels are designed to include adaptive sleep, active sensing, dynamic sensing range, adaptive multi-modality, and constrained communication. Furthermore, surveillance systems usually operate under uncertainty in stochastic environment. Therefore, this research formulates the collaborative decision-making entities as Partially Observable Markov Decision Processes (POMDP). To increase the tracking quality and the level of the information reliability, cooperation between the sensors is adopted, which adds an extra dimension in the design of the proposed SMFs. The propose SMF is implemented using the Jadex platform and is compared to the popular centralized architecture. The results illustrate the operation of the proposed SMF outperforms in terms of tracking quality, detection rate, energy consumption, network lifetime, and scalability.

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Dedication

To my parents, for their unconditional love and support.

To my husband, for being my Tardis.

To my daughter, Farida, for giving me happiness and strength.

Contents

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Nomenclature

ACL	Agent Communication Language
ADC	Analog to Digital Conversion
ADD	Algebraic Decision Diagrams
BDI	Belief-Desire-Intention Model
CCH	Control & Coordination Holon
CCTV	Closed-Circuit Television
DAG	Directed Acyclic Graph
DAH	Decision Assistant Holon
DCT	Discrete Cosine Transforms
DR	Detection Rate
DSR	Detection Success Ratio
DEC	Decision Support Layer
DSH	Decision Support Holon
DQ	Detection Quality
E-HASM	Extended Hybrid Architecture For Sensor Management
ESI	Energy Saving Index
GUI	Graphical User Interface
FSC	Finite State Controller
HMI	Human Machine Interface
IDE	Integrated Development Environments
IntelliSurv	Intelligent Surveillance System
JDL	Joint Directors of Laboratories
JMPD	Joint Multi-target Probability Density
LDA	Linear Discriminant Analysis
MFCCs	Mel-Frequency Cepstral Coefficients
MDP	Markov Decision Processes
mMH	Macro-Management Holon
NET	Network Management Layer
POMDP	Partially Observable Markov Decision Processes
PHY	Physical sensor management
QoSv	Quality of Surveillance
RBF	Radial Basis Function
RFS	Random Finite Sets
RMSE	Root Mean Square Error
ROR	Region of Responsibility

RSS	Received Signal Strength
SA	Situation-Awareness
SEN	Sensor Node Management Layer
SENSH	Sensor Holon
SDM	Sensor Deliberate Module
SM	Sensor Management
SMA	Sensor Management Architecture
SMF	Sensor Management Framework
SN	Sensor Network
SNR	Signal-to-Noise Ratio
SOA	Service-Oriented Architecture
SRM	Sensor Reactive Module
SYS	System Management Layer
SYS-MH	System management holon
SVM	Support Vector Machines
TQ	Tracking Quality
VOI	Volume of Interest
WSN	Wireless Sensor Network
μH	Micro-Management Holon
1GSSs	First Generation Surveillance Systems
2GSSs	Second Generation Surveillance Systems
3GSSs	Third Generation Surveillance Systems

Chapter 1

Introduction

1.1 Motivation

Modern society faces new types of security threats, as such, our security measures have to go through a paradigm shift from centralized and investigative to distributed and preventative. This has instigated significant efforts of research within academia and industry, so as to bring about solutions that can effectively address security as a global threat to our society. The nature, complexity, extent, and spread of the security threats our society has been witnessing in the recent years have made it clear that Smart Surveillance constitutes the most effective cure as it presents a conducive framework for seamless interaction between preventative capabilities and investigative protocols [2,3]. Smart Surveillance adopts automatic data analysis technologies to transform system observations into situation-aware knowledge that is actionable [4].

Pervasive systems have demonstrated strong potential in enabling Smart Surveillance. These systems define what we today know as next-generation Wireless Sensor Networks (WSNs) which comprise a heterogeneous collection of fixed and mobile Sensor Nodes (SN). Pervasive surveillance recognizes and monitors targets moving in its Volume Of Interest (VOI) in a distributed manner. Each sensor has a partial view of the environment, but the network collectively monitors the entire area under surveillance. The need for such systems is recognized in applications such as preservation and wildlife monitoring, natural disasters warning, facility surveillance, health monitoring, to name a few. Pervasive surveillance systems deal with situations that are characterized by a high density of targets, stochastic environment, and dynamic threats. This has pushed the information acquisition problem far from what can be handled by a single sensor. Hence, pervasive surveillance systems need to exhibit capabilities such as collaborative control, heterogeneity, self-organized behaviour, multi-modal data and information fusion. These capabilities provide additional challenges in designing pervasive surveillance systems, and therefore, intelligent sensor management approaches are needed to address these capabilities.

Sensor Management (SM) refers to the process that controls and coordinates the use of the sensory suites in a manner that synergistically maximizes the success rate of the system in achieving its missions. The sensor manager is expected to take decisions that drive the performance of the whole system to reach its objectives. To address the challenges of SM, the research community has directed their efforts to the development of a Sensor Management Framework (SMF) which provides a control system to manage and coordinate the use of sensing resources in a manner that improves the process of situation-awareness, synergistically [5]. Managing heterogeneous sensors involves making decisions and compromises regarding alternate sensing strategies under time and resource availability constraints. A SMF has to handle the overwhelming amount of information collected and adapt to the highly dynamic environments, in addition to network and system limitations. Accordingly, designing an intelligent autonomous SMF is a complex challenge.

1.2 Objective

This work aspires to design intelligent management strategies for large area sensor networks, and to develop decision-making techniques that will mitigate SM under power and resource constraints. An intelligent SMF is sought as the main objective of this work which will address the following issues:

- **Lack of SM standardization:** conceptual analysis of the SM problem is needed to avoid test-bed specific solutions that are hard to extend or reuse.

- **Surveillance over a large area:** The need for large area sensor networks has been recognized in numerous applications. These applications are characterized by large and remote geographic areas, which need large numbers of sensor nodes to cover the VOI.

- **Energy-aware Operation:** Sensor nodes are usually battery-operated and the replenishment of their energy reserve is usually not feasible. Therefore, the lifetime of sensors must be prolonged as much as possible without degrading the system performance.

- **Cooperative multi-sensor management:** The world model of a multi-sensor system can be significantly enhanced with cooperative sensing in applications where the environment dynamics rapidly changes.

1.3 Contribution

This work proposes an intelligent SMF for managing a pervasive system in a surveillance context. The proposed SMF significantly enhances the process of information gathering by coordinating the sensing resources in order to collect the most complete data from a dynamic scene while operating under energy constraints. The proposed SMF addresses the problem of SM from both an organizational paradigm, as well as, local and collaborative decision making strategies. This thesis investigates the SM problem in eight essential folds:

- **Organizational Design Framework:** This work provides a conceptual analysis of the SM problem in a layer structure and introduces an organizational design framework based on the service-oriented architecture to address the requirements of SMF from a stacked layer perspective. The proposed framework addresses the large number of non-functional merits, *e.g.*, modularity, extendibility, and the reusability, to name a few, that can characterize SMFs.

- **Coordination Architecture:** The architecture proposed in this work combines the operation of the holonic, federated, and market-based architectures in a complementary manner. The proposed approach aims to guarantee the scalability, extendibility, and reliability of the proposed SMF.

- **Energy-aware Operation:** Unattended sensor networks suffer from limited battery resources; hence, the battery lifetime of the sensor node1s must be increased as much as possible. This work proposes an energy-aware approach to minimize the power dissipation while maximizing the quality of surveillance.

- **Sensor Utility Modelling:** Each sensor is responsible for independent reasoning and decision-making that affects its state and the overall system state. Every decision-making process produces a final choice; the collective outcome of these decisions affects the system function in its entirety. This work proposes an energy-aware team-theoretic formulation using the Belief-Desire-Intention model and the Joint Intention theory that represents the hybrid architecture components.

- **Adaptive Sensor Behaviour:** This work proposes intelligent schemes to adapt the sensor setting to the changes in environment dynamics and sensor health. Such schemes include adaptive sleep, active sensing, dynamic sensing range, adaptive multimodality, and constrained communication, all are designed to operate under resource limitation constraints.

- **Collaborative Decision-theoretic Modelling:** SM can be viewed as a decision-making process that determines the most appropriate action to perform in order to achieve maximum utility. The decision-making entities need to be able to operate under uncertainty in a stochastic changing environment. Thus, this work formulates the decision-making entities as Partially Observable Markov Decision Processes (POMDP).

- **Source Reliability Considerations:** The quality and accuracy of sensor measurements may vary between different sensors, due to several factors that include: relative sensor location, noise, transducers type, partial or full occlusion, *etc.* The information fusion research field has studied the source reliability as a strategy to represent the credibility of the information acquired from different sensors. This work proposes a light-weight heuristic approach for estimating the reliability coefficients of the sensor sources that include the impact of sensor settings and estimated environment dynamics.

- **Integrated System:** In this work, an intelligent surveillance system (IntelliSurv) is introduced that automatically detects and localizes abnormal events in a distributed collaborative manner. The IntelliSurv system is built using the proposed SMF and helps illustrate the performance of the SMF in operation with different independent modules.

This thesis maintains that by the use of intelligent sensor management strategies in a collaborative manner over a distributed localized structure with consideration to resource and energy constraints, it is possible to achieve a power-efficient large area surveillance system built using low-cost resource-bounded networks under mission-critical constraints.

1.4 Organization

This thesis is organized as follows: Chapter 2 provides a comprehensive background to SM problem from the perspective of pervasive surveillance. A generic multi-layered design framework for SM is devised in Chapter 3. Chapter 4 proposes the Extended Hybrid Architecture for Sensor Management (E-HASM) describing its design details and discussing its performance. An energy-aware team-theoretic formulation using the Belief-Desire-Intention model that represents the hybrid architecture components is proposed in Chapter 5. In Chapter 6, a collaborative decision-theoretic SM algorithm based on sequential decision-making is designed. Chapter 7 introduces an intelligent surveillance system (IntelliSurv) that automatically detects and localizes abnormal events in a distributed collaborative manner managed by the proposed SMF. Finally, the conclusion and future work is presented in Chapter 8.

Chapter 2

Background and Literature Review

This chapter provides an introduction to pervasive surveillance systems and discusses the needs and challenges of designing an intelligent sensor management framework for such systems. Moreover, a literature survey of the state-of-the-art sensor management strategies is reviewed in this chapter. The chapter is organized as follows: a brief introduction of pervasive surveillance and its applications is given in Section 2.1. In Section 2.2, sensor management, its properties and challenges are discussed. Section 2.3 introduces a taxonomy of the various SMF features and components and surveys the state-of-the-art SMFs proposed in literature. Finally, Section 2.4 provides some concluding remarks for the chapter.

2.1 Introduction

Recent world events have amplified the need for enhanced security against natural and man-made threats. Recognizing that modern society faces new types of threats, the concept of surveillance has endured major transformation to be able to address attacks that are directed against civilians and infrastructures. As a result, our security measures have to go through a paradigm shift from being centralized and investigative to being distributed and preventative. This global need has instigated significant research efforts, both academic and industrial, so as to bring about solutions that can effectively address today's security threats.

Traditional surveillance systems have been used as an integral component in addressing a wide range of security threats. From a security stand point, surveillance is the process of monitoring and interpreting the behaviour of objects within a VOI to construct a complete picture of the situation [2]. It involves reliable data collection and analysis, followed by a rapid dissemination of the findings. These findings are used to direct proper resources to investigate the event so as to address it and to develop strategies for preventing such events from happening in the future. Throughout the last decade, digital surveillance systems have provided the infrastructure to collect, store, and distribute data, while leaving the task of threat detection exclusively to security experts. Human monitoring and analysis of surveillance data is a labor-intensive chore. The ability to hold attention and to react to rarely occurring events is an extremely demanding task. Furthermore, this task is prone to human errors due to lapses in attention and subjectivity of the human decision-making.

The nature, complexity, extent, and spread of the security threats our society has witnessed in the recent years have made it clear that smart surveillance constitutes the most effective cure as it presents a conducive framework for seamless interaction between preventative capabilities and investigative protocols [2, 3]. Smart surveillance adopts automatic data analysis technologies to transform system observations into situation-aware knowledge that is actionable [4]. However, it should be noted that smart surveillance systems are decision support systems, thus, the final decision-maker must be a security expert.

The need for smart surveillance systems is equally recognized in homeland defence and homeland security as well as applications such as public safety, health monitoring, disaster area monitoring, reserve and wildlife monitoring, natural disasters warning, and facility surveillance, just to name a few. These mission-critical applications tend to spread over large geographical areas, and hence, may require remote monitoring. To meet the challenges of all these applications, a surveillance system must exhibit capabilities such as heterogeneity, self-organized behaviour, multi-modal information fusion, and collaborative resource control and management. Thus, Smart surveillance systems must possess pervasive capabilities.

2.1.1 Pervasive Surveillance Systems

The latest advances in wireless communication and electronics have enabled the development of low-cost low-power multi-functional sensors that exploit a physical phenomenon to provide data about the state of the environment. These tiny resourceful sensors have instigated the concept of wireless sensor networks [6–9]. A Wireless Sensor Network (WSN) is a collection of spatially distributed autonomous sensor nodes that communicate with each other by forming a multi-hop radio network while maintaining connectivity in a decentralized manner to cooperatively monitor physical or environmental conditions, *e.g.*, temperature, sound, pressure, and/or motion [10].

Under the surveillance umbrella lie many applications that are mission-critical, time-sensitive, and distributed over large geographical areas: crisis management, border control, territory control, transportation and critical infrastructure security, disaster area monitoring, reserve and wildlife monitoring, natural disasters warning, to name a few. Such applications require decentralized intelligent solutions. Hence, the distributed capabilities as well as the increased sophistication of the sensor nodes make the WSNs a suitable match for surveillance applications

Pervasive systems are the next-generation of distributed sensor networks. They are composed of a heterogeneous collection of fixed and mobile sensor nodes, in which the nodes are small and often embedded as part of a larger system. Pervasive surveillance can be defined as the active monitoring of recognized targets as they move through a large monitored area using a network of sensors [11]. Each individual sensor has a partial view of the environment, but collectively the network monitors the entire VOI. Pervasive surveillance systems monitor ongoing and emerging patterns relevant to abnormal behaviour.

Pervasive surveillance systems deal with situations that are characterized by a high density of targets, stochastic environments, and dynamic threats, which results in large amounts of data to be processed. This has pushed the information acquisition problem far from what can be handled by a single sensor. Hence, pervasive surveillance systems need to exhibit capabilities such as collaborative control, intelligent data handling, and adaptive resource management to address the mission-critical application requirements. These capabilities provide additional challenges and complexities in designing pervasive surveillance systems. As a result, the research community has dedicated great efforts in the development of intelligent sensor management approaches to increase the effective utilization of sensor resources.

2.1.2 Pervasive Surveillance Applications

Smart pervasive surveillance systems were first used by military forces in homeland defence applications. The homeland security domain was the first to follow in the footsteps of military applications in adopting such systems. To date, the homeland defence and homeland security applications together form the majority share of the pervasive surveillance market. However, the last decade has witnessed the emergence of many smart surveillance applications. As pervasive systems become an affordable technology, different application domains have originated, as shown in Figure 2.1. For smart sensor applications, the open world market for non-military sensors was expected to grow from US $32.5 billion in 1998 to US $ 50.6 billion in 2008 [12].

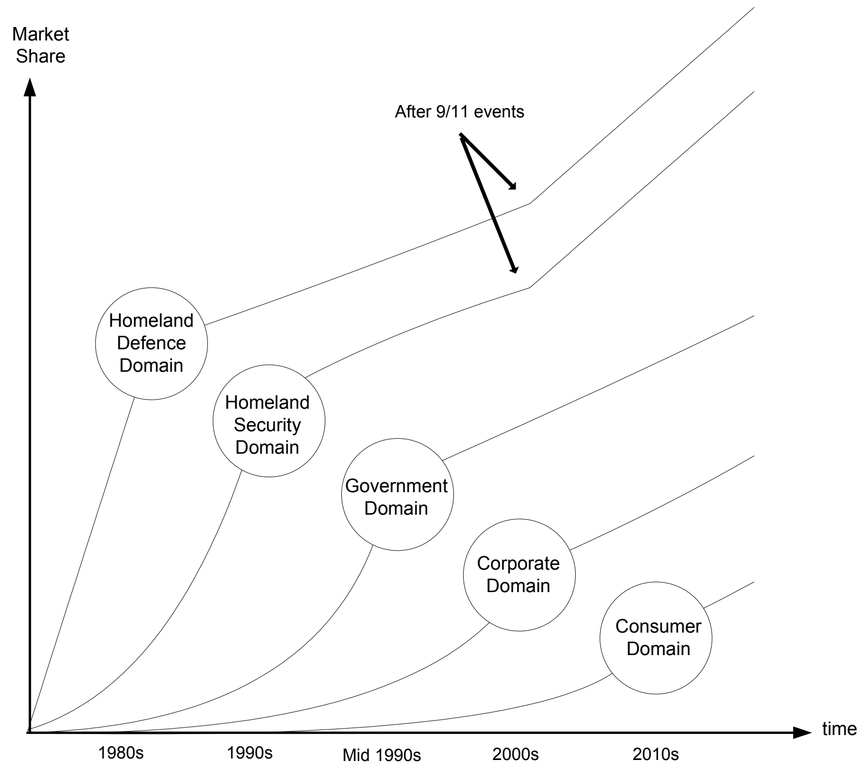


Figure 2.1: The evolution of pervasive surveillance application domain.

Figure 2.2 shows a basic categorization of pervasive surveillance applications. The largest application domain is the homeland defence domain, which includes battlefield monitoring, army base security, and air force and navy surveillance applications, just to name a few. After the end of the cold war, the homeland security paradigm started being formulated as a separate national defence [13]. Applications like crisis management, border security, and territory control are suitable candidates for the use of pervasive surveillance. Subsequent to the 9/11 events, both the homeland defence and homeland security domains have increasingly invested in the development and deployment of smart pervasive surveillance systems to address emerging asymmetric threats [13]. In addition to homeland security programs that are designed to strengthen security along national borders, the growth of this domain is further fuelled by the increased concern over the effects of *"crime on economy"* [14]. In the mid 1990s, government applications such as environmental monitoring, historic sites and artifacts monitoring, and health monitoring have rapidly gained popularity.

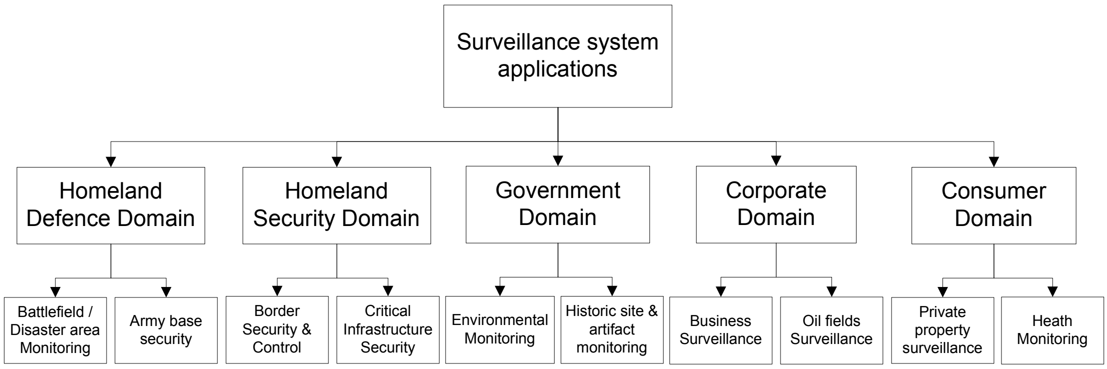


Figure 2.2: Classification of the pervasive surveillance applications according to the application domains.

In the 2000s, big corporations, such as oil and gas companies, have begun to demonstrate interest in pervasive surveillance systems to enhance security of their businesses. Eventually, the advancement in sensor technology has led smart surveillance to be affordable enough to be used for consumer and personal applications. Although these applications still have small market share, smart surveillance systems can play an important role in many aspects of consumers' lives, for example, pervasive surveillance of private properties is an emerging field of application. Wireless operators in North America have already started to provide smart pervasive surveillance services in the form of home security systems.

2.2 Sensor Management (SM)

Pervasive surveillance applications may use hundreds, even thousands, of sensor nodes forming large sensor networks. Sensor networks need intelligent sensor management systems to coordinate the large number of sensor nodes and the large volume of data to produce relevant information that can assist in the process of decision-making. In general, the world model of a multi-sensor system is only as good as the sensors that perceive it and the intelligence that processes it. Single sensor systems provide partial information on the state of the environment. To improve the quality of information about the state of the environment, various sensors have to cooperate and form a multi-sensor system to provide a global view of the surrounding environment. Multi-sensor systems rely on data fusion techniques to combine related data from different sensors to obtain better perception that is then synthesized into situation-awareness. The goal of a multi-sensor system is to provide a synergistic effect that enhances the quality and availability of information about the state of the VOI over that which would be acquired solely from one sensor.

Sensor Management (SM) refers to the process that controls and coordinates the use of the sensory suites in a manner that synergistically maximizes the success rate of the system in achieving its missions. The sensor manager is expected to take decisions that derive the performance of the whole system to reach its objectives. Efficient SM can significantly enhance the process of information gathering by automatically allocating, controlling, and coordinating the sensing resources [15]. SM aims to assess the situation in a timely, reliable, and accurate manner in order to collect complete, relevant, and precise data from a dynamic scene. The criticality of surveillance applications makes intelligent management of sensory systems a necessity due to the need to deal with the high time-sensitivity, large amount of information, and limited resources in these applications. Efficient management of multi-sensor systems is, however, a challenging task due to the spatially distributed nature of the network and the scarcity of the energy and processing resources.

2.2.1 Sensor Management and Data Fusion

Data fusion is the integration of information from multiple sources to produce specific and unified data about an entry. In other words, data fusion techniques combine measurements from multiple sensors, and related information from associated databases, to achieve improved accuracy of data over that achieved by the use of a single sensor. As such, data fusion should be coupled with techniques for smart planning and management of system resources in order to make best use of these assets [16, 17]. Sensor management can aid the information gathering and fusion processes by automatically allocating, controlling, and coordinating sensing and processing resources to synergistically achieve better situation-awareness.

Data fusion researchers are well aware of the correlation between SM and data fusion concepts. The most popular data fusion processing model, Joint Directors of Laboratories (JDL), introduces sensor management as a part of the data fusion process [18], as shown in Figure 2.3. The JDL model differentiates the fusion functions into various levels. The work in [1] has extended the functionality of the JDL data fusion model to address the sensor management problem in the Process Refinement level (level 4). The definitions of the revised JDL model levels, as described in [1], are:

- Level 0 - Sub-object assessment: estimation and prediction of object-observable states on the basis of pixel/signal-level data association and characterization.

- Level 1- Object assessment: estimation and prediction of entity states on the basis of inferences from observations.
- Level 2 - Situation assessment: estimation and prediction of entity states on the basis of inferred relations among entities.
- Level 3 - Impact assessment: estimation and prediction of effects on situations of planned or estimated/predicted actions by the participants (e.g., assessing susceptibilities and vulnerabilities to predicted threat actions).
- Level 4 - Process refinement (an element of SM): adaptive data acquisition and processing to support mission objectives.

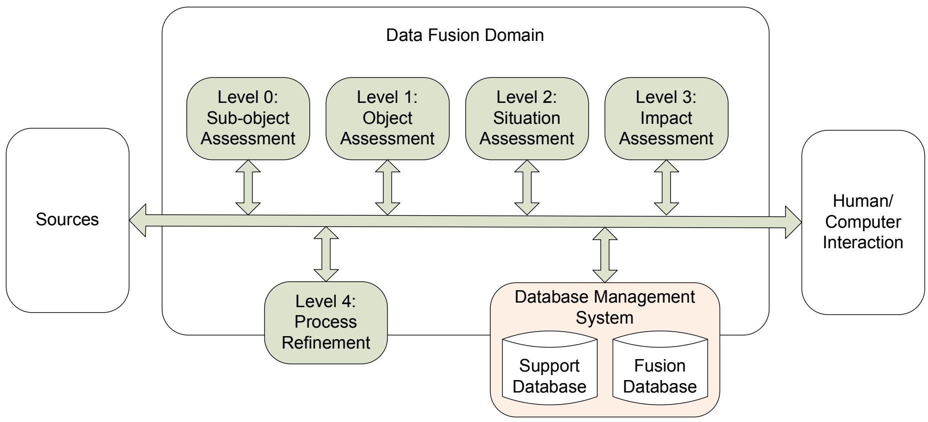


Figure 2.3: The Revised JDL Data Fusion Model [1].

SM provides feedback from the data fusion process to tune the sensor operations, thus, representing the data fusion process as a closed-loop feedback structure [16]. The sensor management on level 4 uses information from levels 0-3 to plan future sensor actions, hence, improving the data collection process. Timeliness of the management feedback is a necessary requirement for rapid adaptation to environment dynamics, that is to say, a prompt decision on sensor functions has to be made before a change in the tactical situation has made such a decision obsolete [16]. However, since sensor management problem is an exhaustive one, the revised JDL data fusion model does not offer a complete solution for such a complicated task. Similarly, other data fusion models, *e.g.*, decentralized data fusion [19], Omnibus [20], and perceptual reasoning [21], have attempted to embed sensor management into their models.

2.2.2 Sensor Management Frameworks (SMF)

To address the challenges of SM, numerous researchers have directed their efforts into the development of sensor management frameworks. A Sensor Management Framework (SMF) is the organizational control system which seeks to manage and coordinate the use of sensing resources in a manner that improves the process of situational awareness, synergistically [5]. A SMF has to handle the overwhelming amount of information collected and adapt to highly dynamic environments under network and system limitations. The collective performance of individual sensors dictates the performance of the whole system. Accordingly, the SMF determines the overall performance and capabilities of the system.

A SMF aspires to provide an optimum sensor configuration based on predicted system performance [22]. The SMF must allocate the available sensors to the tasks that maximize the effectiveness of the whole sensing process while reducing the workload on the human operator. Moreover, the SMF should result in a highly sensitive and self-calibrating system that compensates for sensor non-linearities, thus maximizing the information acquisition process. Furthermore, the SMF manages the sensor network to rationalize the power consumption and the data link usage to increase system lifetime and throughput. Hence, SMFs aim to provide an intelligent system control that leads to low-cost high resolution sensor data and high reasoning capabilities. Many research projects have proposed various SMFs as a standalone approach to address the SM problem [15, 23, 24]. However, the performance comparison between these SMFs is a difficult task due to the lack of a unified range of non-functional merits that are strived for in the design of the SMF.

2.2.3 SMF Non-Functional Merits

The SMF non-functional merits are the desirable features and properties that characterize a system. These features have to be accounted for in the different design phases of the SMF system. Figure 2.4 offers a basic taxonomy for the SMF non-functional merits. The taxonomy is based on the design concept in which such merits are incorporated into the system. The design process of a SMF can be divided into three main categories; design for architecture, design for development, and design for deployment. To establish a unified perception, the following lists the different categories, the associated non-functional merits and their definitions from a pervasive surveillance perspective:

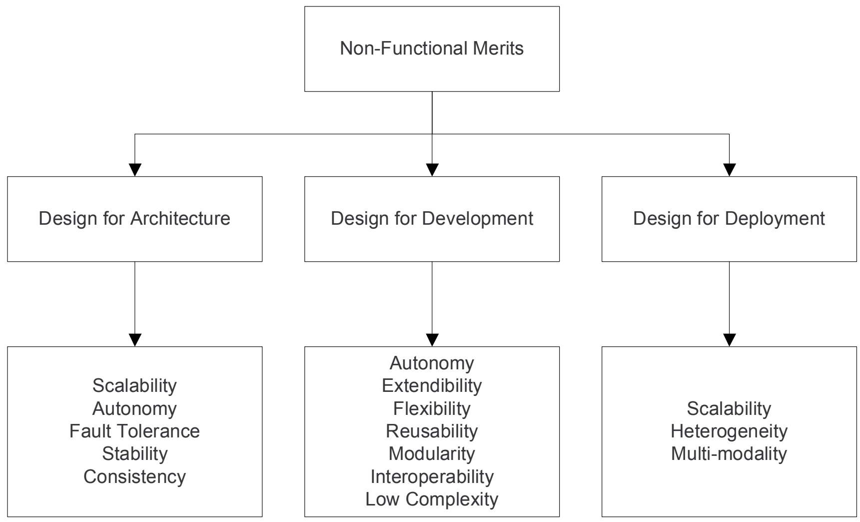


Figure 2.4: The proposed non-functional merits taxonomy.

2.2.3.1 Design for Architecture

Design for architecture is a phase where the specification of the system topology and communications network are identified and defined. The associated non-functional merits include:

- **Scalability:** a desirable property of a system, a network, or a process, which indicates its ability to either handle growing amounts of work in a graceful manner or to be readily expanded. It is an important feature in surveillance applications due to the size and scope of such systems. From a network point-of-view, a scalable system has to be well designed to take into consideration the implications of an increasing number of sensors. Such implications can be in the form of increased power consumption and communication overhead due to congestion and collision. Larger numbers of sensors means increased management complexity, as well as a more complex programming model. Other issues like efficiency, security, throughput, and latency between nodes are trade offs on the size of the system.

- **Autonomy:** having the power of self-governance. An autonomous agent is an agent which can perform desired tasks in unstructured environments without continuous human guidance. Autonomy is a new trend used in surveillance applications as a result of the need to address emerging types of threats. Autonomous agents collaborate by deploying a communication network between them. Computational complexity, communication overhead, and decision optimality are issues that impact the system autonumy.

- **Fault tolerance:** the property that enables a system to continue operating properly in the event of the failure of some of its components. Surveillance applications have to be highly fault tolerant due to their safety-critical nature. One of the basic ways to achieve fault tolerance in networking is through redundancy, however, issues like cost, efficiency, and system utilization have to be taken into consideration.

- **Stability:** the property of the system to operate with consistent performance over time with no changes made to the system. It is vital for surveillance applications to be stable because they are expected to run with consistent performance for long periods of time. Design for stability comes early on in the design for architecture phase. It also affects the choices of network hardware as well as the network protocols deployed.

- **Consistency:** the property whereby information and decisions are to be compatible with system information reservoirs and system objectives and goals. In applications such as pervasive surveillance, the integrity of the information is essential to the performance of the system since inaccurate information may result in failure to detect threats. Sensor measurements are collected and aggregated over the network. Reliable communication, time synchronization, as well as, localization are important aspects to guarantee the integrity and correctness of information.

2.2.3.2 Design for Development

Design for development is a phase related to the implementation issues and the choice of the network protocols and software development. The associated non-functional merits include:

- **Extendibility:** is a system design principle where the implementation takes into consideration future growth. It is a systemic measure of the ability to extend a system and the level of effort required to implement the extension. System extendibility is considered in the design for development phase. It is a desirable feature from the software design point-of-view for surveillance applications since the nature of possible threats is ever-changing. In recent years, the importance of extendable systems has become more apparent as more functionalities may be added to the system to address new types of threats.

- **Flexibility:** is the ability of a system to respond to potential internal or external changes in a timely and cost-effective manner. Flexibility is considered in the design for development phase and, from the software design point-of-view, it is an advantageous feature to incorporate in surveillance applications due to the dynamic nature of their environment. Wireless networks have the advantage of being flexible systems that adapt to environmental changes by route discovery and network reconfiguration.

- **Reusability:** is the property that indicates that the majority of the objects can be reused for various kinds of applications. Reusability is considered in the design for development phase. From the software design point-of-view, reusability is a desirable feature for surveillance applications, especially in the private sector, because it may save a significant amount of time and money in developing other applications.

- **Modularity:** is an approach that subdivides a system into smaller parts, *i.e.*, modules, that can be independently created and then used in different systems to derive multiple functionalities. Besides reduction in cost, due to less customization and high flexibility in design, modularity offers benefits such as augmentation and exclusion. Modularity is a desirable feature from the software design point-of-view and also provides good programming practice. Although, modularity is not a necessity in the design of surveillance applications, it can become beneficial in such applications due to their need to change and adapt to face the ever-changing threats.

- **Interoperability:** is a property referring to the ability of diverse systems and organizations to work together. Moreover, it is the ability of systems to provide services to and accept services from other systems, and to use the services exchanged to enable them to operate effectively together. The lack of interoperability can be a consequence of a lack of attention to standardization during the design of a system. Similar to modularity and reusability, interoperability is a desired feature but not a necessity in the development of surveillance applications.

- **Low complexity:** is the property that is concerned with the amount of resources required to run algorithms. Due to the nature of surveillance applications, efficient algorithms need to be used to reduce the power consumption of the battery-operated sensor nodes as well as the processing time.

2.2.3.3 Design for Deployment

Design for deployment is for specification of the system components, functional organization, and configuration. The associated non-functional merits include:

- **Heterogeneity:** is the property of the system to support static and mobile sensors. Static sensors are the most popular type of sensors in the surveillance applications. However, the deployment of mobile sensors have received increased attention in recent years. Nevertheless, mobility adds new challenges from network points-of-view, such as, localization, link breakage, handoff management, routing and tunneling.

- **Multi-modality:** is the property of the system to support different types of sensors, *e.g.*, , infrared, ultrasound, video. Surveillance applications usually utilize variety of sensors to best capture the scene in the VOI. The ability of different sensors to communication will increase the accuracy for the data fusion process, however, issues like compatibility and standardization should be taken into consideration.

- **Other merits:** like availability, reliability, and support of wide range of applications.

2.2.4 Challenges of Sensor Management

There is a number of issues that make sensor management a challenging task. The majority of these issues arise from the limited resources versus application requirements. Achieving efficient SM is a challenge due to the following:

- **System dimensionality:** Designing a system that manages hundreds to thousands of sensor nodes is, in itself, a complicated problem. The large number of sensor nodes results in a large number of sensory measurements. A SMF must be able to handle the overwhelming volume of information which must be processed and filtered to derive situation-aware knowledge.

- **Wireless technologies:** The spatially distributed nature of pervasive surveillance applications results in the use of wireless technologies. These technologies introduce a set of new challenges, *e.g.*, coping with dynamic and uncertain environments, limited network resources, and addressing information relay capability and reliability.

- **Sensor node limitations:** Sensor nodes suffer from limited capabilities as a corollary to the use of wireless technologies. Thus, SMF has to address the limited individual sensor capabilities such as, processing power, storage capabilities, battery lifetime, in addition to coping with individual sensor failure.

- **System tasks:** Due to the increasing demand for high reasoning operations, SM solutions are expected to exhibit intelligent behaviour and provide an efficient decision support. Accordingly, implementations of SMFs have to perform numerous functional tasks autonomously and simultaneously, *e.g.*, task allocation, scheduling, conflict detection, and cooperation, *etc.*

- **Intelligent operations:** the system is expected to provide an intelligent decision support to the human in the loop. Decision support algorithms highly depend on the quality of information provided by the data fusion algorithm. A SMF has to manage and improve the data fusion capabilities of the system. However, the need to reduce the data link utilization causes the data fusion and processing of information to take place onboard the sensor.

- **Operation timeliness:** Intelligent SMFs are usually used in mission-critical applications. Such mission-critical applications dictate timely response to environmental stimuli, thus, providing fast adaptation to environment changes which is a necessary requirement for the feedback management of sensors.

- **Network efficiency:** The conflicting requirements for low-cost sensors that have high resolution and accuracy creates new challenges for the sensor management framework. The SMF is expected to compensate for the non-linearities in the sensed data and maximize the information acquisition process and its accuracy.

- **Network dynamism:** As a result of the time-varying wireless link, as well as, the hostile environment, WSNs are characterized with being highly dynamic. Moreover, sensor node mobility adds another dimension to the network dynamism.

2.2.5 Network Considerations and Issues

Despite the numerous applications of WSNs, these networks have several restrictions, e.g. limited energy supply, limited computing power, and limited bandwidth of the wireless links connecting sensor nodes. When designing a WSN, there are several practical network factors that need to be considered:

- **Hardware Constraints:** A sensor node comprises four main components; a sensing unit, a processing unit, a transceiver unit, and a power unit. Additional application-dependent components such as a location finding system, power generator, and mobilizer, can also be included in a sensor. Since sensors are usually battery-operated, their power units may be supported by power scavenging units, *e.g.*, solar cells. Furthermore, limitations on the size of the sensors and their circuits add new challenges to the design of sensor nodes. Sensor nodes have some other stringent constraints in terms of power and processing capabilities. Sensor networks operate under extreme low power, high volumetric densities constraints and should have low production cost, be dispensable, operate unattended in an autonomous manner, and be adaptive to the environment. The choice of the sensor hardware defines the capabilities, functionalities, as well as lifetime of the sensor network.

- **Production Costs:** Since WSNs consist of a large number of sensor nodes, the cost of a single node is important to justify the overall cost of the network. As a result, the cost of each sensor node has to be kept low while addressing the increased need for high resolution, low power small-sized sensors.

- **Sensor Network Topology:** Large number of nodes (hundreds to thousands) are deployed throughout a field within tens of meters of each other [8]. Deploying a large number of sensor nodes in high density requires careful handling of topology maintenance. Topology maintenance can be divided into three phases:

  - Predeployment and deployment phase: Sensor nodes can be either thrown in as a mass or placed one by one in the sensor field. They can be deployed by dropping from a plane, delivered in an artillery shell, rocket, or missile, or placed one-by-one by either a human or a robot.
  - Post-deployment phase: After deployment, topology changes may occur as a result of changes in the sensor position, reachability, available energy, or malfunctioning.
  - Redeployment of additional nodes phase: Additional sensor nodes can be redeployed at any time to replace malfunctioning nodes or due to changes in task dynamics.

  Consequently, WSNs has to adapt efficient network configuration and route recovery, as well as, techniques to guarantee information integrity and consistency over the network in case of any failure.

- **Environment:** Sensors are deployed in a dense manner that usually results nodes that are in-close proximity to phenomena of interest. WSN applications usually cover large geographic areas that are remote, thus the sensors have to operate unattended. Pervasive surveillance applications are characterized by extreme environments that provides additional demands on the WSNs.

- **Power Consumption:**

  Wireless sensor nodes are equipped by batteries and operate on limited energy budgets where replenishment of power resources might not be feasible [6]. When a sensor node energy is depleted or falls below a certain threshold, the sensor will fail to monitor and communicate any abnormal phenomenon in its sensing range. Moreover, each sensor node plays the dual role of data originator and data router forming a multi-hop network. Thus, the drainage of the energy reserve of a sensor node will result in the unavailability of the node monitoring and relaying capabilities and may result in significant topological changes. Hence, power conservation and power management take on additional importance.

2.3 State-of-the-Art Sensor Management Frameworks

Although the SM research field dates back to the early 90s [25–29], it has started to receive increased attention from the research community during the last decade. This is attributed to the changing nature, characteristics, cost, and use of wireless sensors, as well as, the emerging application domains of WSNs. Over the past decade, a number of research projects have provided a study of the SM problem [30–33]. Nevertheless, a truly comprehensive critical study of SM methodologies and design approaches is still absent.

In 2000, Ng et al in [30] provided the first study that focuses on the SM problem as it was understood at the time. In 2003, the work by Feng in [31] provides a short introduction to SMF. Although the work by Hero in [33] provides a recent study to sensor management, it mainly focuses on the combinatorial problem solving techniques in contrast to the work offered in this chapter which provides a comprehensive study to problem solving strategies used in literature as well as studies the various aspects of designing SMFs.

A survey of the state-of-the-art sensor management approaches is provided in this work. This section studies the various features of the SMFs and categorizes the state-of-the-art according to their underlying techniques. Figure 2.5 shows the high-level components that comprise a SMF and its interaction with the environment. Each of these components comprise a module in the SMF that defines the SMF operation, from capturing the data characteristics, to sensors interaction, and decision-making. A detailed taxonomy is presented in Figure 2.6 based on the SMF components and features. Further discussions of the SMF features and their subcategories will be explored in the rest of this section.

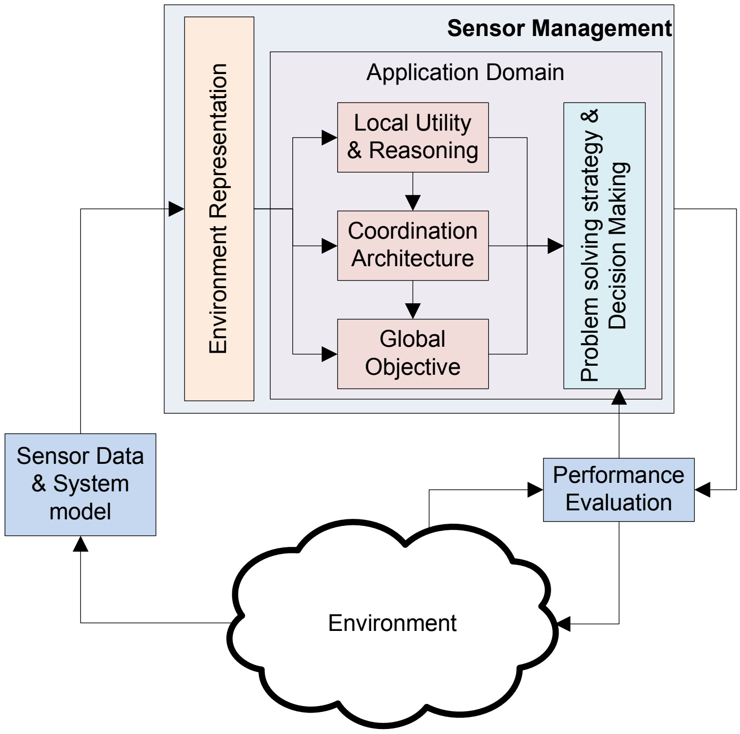


Figure 2.5: SMF high-level component design.

2.3.1 SM Environment Representation

Representing knowledge of the environment is a primary challenge in designing intelligent SM systems. In order to reach a satisfactory level of autonomy, the SM system should be provided with a compact, though effective, method for modeling the environment. There are several ways researchers in the field of sensor management adopted to capture and model the properties of the environment.

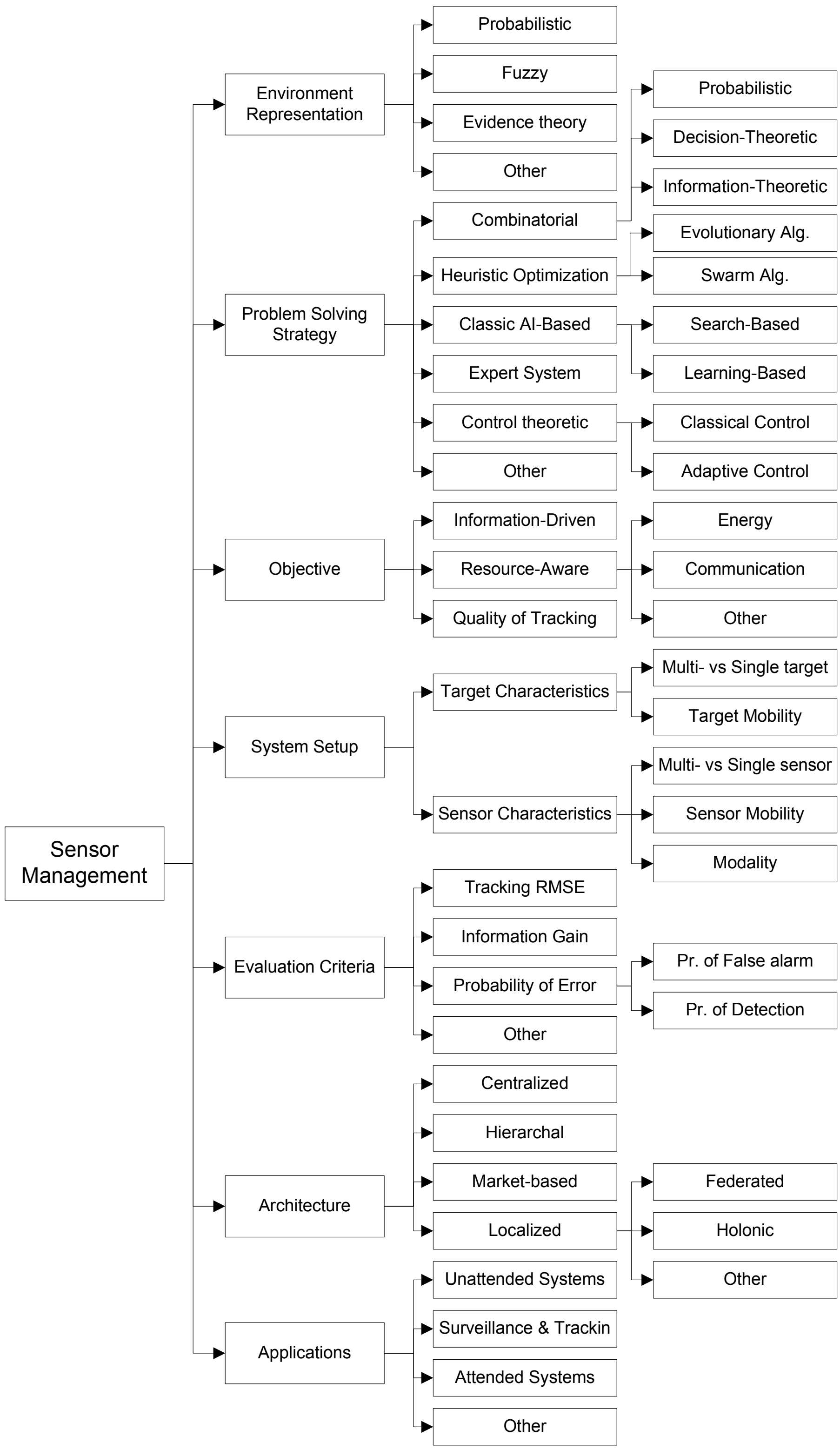


Figure 2.6: The proposed SMF categorization based on their components and features.

2.3.1.1 Probabilistic Representation

The most popular method to model a sensor network environment used is the probabilistic environment representation. This is attributed to the natural characteristics of the environment, *e.g.*, the stochastic occurrence of events, noise in the sensed data, and partial-view of the environment. The work in [34–51] have used various probabilistic methods to capture the uncertainty in environment. One of the most prominent work that used probabilistic environment representation is the work by Kreucher et al. in [42–51] where a Joint Multi-target Probability Density (JMPD) is used. The JMPD is a single probabilistic entity that represents all of the uncertainty about a surveillance region including uncertainty about the number of targets present in the region, as well as the kinematic state, class, and mode of each. The JMPD is computed recursively by fusing measurements, target models, sensor models, and ancillary information over time.

The use of probabilistic environment representation offers high degree of flexibility because it accounts for the credibility and correlation of the experts. Moreover, the probabilistic representation makes it easier for a decision maker to rank alternative options. Nevertheless, it does not help the decision-maker assess the relative importance of imprecision over random uncertainty. Furthermore, the system operates under assumptions of the *Prior* and the *Error* in the estimations which can affect the performance of the system significantly.

2.3.1.2 Fuzzy Representation

In this approach, the environment is represented using principles of Fuzzy logic. Fuzzy logic utilizes the underlying modes of reasoning which are a way of processing data by allowing partial set membership rather than crisp set membership. The importance of fuzzy logic derives from the fact that most modes of human reasoning, and especially common-sense reasoning, are approximate in nature. In fuzzy logic, knowledge is interpreted as a collection of elastic fuzzy constraint on a collection of variables.

Limited attention have been given by the research community to fuzzy environment representation to address the SM problem. However, an interesting work in [52] used fuzzy inference in modeling the environment to evaluate the multi-sensor tasks priority in defence surveillance applications.

2.3.1.3 Evidence-theory and other Representations

A number of research projects have used the principles of evidence theory to model the environment. Shafer's evidence theory is a branch of the mathematics of uncertain reasoning that allows for novel possibilities to be conceived by a decision-maker. Evidence theory does not attempt to formalize the emergence of novelties, but it is a suitable framework for reconstructing the formation of beliefs when novelties appear.

The evidence theory approach does not require the user to assume anything beyond what that is already available. This approach treats uncertainty due to imprecision differently than uncertainty due to randomness. Evidence theory yields maximum and minimum bounds of the probability of survival and the probability of failure of a system, which can help assess the relative importance of the two types of uncertainty. These results could help a decision-maker decide if it is worth collecting additional data to reduce imprecision. On the other hand, if the gap between maximum and minimum probabilities was large, the decision-maker would have difficulty ranking alternative options. If the decision-maker needs to make an immediate decision, evidence theory does not indicate which option is better. Research work in [53–56] have used evidence theory to establish an environment model for SMFs that can capture the uncertainty and randomness of the environment dynamics.

2.3.2 SM Problem-solving Strategies

SM is a complicated problem; this is attributed to the various limitations of the sensory nodes, the network restrictions, and large number of environmental constraints to be consider. Numerous problem-solving strategies were used in literature to address the SM problem. In this study, the authors categorize the SM problem-solving strategies into six main subcategories; combinatorial, heuristic optimization, classical AI, expert systems, control-theoretic, and other strategies. In the rest of this section, each of these strategies is explored in the context of the related state-of-the-art SMF.

2.3.2.1 Combinatorial Strategies

Combinatorics is "a branch of mathematics concerning the study of finite discrete structures" [57]. The research community has focused significant attention on the use of combinatorics in solving the SM problem. This is due to the natural formulation of the SM problem as a combinatorial one with uncertain parameters and numerous attributes. Combinatorial strategies adopt mathematical techniques, such as probability theory and graph theory, to address the SM problem as discussed in this section.

2.3.2.1.1 Probabilistic Strategies Probabilistic Strategies employ probability theory to study the SM problem. Due to sensing errors, low sensor resolution, lack of sensor calibration, and sensory data noise, sensor information is presented with a degree of uncertainty. This set of strategies take into account the uncertainty nature of SM and derive a set of solutions that aims to deals with such uncertainty.

The most popular probabilistic strategy used is Bayesian networks. A Bayesian network is a probabilistic graphical model that represents a set of random variables and their conditional dependencies via a Directed Acyclic Graph (DAG). This approach has been used in the work presented in [58–65] to address the SM problem. However, the system operates under assumptions of the *Prior* and the *Error* in the estimations which can affect the system performance significantly. Moreover, the use of such techniques may suffer from combinatorial explosion as the size of the problem increase.

An emerging approach used in [66] and [67] is based on the formal theory of Random Finite Sets (RFS), originally proposed by Mahler [68]. Using the mathematical tools of the framework of finite set statistics, Mahler generalized the well-known Bayesian state-space estimation recursions for a single object, to their multi-object counterparts. The RFS framework is completely free of explicit data associations. A RFS is simply a random variable which is random in both the number of elements and the values of the elements themselves. In order to deal with situations where both the number of objects and their positions in the state space are random and unknown, a multi-object state is modelled by a RFS. However, the RFS may become intractable as the size of the problem increases.

2.3.2.1.2 Decision-theoretic Strategies Sensor management can be viewed as a decision-making problem. Numerous researchers have modeled the SM problem as a stochastic decision making one. The most popular decision-making approach, Markov Decision Processes (MDP), provides a mathematical framework for modeling decision-making in situations where outcomes are partly random and partly under the control of a decision maker. MDPs are useful for studying SM coupled with dynamic programming and reinforcement learning. The main drawback of such stochastic approaches is the proposed algorithms may suffer from combinatorial explosion when solving moderate to large size problems.

Research projects such as [34, 35] have applied Markov decision processes as a mechanism for decision-making in SMF. Other work in [36–39] have modeled the SM problem as a Partially Observable Markov Decision Processes, while work in [40] adopted hierarchal MDP in solving the SM problem. A comprehensive study of the formulation of the SM problem as MDP is offered in [41, 69].

2.3.2.1.3 Information-Theoretic Approaches In this strategy, a multi-sensor system is concerned with increasing the amount of information, thereby reducing the amount of uncertainty about the state of the external world. As such, the task of the SMF is to optimize the data acquisition in a manner that maximizes the information obtained whenever a measurement is made. Methods; like Kullback Leibler divergence, Information gain ratio, and other information theory measures, can be used to measure the amount of information gained.

Information-theoretic approaches use probabilistic methods to estimate the future information gain of a sensor measurement. Information-theoretic approaches have received significant attention in the last decade. The most prominent work in this field has been carried by Kastella in [70], Kolba in [71–76], and Kreucher in [42–51]. Also, more recent work has been proposed in [77] which use 3-D noisy projection and object feature extraction to manage the sensor resources in a target tracking mission. However, the information-theoretic approaches can give over-emphasizes on the quality of information on the expense of various network parameters, *e.g.*, energy, bandwidth, network life-time, *etc.*

2.3.2.2 Heuristic Optimization Techniques

Heuristic strategies are experience-based techniques that attempt to solve SM problems using learning and discovery. A heuristic method seeks near-optimal solutions at a reasonable computational cost without being able to guarantee either feasibility or optimality, or the quality of the found solution compared to the optimal solution. Research projects have used heuristic optimization techniques to address difficulty and size of the sensor management problem.

The most popular heuristic optimization techniques are genetic algorithms and swarm optimization. Genetic algorithms are search heuristics that mimics the process of natural evolution and have been used to address the SM problem in [11, 54, 78]. Also, swarm optimization belongs to the class of direct search methods used to find an optimal solution to an objective function in a search space. Particle swarm optimization is one of the most popular fields of swarm optimization [79, 80]. Many research studies have tried to address SM by using particle swarm optimization techniques [23, 81, 82]. The heuristic optimization techniques are computationally expensive to evaluate onboard of the sensor due to its limited processing resources and limited power supply. An off-line estimation approaches have been used, however, it decreases from the system overall optimality and the quality of solution is dependent on the training data.

2.3.2.3 AI-based Strategies

Various AI-based strategies were attempted to solve the sensor management problem, notably search-based and learning

2.3.2.3.1 Search-based Strategies Many problems in AI can be solved, in theory, by intelligently searching through many possible solutions. In other words, reasoning can be reduced to performing a search through the solution-space. However, simple exhaustive searches are rarely feasible for most real world problems; the search space can quickly grow to astronomical numbers. This leads to a search that is too slow or never completes. The solution, for many problems, is to use "heuristics" or "rules of thumb" that eliminate choices that are unlikely to lead to the goal, *e.g.*, pruning the search tree. The work in [83, 84] have employed search-based techniques to address the SM problem. These techniques are computationally expensive even for small sized problems. Hence, search-based techniques may drain the sensor resources and lack fast adaptation to environment stimuli.

2.3.2.3.2 Learning-based Strategies are a set of algorithms that allow computers to evolve behaviours based on empirical data, such as from sensor measurements or databases. A system can take advantage of data examples to capture characteristics of interest and their unknown underlying probability distribution. Data can be seen as examples that illustrate relations between observed variables. Learning-based strategies aim to automatically learn to recognize complex patterns and make intelligent decisions based on available data. However, the difficulty lies in the fact that the set of all possible behaviours given all possible inputs is too large to be covered by the set of observed training data. Research work in [60, 85, 86] have adopted various learning techniques to increase the system ability to gather experience through interactions within the environment. Issues like the online versus offline learning and the size of data sets add limitations to the system performance and stability.

2.3.2.4 Expert Systems

An expert system emulates the decision-making ability of a human expert. Expert systems are designed to solve complex problems by utilizing and reasoning about knowledge provided from an expert. Designing SMFs using such strategy is a widely popular approach for SM, especially in military applications. Research projects based on this approach include [87–94]. However, this approach is the least flexible or reusable of those studied here as it is highly application and platform dependent.

2.3.2.5 Control-Based Approaches

Control-based approaches are the algorithms that define the aggregate of responses to internal and external stimuli. These approaches can either be classical or adaptive control architecture implemented to address a specific problem in a known context. The classical architecture provide a rigid control to the sensor management problem with no feedback from the environment. However, the adaptive control architectures can adjust to various situations autonomously and they mainly depend on a flexible organizational architecture for defining the interactions between the different components of the system and providing a closed-loop feedback from the environment. Work in [5, 15, 95–97] are an example of the control-based SM approaches. Control-based approaches lack intelligent reasoning and are application-specific, thus, lack reusability.

2.3.2.6 Other Problem-solving Strategies

There are number of promising approaches that have been used to address the SM problem in literature, however, these approaches have received limited attention up-to-date.

Game-Theoretic Approaches: Game theory defines strategic interactions among agents to produce outcomes with respect to agents preferences or goals. Game theoretic approaches have been utilized to solve the sensor management problem in [98].

Belief-Desire-Intention Model (BDI): BDI is a software model developed for programming intelligent agents such that each agent has a set of beliefs, desires and intentions. Sensor nodes are modeled as intelligent agents that deliberate about different plans to achieve various goals. The work in [99, 100] have used the concepts of BDI in SM design.

Fuzzy Logic Approaches: Fuzzy logic deals with reasoning that is approximate rather than fixed and exact. SMF based on the concepts of fuzzy logic has been proposed in [52, 101].

2.3.3 SMF Objective

The research community have studied the SM problem with a focus of number of key objectives. These system objectives pave the path for the performance of the SMF. There are three recurrent system objectives that were considered in the design of state-of-the-art SM.

2.3.3.1 Information-Driven

Information-driven SMFs aims to maximize information gain. Such systems refer to choosing the best action for a sensor to take such that the total sensor information is maximized. These actions may include where to point, what mode to use, or where to move. Actions are ranked based on the amount of information expected to be gained from their execution. The information-driven objective has several advantages; the policies that optimize information gain are near universal. They perform nearly as well as task-specific optimal policies for a wide range of tasks, *e.g.*, minimize target tracking MSE, or target misclassification. However, focusing on the information gain only can drain the system resources and decrease the network lifetime.

2.3.3.2 Resource-Aware

Resource management in distributed sensor networks is a challenging problem. This can be attributed to the fundamental trade off between the value of information in a distributed set of measurements versus the cost of acquiring measurements, fusing them, and transmitting the fused data. Numerous research worked on designing SMFs that try optimize energy consumption, communication overhead, as well as, computational overhead, among others.

2.3.3.2.1 Energy Consumption Sensor nodes operate on limited energy budgets where replenishment of power resources might not be possible. When a sensor node energy is depleted or falls below a certain threshold, the sensor will fail to monitor and communicate any abnormal phenomenon in its sensing range. In a multi-hop sensor network, each node plays the dual role of data originator and data router. The drainage of the energy reserve of a sensor node will result in the unavailability of the node monitoring capabilities and may result in significant topological changes. Hence, power conservation and power management take on additional importance. It is for these reasons that researchers are currently focusing on the design of power-aware SM for sensor networks [37, 97, 102–104].

2.3.3.2.2 Communication Overhead A WSN consists of a large number of spatially distributed autonomous sensor nodes that communicate with each other by forming a multi-hop radio network while maintaining connectivity in a decentralized manner. Due to the broadcast nature of WSNs, bandwidth is a scarce resource that needs to be responsibly used. The limited caching of the sensor nodes is another example of a scarce resource that may affect the network performance. The research community attempted to address the network challenges via efficient bandwidth utilization, congestion-awareness, as well as communication overhead reduction [105–108].

2.3.3.3 Application-specific Objectives

Every sensor system can mandate a set of specific objective to be achieved to address the requirements of such application. Cost functions are used to model the application specific objectives. As an example, Quality of Surveillance (QoSv) is a newly used notion in [109] that can evaluate the performance of a surveillance system. QoSv reflects the overall system performance regardless of the WSN coverage.

2.3.4 System Setup

This section studies the different system parameters used in the design as well as the evaluation of the state-of-the-art SMFs. The system setup refers to the model deployed in the design and simulations and/or experimentations phases that are carried to verify the operation of a SM system. The state-of-the-art have studied various system models in the design of SMFs. These models comprise different sensors and targets characteristics, like number of sensors/targets, as well as, their mobility, and modalities to name a few. The work in [36,51,110] have considered the design of a SMF for a multiple mobile sensor system, while research in [34, 35, 39, 84, 111] have adopted a multiple static sensor system. Also, the case of sensor multi-modality has been studied in the work done by Kolba in [110]. Moreover, various target characteristics were studied in literature; the multiple mobile target system was adopted in the SMF design in [39, 51, 84] and the multiple static target has been considered in [111].

2.3.5 Evaluation Merits

In literature, the most popular SMF evaluation metric used in pervasive surveillance applications is the tracking error [39,40,108,112,113] that is presented in the form of Root Mean

Square Error (RMSE). Although the RMSE gives a good indication of the accuracy of the system at hand, however, it fails to reflect the performance of the surveillance system and its management. The normalized root mean square tracking error ($Err_s^k(t)$) is computed by

$$Err_s^k(t) = \frac{\sqrt{E[\ ||\zeta_{pos}^k(t) - Z_s^k|(t)||^2]}}{\zeta_{maxpos}^k(t) - \zeta_{minpos}^k(t)}\ , \tag{2.1}$$

where $\zeta_{pos}^k(t)$ is the actual position of target t at time k and $Z_s^k(t)$ is the observed position of target t by sensor s at time k.

In information-driven systems, the information gain metric is used as a performance indicator. The information gain metric indicates the added value by further sensor measurements using probabilistic distribution divergence such as the Kullback Leibler divergence. The expected value of the information gain is the mutual information I(X;A) of X and A, *i.e.*, the reduction in the entropy of X achieved by learning the state of the random variable A.

Other metrics like the probability of error and misclassification ratio has been used to evaluate the performance of the SMF [111]. Furthermore, SMF-specific cost functions were used in [34, 97] to evaluate the system performance, however, the use of SMF-specific cost function make it hard to compare the performance of the system to the related work.

2.3.6 SMF Coordination Architecture

The architecture of a system defines the organizational behaviour of the nodes that comprise it and the inter-node communications pathways that enable control and flow of data [15]. The coordination design employed by an agent system can have a significant effect on its characteristics and performance. A range of coordination architectures have emerged from research, each with different strengths and weaknesses [114, 115]. This section surveys the popular coordination paradigms in the context of SMFs. The advantages and disadvantages of each are discussed with reflections on the surveillance applications.

2.3.6.1 Centralized Architectures

The centralized strategy typically involves the classical techniques of control theory applied to the analysis and design of small-scale systems [116]. The centralized approach is one of the oldest and most popular techniques used. Significant SMF research efforts have been conducted on centralized approaches [37, 40, 72, 87, 97, 110, 112, 113, 117]. A centralized system is one in which most processing and control overhead are carried over one or more major central nodes. This simple approach allows a cohesive, consistent view of the world, as well as, a central decision node. Figure 2.7 illustrates the centralized architecture.

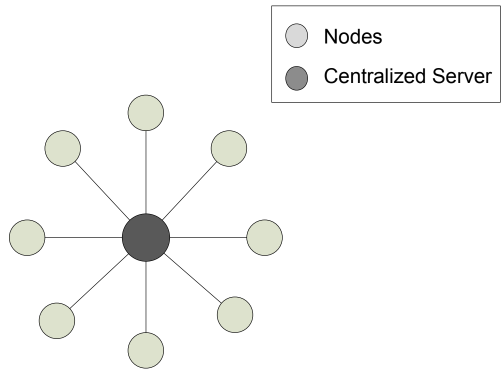


Figure 2.7: Centralized architecture.

Earlier, the centralized approach was the main architecture deployed in the homeland security applications due to its simplicity, consistency in information handling, and single-point decision operation. However, the scale and scope of homeland security applications have grew extensively in recent years. The inability of the centralized architecture to scale well as the control problem grows made it fall short in addressing such critical applications. In particular, when large-scale systems, such as border security and control, are considered, the problem becomes difficult, if not impossible to solve using the techniques of classical centralized control theory. Furthermore, the single-point decision advantage can also be a major disadvantage as it becomes a single-point of failure. The central node can also suffer from congestion and overload and can become a bottleneck to the system.

2.3.6.2 Decentralized Architectures

In a decentralized architecture, there are at least two nodes with two or more paths between them to provide redundant paths forming a mesh topology. The full-mesh topology connects all devices to each other for redundancy and fault tolerance. Full mesh topology provide a high degree of reliability due to the multiple paths for data, as shown in Figure 2.8. In case of link failure, information can flow through other links to reach its destination. In partial mesh topology, at least one devices maintains multiple connections to others without being fully meshed, a partial mesh topology still provide redundancy by having several alternative routes.

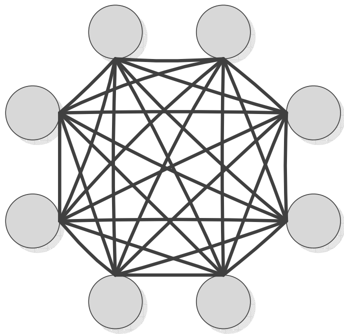


Figure 2.8: Decentralized architecture - full mesh topology.

This decentralization is the main advantage of the mesh topology since it compensates for the single-point failure disadvantage that is present when using a single device as a central node. The number of arbitrary forks in mesh networks makes them more difficult to design and implement, however, their decentralized nature makes them useful. The fully connected mesh topology is generally too costly and complex in terms of communication overhead and management for practical large scale networks. Though, the topology can be efficiently used when there are only a small number of nodes to be interconnected. The decentralized architecture is also unsuitable for the pervasive surveillance problem because of its lack of the necessary structure needed for such mission-critical applications. This makes the decentralized architecture relatively robust because there is little to break, but also makes it difficult to control, which can lead to an undesirable chaotic behaviour.

2.3.6.3 Hierarchical Architectures

The hierarchal architecture is a structured organizational design [118]. Agents are conceptually arranged in a tree-like structure, where each agents in a higher layer in the tree have higher authority over lower agents and have a larger global view than those lower in the tree. The data collected by lower-level nodes travels upwards to the upper layer nodes in the hierarchy, while control flows downward as the higher level agents provide direction to those below. The hierarchy efficiency is derived from this notion of decomposition, such that the divide-and-conquer approach allows the system to be come more scalable by using large number of agents efficiently. Figure 2.9 shows the hierarchal organizational architecture.

In hierarchies, every node is constrained to a number of interactions that are small relative to the total population size. As a result, control actions and decisions commands become more tractable, parallelism between various sub-trees of the hierarchy can be ex-

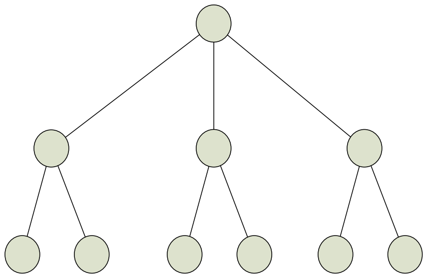


Figure 2.9: Hierarchal architecture.

ploited. However, a hierarchical architecture can also lead to an overly rigid or fragile organization, prone to a single-point of failures with potentially global consequences. Moreover, the hierarchical architecture may suffer from bottleneck effects if not effectively managed. A centralized system is considered a flat hierarchal system. Research projects such as [40] have proposed a hierarchal SMF.

The structured control, as well as, the increased parallelism of the hierarchal architecture makes it a good candidate for the homeland security applications. The hierarchal architecture can scale gracefully for applications like border security and control due to its divide-and-conquer nature. However, being prone to single-point failures is a major disadvantage for using this architecture in such a safety critical applications.

2.3.6.4 Market-based Architectures

The market-based architecture is composed of buying agents, who place bids for items or services of interest, and selling agents. Selling agents are the agents that provide items or services to the market to be sold. Auctioneers are intelligent agents that are responsible for handling the bids and determining the winner. This arrangement creates a producer-consumer system which models and enables real-world market economies. Market architecture is based on the idea of a distinguished individual or group of individuals, *e.g.*, auctioneers, that is responsible for coordinating the activities of a number of other agents. The agents in a market-based architecture are usually competitive and they do not cede operational authority to the auctioneers, however, participants do trust the entities managing the market and abide by decisions they make. Figure 2.10 shows a market-based architecture.

Markets operate typically as an open systems such that agents can participate in the system activities as long as they abide by the system rules and interface. There market-based architectures suffer from several drawbacks. The first is the potential complexity

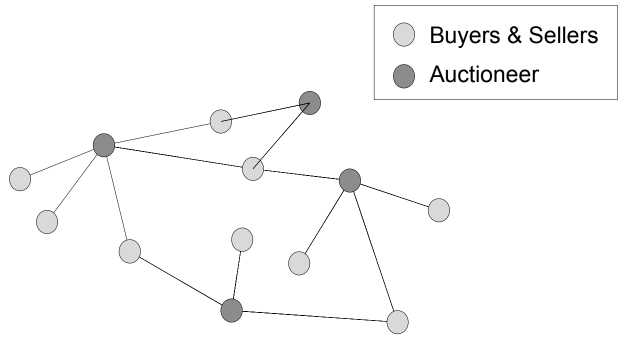


Figure 2.10: Decentralized market-based architecture.

required to both reason about the bidding process and determine the auction outcome as the number of participants increase. The second is the communication overhead incurred as a result of communicating bids. In addition, the security issues inherent in any open system presents a drawback. Moreover, the validity of the auction approach must be verified to avoid collusion. The market-based architectures have been applied to the SM problem in [5, 109].

The market-based architecture is a highly flexible architecture that can be used in various types of applications, thus, it can be a possible candidate for the homeland security applications. Market-based applications can be used in the border security and control application, however, there is a trade of between the number of participants and the system performance and efficiency as the number of participants significantly grows. This is attributed to the auction reasoning complexity and the bids communication overhead.

2.3.6.5 Localized Architectures

These architectures operate in distributed manner where nodes form clusters based on proximity to cooperate.

2.3.6.5.1 Holonic Architectures The holonic architecture is an organizational design that consists of a set of autonomous holons that cooperate to achieve the system objective [119]. Holons are autonomous, self-reliant units that can be a single sensor or a group of sensors. The holonic architecture posses intermediate properties compared to both the decentralized and the hierarchal architectures. The holonic concept was first introduced by Arthur Koestler in [120] as a result of two observations. The first is that simple systems can evolve and grow to satisfy increasingly complex and changing needs by creating stable intermediate forms which are more capable than the initial systems. The second observation is that, in living organisms and social organization, it is generally difficult to distinguish between wholes and parts in an absolute manner; almost every distinguishable element is simultaneously a whole, *i.e.*, an essentially autonomous body, and a part, *i.e.*, an integrated section of a larger, more capable body. These observations inspired Koestler to coin the term "holon" to describe the hybrid nature of sub- wholes/parts in real-life systems. Holon is derived from the Greek word "holos" meaning whole and the suffix "on" implying particle as in proton or neutron. A holon is both a distinct entity built from a collection of subordinates and as part of a larger entity. Figure 2.11 illustrates the holonic architecture.

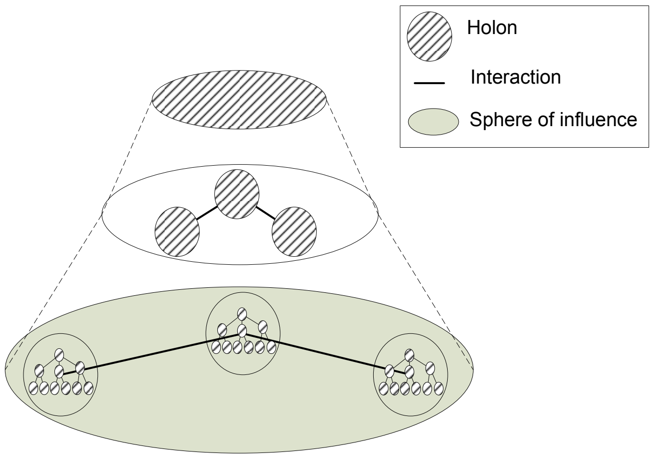


Figure 2.11: Holonic architecture.

The key properties of a holonic system, as developed in Koestler s model [120], are autonomy, cooperation, self-organization, and reconfigurability. Another important holonic concept is the notion of functional decomposition. The complexity of dynamic system can be dealt with by decomposing the system into smaller parts. Thus, recursiveness appears as a consequence of this decomposition, *i.e.*, the idea that holons can contain other holons. Koestler defines a holarchy as a hierarchy of self-regulating holons which are groups of cooperative basic holons and recursive holons that are themselves holarchies. One of the major differences between holons and agents concerns recursiveness. A holon may be composed of other holons, while there is no recursive architecture as such in multi-agent systems. Moreover, holons are cooperative in nature and they cannot be competitive, thus, there is no potential of gaming in a holonic architecture. In a nutshell, the holonic paradigm models different entities of the system as an autonomous holons that work to achieve local objects. Together these holons can cooperatively form a localized holarchies to achieve sub-system or system goals. one of the major disadvantages of the holonic architecture is the lack of predictable system performance due to the increased decomposition. In the recent years, few research projects have considered applying the holonic paradigm to the sensor management problem [15, 22, 78, 121].

Although the application of the holonic architecture as an organizational paradigm is relatively recent, several research work have been directed to design and develop holonic SMF for homeland security applications. [15, 22, 121]. For the border security and control application, holonic architecture can scale seamlessly, moreover, the autonomous agents can cooperate to handle increasing amounts of data. However, the holonic architecture has to be well-designed to avoid the possible chaotic behavior that might result for excessive system decomposition.

2.3.6.5.2 Federated Architectures This organizational style is modelled on the governmental system, where regional provinces retain some amount of local autonomy, while operating under a single central government, *e.g.*, the delegate. The delegate is a distinguished member of the group, sometimes called a facilitator. Delegation members interact only with the delegate, which acts as a facilitator between the member of the delegation and the outside world. As a result, the group is provided with a single, consistent interface. Figure 2.12 demonstrates the federated architecture.

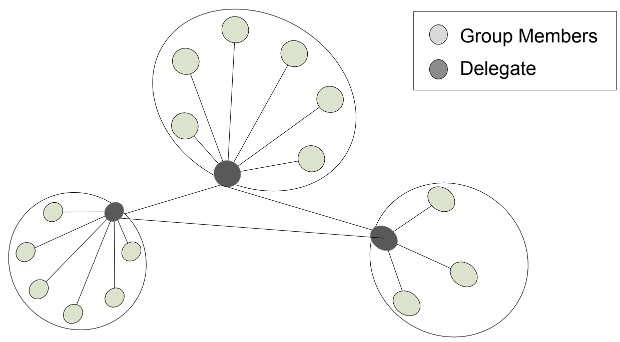


Figure 2.12: Federation architecture.

The delegate must be able to interact with both its local federation members as well as other delegates. The capabilities of the delegate masks the differences between the delegations. As a result, member nodes of a delegation do not require a common language with other system components, as they never directly interact. Thus, a delegate reduces the complexity and messaging burden on the outside world, however, it may suffer from the potential bottleneck problems.

The federated architecture can lend itself to the homeland security applications due to its distributed nature with structured-control. In the border security application, the use of the federated system by deploying an intermediary node allows better system scalability and hides the system complexity from the nodes within a federation. A federated system can be coupled with a cluster-based network topology, thus, utilized the fact that phenomena are usually localized. However, this architecture may suffer from the single-point failure again, nevertheless, in case of the intermediary failure, the architecture suffers only local consequences; a proficiency the hierarchal architecture lacks.

2.3.6.6 Other Architectures

There are number of other architectures that posses characteristics that can be used to address the SM problems.

Coalitions: Coalitions is defined by Horling in [114] as "a flat organizational structure that in general is goal-directed and short-lived". Coalitions are formed agents to cooperate and address a specific purpose. Agents join coalition to maximize their individual gain and the coalition is dissolved when specific goal is achieved or when it fails to address that goal.

Teams: A team architecture comprise of a group or cooperative agents that jointly work to achieve a common goal [114]. In comparison to coalitions, teams attempt to maximize the utility of the team itself, rather than that of the individual members. Within a team, the type and pattern of interactions can be quite arbitrary.

Congregations: Agent congregations are similar to the coalitions and teams in the sense that a group of agents form a typically flat architecture such that additional benefits can be derived by its members [114]. Congregations are long-lived and have a heterogeneous purpose behind each grouping. Agents may join and depart the congregation dynamically.

2.3.7 Application Context

The application context of WSNs dictates the characteristics of the SMF. For example large and remote surveillance systems need large numbers of sensor nodes to cover the VOI and needs a SMF that can deal will such dimensionality. Moreover, unattended networks add new challenges as well as complicate the sensor management (SM) problem. As discussed in Section 2.1.2 homeland defence and homeland security applications are the most dominant applications to the sensor management market. Such applications demands that the sensory system is able to scale to high dimensionalities and to function autonomously is a hostile environment. While, consumer-based property surveillance applications may not demand such scalability or intelligence as that of the homeland applications.

2.4 Summary

Pervasive surveillance systems are embedded systems that are composed of self-organizing sensor networks managed by an intelligent sensor framework. Pervasive surveillance have wide range of applications in military and homeland security, as well as commercial and consumer-based. To achieve efficient pervasive surveillance, sensor management approaches have to be deployed. A Sensor Management Framework is the organizational control system that seeks to manage and coordinate the use of sensing resources in a manner that improves the process of situation-awareness. This chapter has discussed the fundamentals of sensor management, and its non-functional merits. Many challenges face the design of an intelligent SMF, *e.g.*, handling the limited node and network resources, the need of intelligent real-time operation, and managing the large number of nodes and extensive amounts of data. Thus, the sensor management problem is a highly complex one.

Based on the study of the state-of-the-art, it can be noticed that most SMFs proposed to-date are point solutions that do not use generic SM design framework, so their applicability and reusability beyond their original test-beds is not guaranteed. Therefore, an organizational design framework is needed to provide a common base for design and comparison between different SMFs. In the next chapter, a generic organizational design framework for the SM will be proposed based on the popular service-oriented architecture to provide a modular, reusable, and extendable organizational framework.

Chapter 3

Organizational Multi-layered Design Framework

This chapter introduces a new generic multi-layered organizational design framework for sensor management and provides a conceptual analysis of the functional properties of the SMFs. The proposed design framework is based on the Service-Oriented Architecture (SOA) and provide a framework for the design of modular, extendable, and reusable SM solutions. The chapter is organized as follows: Section 3.1 discusses the motivation for the multi-layered design framework. Section 3.2 gives a brief introduction on the Service-Oriented Architecture (SOA). Section 3.3 provides a literature survey of the state-of-the-art. In Section 3.4, SMFs are viewed in a layered perspective. Section 3.5 presents the proposed layered organizational design framework. Section 3.6 addresses the different functional properties of a sensor management system. Section 3.7 describes the use case adopted in this thesis. Simulation results for a case study using the multi-layered framework are introduced in Section 3.8. Finally, Section 3.9 summarizes this chapter.

3.1 Introduction

Pervasive surveillance applications deal with situations that are characterized by dense and highly dynamic environments, thus, producing large amount of sensor measurements. As a result of the size of the sensor observation space, the sensory system has to use automatic data analysis technologies to transform sensor observations into situation-aware knowledge.

3.1.1 Situation-Awareness

The term Situation-Awareness (SA) is defined by [4] as "the perception of environmental elements within a volume of time and space, the comprehension of their meaning, and the projection of their status in the near future". The use of the SA term can be traced to World War I where it was recognized as a crucial component for crews in military aircraft [122,123]. The most popular theoretical model for situation-awareness is provided by Endsley [124]. The SA model is composed of four levels: sensing, perception, comprehension of sensed data, and projection of this data into the future. Figure 3.1 shows the SA module, in addition to the sensing module.

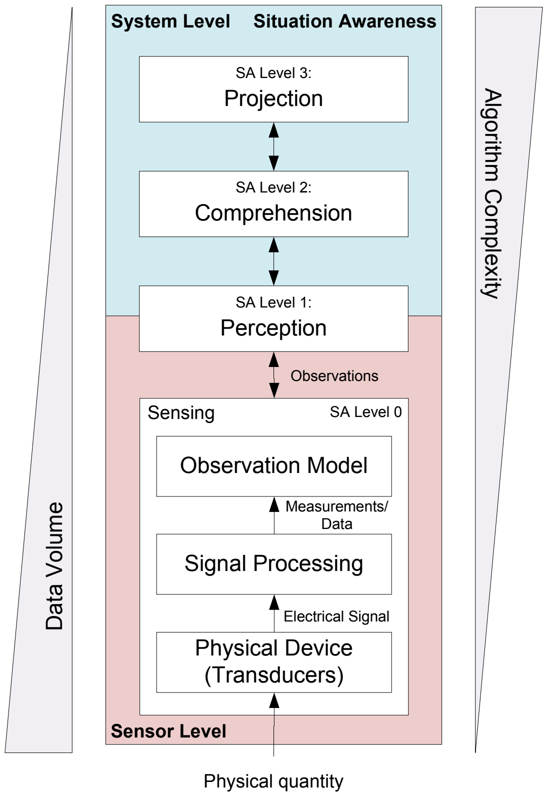


Figure 3.1: Situation-awareness model.

The basic step in achieving SA is to sense the status and attributes of elements in the environment. Sensing is the observation or measurement of physical quantities that arise from physical stimuli. Sensing, in its raw meaning, does not imply the assessment or the understanding of this physical stimuli. However, perception [125] is the process of attaining awareness and understanding of sensory information. In essence, perception constitutes the first level of the SA model and involves the processes of simple recognition of situational elements, *e.g.*, objects and people, and the observation of the dynamics of relevant elements in the environment.

The next step in SA formation is the comprehension of the perceived situational elements through the processes of pattern recognition and interpretation. SA level 2 requires integrating the acquired information to understand its impact on individual goals and objectives. Finally, the third and highest level of SA involves the ability to project future actions of the elements in the environment. SA level 3 is achieved through extrapolating the information forward in time to determine the way the current state will affect future states of the environment. Figure 3.1 depicts that the algorithmic complexity increases going upwards in the SA model; however, the data volume passed upwards from one level to the other decreases.

Situation-awareness modules analyze target intent and capability and environmental opportunity to evaluate the threat behavioural pattern. Target intent is the goal and the course of action of the threat. On the other hand, target capability is assessed by evaluating whether the threat has sufficient resources to achieve its goal or execute its plan. Environmental opportunity is evaluated by verifying that the environment provides the required preconditions for the threat plan to succeed. By adapting situation-awareness models in autonomous surveillance applications, the raw sensory observation is transformed into situation-aware knowledge, thus, resulting in a more efficient and smart surveillance system.

3.1.2 Motivation

In smart sensor management, sensor observations are collected and examined from different aspects and by different layers of reasoning to constitute situation-aware knowledge. Therefore, the SMF has to offer numerous services that enable the deployment of different algorithms that can be applied to formulate the situation-aware knowledge.

Various research projects have proposed various SMF architectures [87–90, 92–94] as a solution for the SM problem. However, most SMFs proposed in the literature are "point solutions" that do not use generic SMF development architectures. As a result, applicability of the SMFs proposed in the literature beyond their original test-beds is not guaranteed. Moreover, in the absence of a generic design framework, the SMFs proposed to-date are application-oriented solutions, hence, these solutions are hard to compare or reuse in a different application. Furthermore, the available SMFs suffer from the lack of a unified range of functionality, *e.g.*, cooperation, data fusion, and resource management, that establish the minimum requirements for the SMF.

The management of a large number of sensor nodes in a typical SMF application requires a flexible, extendible, modular, and reusable development methodology. The service-oriented architecture is a software engineering concept that facilitates the building of extensible and reusable software solutions. Hence, in this work, a layered generic design framework based on the service-oriented architecture is proposed as a software engineering solution to address the design and development issues of the SMFs.

3.2 Service-Oriented Architecture (SOA)

Service-Oriented Architecture (SOA) [126,127] is a software engineering concept that views a software solution as a set of distributed capabilities offered by a system. SOA divides the system capabilities into distinct service blocks in which each service block performs a specific function. The SOA solution is formulated using well-defined, independent, and inter-operable service blocks with a simple interface that abstracts away the implementation complexity. The collection of services that form the SOA solution communicate with each other through defined protocols and do not include embedded calls to any other services. There are two types of services offered by SOA: fine-grained and coarse-grained services. Fine-grained services perform a single discrete function, while coarse-grained services are composed of a related set of functions [126].

Dividing the system into a set of service blocks results in increasing the system granularity and modularity, thus enabling other applications to reuse the provided services. Moreover, the SOA allows the sharing of functions in a widespread and flexible manner. Traditionally, the use of SOA technology refers to allowing "plug and play" features in software design. Numerous SOAs for developing wireless sensor network applications have been proposed in the literature [91, 128–130]. However, the task of developing an autonomous control management systems did not receive enough attention in the literature.

3.3 Related Work

Due to the complexity of the SM problem, several research projects have attempted to propose design frameworks to facilitate the development of SMFs. Sentire [131] is a development framework for building middleware for sensor networks. Sentire aims to addresses the lack of reusability and inter-operability in the custom code written for sensor applications. The approach proposed in [131] divides the SMF into a set of different manager objects, *i.e.*, resource, interface, data, and sensor and actuator managers. However, Sentire lacks standardization and only provides a basic solution.

The work in [93] proposes a software framework approach for the management of large-scale video surveillance networks. The approach is built around the use of a blackboard architectural style and specifies three architectural views of a system: functional, physical, and interactional. However, the architecture developed in [93] is application-specific, lacks standardization and does not address the reusability and extendibility of the target application.

In [132], the authors proposed a P2P-based framework for managing distributed sensor information, where the sensing data is semantically analyzed. The architecture designed in [132] consists of three layers: the raw layer, abstract layer, and logical layer. The architecture allows the generation of the necessary information from the retrieved data, semantically. However, the architecture in [132] also lacks standardization and does not address the reusability and extendibility of the targeted application.

3.4 A Multi-Layered Perspective of SMF

Designing a SMF is a challenging problem due to the significant sensory system size and complexity. SOA can provide a promising development framework for such a complicated problem. To establish a generic SMF development framework, the system must first be viewed from the point of view of the services being offered. This section will break down the operation of SMFs into different service layers, where each service layer is subject to further handling by the SOA.

The goal of the SMF is to assist the human operator in setting the strategic goals of the whole system. Relying on a divide-and-conquer approach, the SMF has the responsibility of analyzing and dividing the system strategic goals into tactical tasks. These tasks can be carried out either by a single sensor, or by a group of cooperating sensors that manage their operation and the functionality of the whole system. Dividing the strategic tasks into tactical and data centric ones inspired the division of the whole SMF into layers that support the various levels of task complexity. Figure 3.2 illustrates a layered perspective for a generic SMF from the strategic view down to the tactical view. The proposed layered perspective divides the sensor management system into five layers, listed as follows:

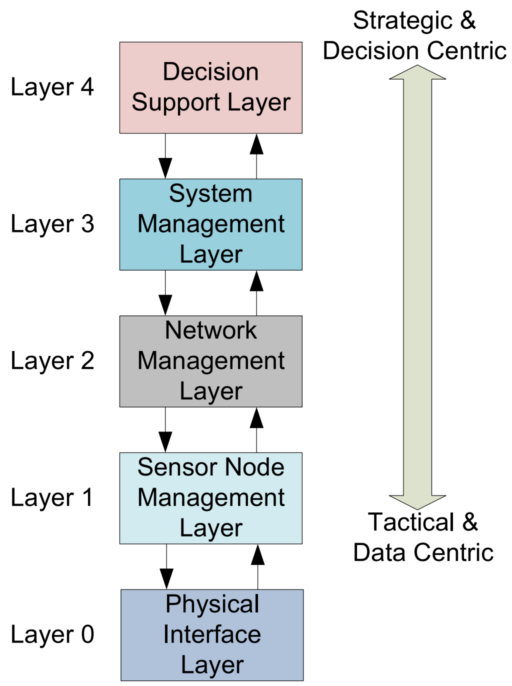


Figure 3.2: Layered view for sensor management system.

- Layer 0 provides an interface with the physical hardware of the smart sensors and transducers.
- Layer 1 performs the sensor level tasks though managing the operation of each sensor individually, *e.g.*, sensor model, sensor measurement interpretation, and sensor mode management.
- Layer 2 supports the network level tasks by managing the communication between the different nodes in the system.
- Layer 3 supports the system level tasks by enabling collaboration between different system entities to achieve the functional tasks.
- Layer 4 takes the computer aided decisions and presents them to the human observer. It should be noted that this layer is optional.

3.5 Layered Organizational Design Framework for SM

Based on the SOA and the layered view of the SMF presented in Section 3.4, this Section proposes a layered organization design framework for SMFs that allows granularity, modularity, and interoperability. The design framework views the SMF as a set of layers with standardized interfaces between them, where each layer carries out the execution of some functional tasks. Each functional task is mapped into a single SOA service. The communication and collaboration between the different tasks is done through a standardized interface. Figure 3.3 shows the details of each layer in the proposed organizational framework.

Figure 3.4 illustrates the interaction of the different layers and the flow of communication. In the proposed organizational design framework, each layer is divided into several SOA modules, which are further subdivided into a number of SOA services. These modules can either be simplex or complex modules. The simplex modules are modules that implement a single task that cannot be further broken down. On the other hand, complex modules implement coarse-grained tasks which consist of a number of related tasks.

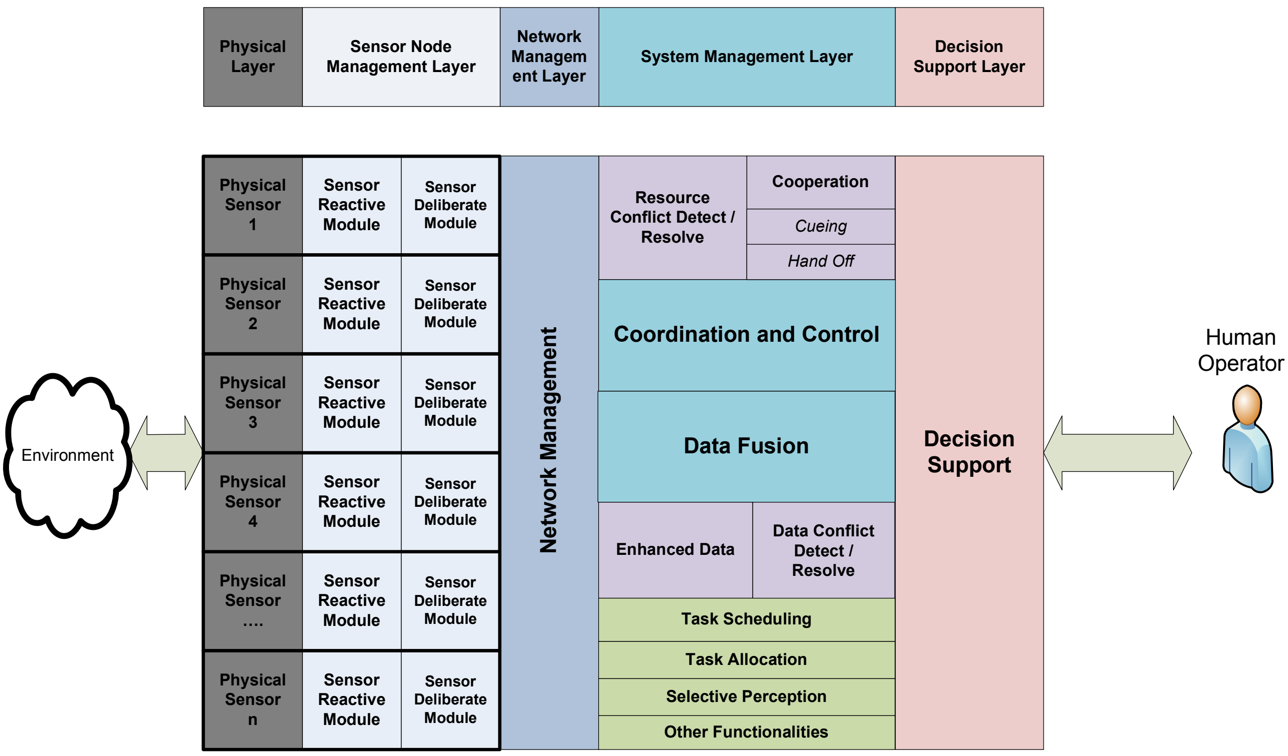


Figure 3.3: Layered SM organizational design framework.

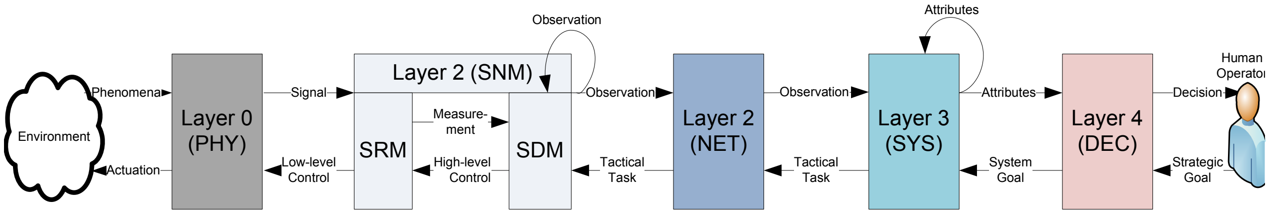


Figure 3.4: The signal flow and the interaction of the different layers in the SMF organizational design framework.

- **Physical Layer:** corresponds to layer 0 in the layered view of the SMF and consists of a physical sensor module (PHY) for each sensor in the network. The PHY is a simplex module that implements the low-level interaction model of the physical hardware of the smart sensor, *i.e.*, transducers, micro-controller, actuators, and communication unit. The physical layer allows for the utilization of different sensors types in a seamless manner for the rest of the SMF by only replacing the PHY module.

- **Sensor Node Management (SEN) Layer:** maps to layer 1 in the SMF layered view. The SEN is divided into two submodules in the organizational design framework, where each submodule provides a different SOA service to the SEN layer. The first submodule is the Sensor Reactive Module (SRM) which responds to the raw signals received from the physical layer and converts it to normalized sensor measurements. The SRM also responds to high-level control signals by analyzing them and setting the corresponding actuator to perform the appropriate action. The SRM is a simplex module.

  The second submodule is the Sensor Deliberate Module (SDM), a complex module which acts as the brain of the sensor. The SDM processes the sensor measurements received from the SRM to convert them into sensor observations that can be used to locally determine a simple action to be carried out by the sensing node. The SRM uses less computational resources compared to the SDM. Moreover, the SRM uses the short-term memory of the sensor node, while the SDM uses long term memory. Furthermore, tactical tasks can also be passed to the SDM to result in high-level control signals.

- **Network Management Layer (NET):** represents layer 2 in the layered view of the SMF. This layer is responsible for managing the connectivity between the sensor nodes and the control center and maps with the datalink layer, the routing layer, and transport layer in the network protocol suite. Although the NET layer is concerned with networking more than management, this work adds it to the organizational design framework as a black box to allow future extendibility of the SMF *e.g.*, to add QoS assurance and utilize data retrieved from routing tables.

- **System Management Layer (SYS):** supports the system level tasks and represents layer 3 in the layered view of the SMF. This layer consists of various modules where each module is an implementation of a functional task according to the SOA. The processing of the modules is either handled by a single node for the whole system or is distributed between various nodes. The SYS layer receives sensory observations for processing, converting them into attributes. These attributes are divided into kinematic attributes such as the position of the target, its speed and acceleration; geometrical attributes such as height, width and length of the target; and identification attributes such as the object ID. These attributes are processed further resulting in tactical tasks for the system. The system goals are fed to this layer, where they are analyzed and broken down into simpler tasks.

  The SYS layer manages the coordination and control tasks, in addition to the data fusion tasks that refine the perceived information in accordance with the system goals. The control module of the SYS layer manages two optional submodules that perform resource conflict detection, resolution tasks, and cooperation tasks, *e.g.*, cueing and handoff tracking. Similarly, the data fusion module manages data conflict detection and resolution and selective perception.

- **Decision Support Layer (DEC):** represents layer 4 in the layered view of the SMF. The DEC provides computer-aided decision capabilities to the human operator. This layer can also have a submodule for Human Machine Interface (HMI) in addition to the decision support submodule. The main objective of the DEC layer is to reduce the workload on the human observer by providing decision fusion that facilities threat assessment.

3.6 SMF Functional Properties as SOA Services

SMF Functional Capabilities are the set of tasks a SMF can perform to control and manage the sensory system. By viewing the system from a layered perspective, this work proposes dividing the SMF tasks into three main categories: sensor management, network management, and system management, as shown in Figure 3.5.

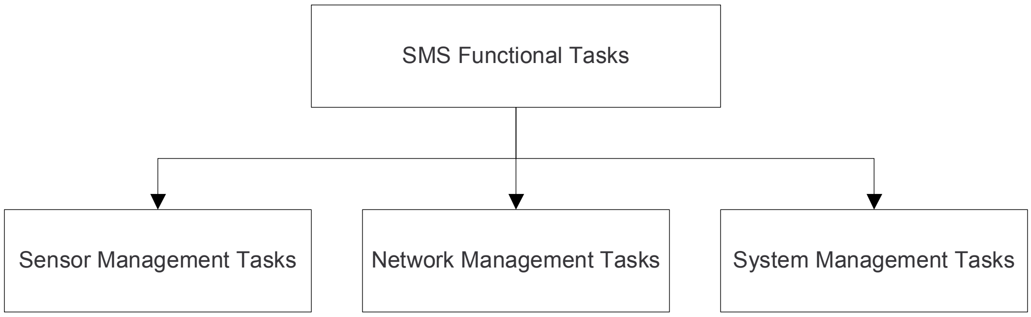


Figure 3.5: SMF functional properties categorization.

3.6.1 Sensor Management Tasks

Sensor management tasks are the set of tasks that manage the operation of each sensor individually. Sensor management tasks are processed locally by each sensor and lead to a decision that is implemented only by that sensor. Since sensors are autonomous devices that interact directly with the environment, the SMF has to address the following challenges:

- **Managing limited capabilities:** The SMF on the sensor level has to address the limited individual sensor capabilities. Each sensor has to minimize its power consumption, usage of memory and cache, and choose an operating mode suitable to its current resources.

- **Managing limited processing:** The SMF has to address the trade off between onboard processing on the sensor or transmitting the raw sensed data to a fusion node for further processing.

- **Managing node failure:** Sensor nodes are cheap, small in size with sensing, processing, and communicating units that are highly prone to failure. Each sensor node has to cope with individual sensor failure, that may result from hardware limitations, software limitations, or external environmental influence.

3.6.2 Network Management Tasks

A Wireless Sensor Network (WSN) consists of a large number of spatially distributed autonomous sensor nodes that communicate with each other by forming a multi-hop radio network while maintaining connectivity in a decentralized manner. These properties of sensor networks lead to the emergence of a new set of responsibilities for the SMF to manage such a network. The network management tasks are the set of tasks that are responsible for managing the connectivity between the sensor nodes and the control center. The SMF must be designed to address these system challenges:

- **Handling dynamic environments:** The SMF has to be able to cope with highly dynamic and uncertain environments. Hence, there is a need for the SMF to be highly adaptable to rapid and unpredictable changes in the environment.

- **Managing communication:** Due to the absence of global identification in sensor networks, the network management level in the SMF has to allow for different identification schemes.

- **Performing information relay:** Sensor networks are multi-hop networks, where each node acts as both a host and a router, thus, appropriate protocols need to manage multi-hop communication. Moreover, due to the instability of the wireless link, the sensor network has to be able to quickly recover from link failures, node failures, and path breakages. Furthermore, the SMF has to maintain information relay reliability.

- **Managing insufficient resources:** Due to the broadcast nature of wireless sensor networks, bandwidth is a scarce resource that needs to be used responsibly. The limited caching of sensor nodes is another example of a scarce resource that may affect network performance.

- **Handling random deployment:** The random deployment of WSNs puts additional requirements on sensor network protocols and algorithms to be self-organizing and to provide distributed capabilities. Since the exact location of a particular phenomenon is unknown, distributed sensing results in a larger coverage area and a higher probability of close proximity to the phenomenon.

3.6.3 System Management Tasks

Besides managing the framework at the sensor and the network level, many challenges remain to enable the SMF to manage and improve the understanding of the system on the global world view. The SMF has to perform various tasks to address the following system requirements:

- **Enhance data fusion:** The SMF on a system level aims to improve the information data fusion capabilities. This can be achieved by using feedback from the data fusion algorithm to redirect the sensing resources to gather relevant data about a specific phenomenon.

- **Task allocation:** Task allocation is the problem of allocating a set of sensor nodes to a set of sensing tasks. Task allocation has been intensively studied in the literature [133, 134].

- **Cooperation:** In multi-sensor systems, cooperation among sensors entails the harmonization of effectively unifying the information obtained from each sensor [135]. It is a joint or collaborative behaviour that is directed towards improving situation-awareness by sharing information among distributed sensing resources [136]. In surveillance applications, there are two primary cooperative functions: cueing and handoff [137, 138].

- **Scheduling:** Since the limited lifetime of batteries directly impacts the lifetime of sensor networks, one of the key considerations in the design of sensor networks is the ability to maximize battery lifetime. Task scheduling aims to maximize the lifetime of the sensing network by minimizing energy consumption while fulfilling its requirements.

- **Conflict detection and resolution:** Due to the distributed nature of sensor networks, simultaneous accessing of a shared resource by different sensors has to be efficiently managed and coordinated. Furthermore, if two or more sensors provide conflicting data, the SMF has to detect this inconsistency and take the necessary actions to resolve it.

- **Control and coordination:** Control and coordination are the tasks responsible for managing and organizing the information and command flow of the sensor management architecture. The main role of control and coordination is to generate actions based on the state of the resources, the sensing information, and the goals of the architecture.

- **Synchronization:** Time synchronization is a critical piece of infrastructure for any distributed system. Distributed WSNs make particularly extensive use of time synchronization to integrate data, to localize objects, to distribute control commands, or to suppress redundant messages and information [139]. Thus, the SMF has to provide a synchronization mechanism that has unique requirements in terms of the scope, lifetime, and precision of the synchronization achieved, as well as the time and energy required to achieve it.

- **Selective perception:** Due to the overwhelming amount of information that must be processed and filtered to derive situation-aware knowledge, the SMF has to be able to support selective perception. Selective perception is the ability of a system to focus its resources on certain phenomena, thus minimizing the amount of irrelevant data with respect to the studied phenomena.

- **Others:** There are many other functionalities that can be supported by the SMF depending on the application and the sensed environment, *e.g.*, focus of attention, mode control, mode switching control, emission control, failure recovery, and contingency handling.

3.7 Airport Security & Border Control as a Use Case

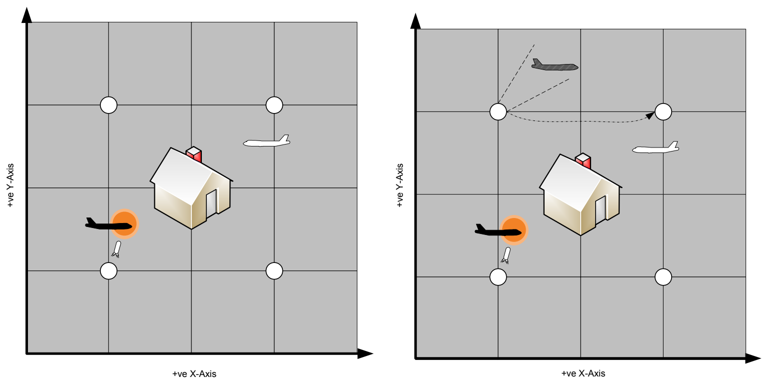
Border control deals with the problems of impeding the entrance into a national territory of unauthorized persons and materials. It typically deals with illegal immigration and smuggling, but can also be concerned with more serious issues such as incoming weapons of mass destruction [13]. National borders typically stretch over thousands of kilometres and are split into blue (sea side) and green (land side) borders. The green borders typically have designated border crossing points which monitor millions of human and vehicle crossings. Another form of border crossing are the international airports, where people arrive from different parts of the world to enter a specific country.

Airports are can be seen as stations for airplanes that consist of buildings and airfields that serve to house airplanes and provide runways for takeoff and landing. Most airports have terminals for passengers to transfer onto and disembark from airplanes. A large number of people pass through airports everyday; this presents potential targets for terrorism and other forms of crime because of the number of people at a particular location. Moreover, given the high concentration of people on large airliners, the potentially high death rate resulting from attacks on aircraft, and the ability to use a hijacked airplane as a lethal weapon may provide an alluring target for terrorism.

Airport security refers to the techniques and methods used to protect passengers, staff and aircraft at airports from accidental or malicious harm, crime and other threats. Airport security attempts to prevent threats from entering the country or potentially dangerous situations from arising. As such, the nature and size of the VOI, as well as the randomness and scarcity of the events make airport security applications a highly challenging problem. Moreover, the need to aggregate information, collect statistics, and alert security experts in the case of an event imposes further demands on the problem.

3.8 SMF organization design framework Experimentation

This Section provides a case study of the proposed layered organizational design framework. This case study aims to investigate the extendibility and reusability of a scenario implemented using the proposed design framework. The experiment is carried out in two phases, where phase two is an extension to phase one.



(a) Phase 1 (b) Phase 2

Figure 3.6: Case study scenario.

Table 3.1: Simulation environment setting.

Parameter	Value
Area	4x4 grid
# Sensors	4
# Targets	10, 20, 30, 50
Target motion	4 direction
Simulation time	200 sec

3.8.1 Phase One

The adopted scenario, shown in Figure 3.6, is for a surveillance application and is implemented using Matlab software. The area under surveillance, $AREA_X$, is represented by a 4x4 mesh grid monitored by four sensors. Each sensor has a sensing range that encompasses the four surrounding square units of the grid. It is assumed that each sensor node can sense targets anywhere within the four block area. Suppose that the surveillance system has to protect $AREA_X$ from a certain type of aircraft, *e.g.*, Falcon aircrafts. Assume that nearby there is an airport where only one type of airplane lands, *e.g.*, Airbus planes, hence, Airbus planes are considered friendly targets. The aircrafts are modelled as mobile targets that can move in a straight line in only one of four directions, $+x$, $+y$, $-x$, and $-y$. The number of mobile targets introduced to the environment varies from 10 to 50 targets. The type of the aircraft, *i.e.*, the threat level, is randomly generated, as well as their entry point into $AREA_X$. The simulation was carried out for 200 seconds. Table 3.1 summarizes the simulation parameters used.

In the first part of the experiment, shown in Figure 3.6(a), the sensor system can perform a certain set of actions: detect, classify, and destroy. When the system detects and identifies a target, the target is assigned a threat level. In this part of the scenario, the threat level is either low or high. If the system classifies an aircraft as a low threat level, *e.g.*, Airbus planes, the system will only record it in the database. However, when the system identifies a high threat level, it passes the information to the human operator who may run a destroy module. Figure 3.7 shows the UML class diagram for phase one of the experiment designed according to the SMF layered organization design framework methodology.

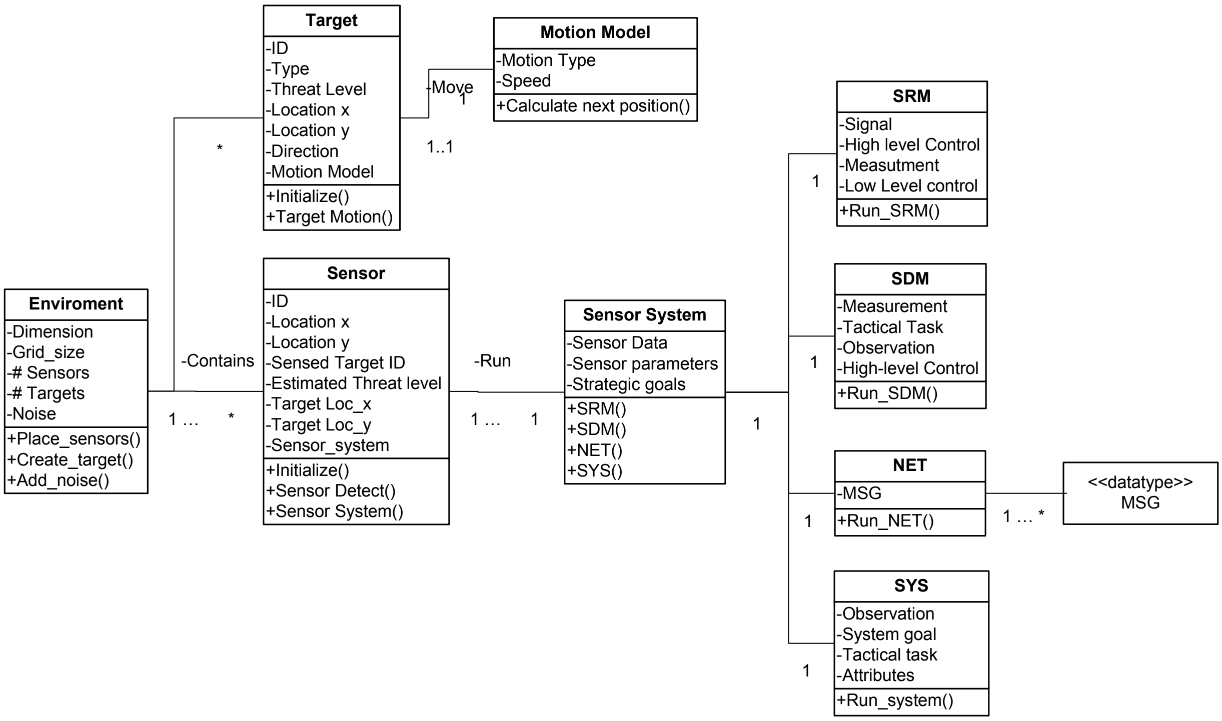


Figure 3.7: UML class diagram for the surveillance scenario.

3.8.2 Phase Two

It is assumed that in emergency situations, various types of aircrafts are authorized to land in the airport. These aircrafts may also be military aircrafts. Hence, the sensor system has to extend its functionality to tracking these planes in order to secure the premises. The tracking function as implemented includes two submodules: cueing and handoff. In this scenario, three threat levels are introduced: low, unidentified, and high, as shown in Figure 3.6(b). Taking into consideration that sensor data is often corrupted by statistical noise inherent in the transducers, discretization from the digitalization process, and occasional nonsensical values [6], a noise module is added to provide a more realistic scenario. Figure 3.8 shows the UML class diagram for phase two designed according to the SMF layered organization design framework methodology.

By comparing Figure 3.7 and Figure 3.8, it is noted that to extend the system to allow tracking by contact-level cueing and handoff, and to add statistical noise to the simulation, only two simple classes were added. This illustrates that a SMF designed using the layered organizational design framework enables a more seamlessly extendible solution than by means of a custom code written to the SMF development. To study the reusability of the

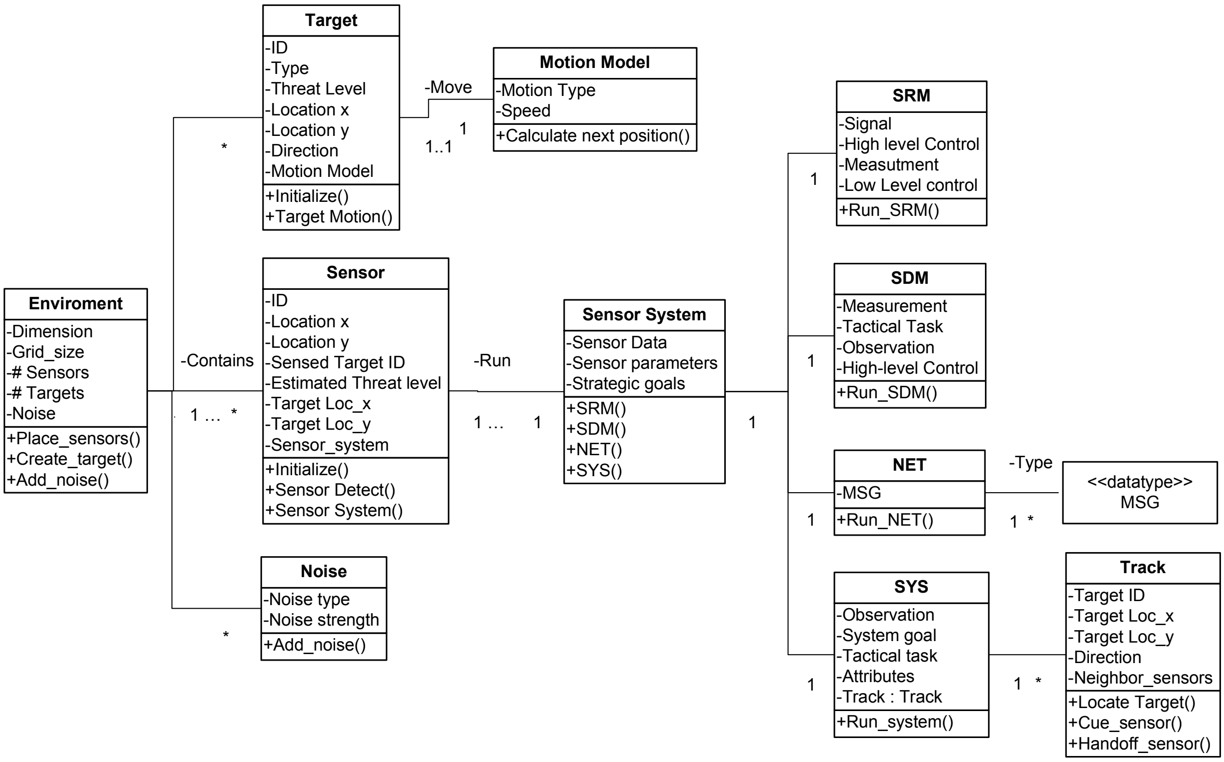


Figure 3.8: UML class diagram for the extension of the surveillance scenario.

system, a code reusability metric is used. The reusability ratio is the percentage of the number of reused source code lines to the total number of source code lines [140].

$$Reusability\_Ratio = \frac{\#Reused\_SLOC}{TotalSLOC} * 100\% \tag{3.1}$$

where SLOC is the number of lines of source code. The value of the reusability metric in the adopted case study is 85.2%. This shows that extending a SMF based on the layered organizational design framework enables the reusability of the code to a great extent.

3.9 Summary

Most SMFs that are proposed in the literature to-date are “point solutions” that do not use generic SMF design frameworks, so their applicability beyond their original test-beds is not guaranteed. This chapter introduces a layered generic organizational design framework for the development of the SMF based on the service-oriented architecture. Sensor management is studied from a layered perspective and the functional tasks carried by the

SMF are categorized into three categories: sensor management, network management, and system management. Two case studies are presented to demonstrate the extendibility and reusability of the organizational design framework. The proposed organizational design framework is used in the design and development of the extended hybrid architecture for sensor management introduced in following chapter.

Chapter 4

Extended Hybrid Architecture for Sensor Management

The size and complexity of pervasive surveillance systems requires efficient coordination of the flow of information and control commands between system components. This chapter introduces the proposed Extended Hybrid Architecture for Sensor Management. The chapter is organized as follows: Section 4.1 provides an introduction to the proposed work. In Section 4.2, the Belief-Desire-Intention model is introduced. In Section 4.3, the architectural design details of the proposed coordination architecture are discussed. Section 4.4 provides the mathematical model for the proposed evaluation metrics used to analyze the performance of the SMFs. Simulation results for a pervasive surveillance scenario are introduced in Section 4.5. Finally, Section 4.6 summarizes this chapter.

4.1 Introduction

The management of resource-bounded heterogeneous sensor nodes involves making decisions regarding sensors' operations and interactions. The collective performance of all the sensors dictates the performance of the whole system. Thus, defining efficient coordination approachs between sensor nodes is of great importance. The Sensor Management Architecture (SMA) coordinates the flow of information and control commands between sensor nodes and determines the overall performance and capabilities of the system. A SMA has to handle the overwhelming amount of information collected and adapt to highly dynamic environments under network and system limitations.

This work focuses on developing an autonomous SMF that strives to achieve the system objectives while maximizing the lifetime of the sensor network. The proposed Extended Hybrid Architecture for Sensor Management (E-HASM) addresses the sensor management problem from a control perspective. The proposed E-HASM is designed based on the SOA organizational design framework introduced in Chapter 3. The proposed E-HASM architecture combines the holonic, federated, and market-based architectures in a complementary rather than a competitive way and models the system subcomponents as intelligent nodes using the Belief-Desire-Intention model [141]. The main goal of the proposed paradigm is to guarantee scalability, flexibility, and structured control, as well as, localized operation, and distributed autonomy.

Though this research work is concerned with the design and development of SMA that can address the functional and non-functional aspects of a sensor network, emphasis will be made on aspects that relate to coordination, control, and decision-making. Aspects such as task allocation, data fusion, and scheduling, are highlighted in light of their role in sensor management, but are excluded from the scope of this research.

4.2 Belief-Desire-Intention (BDI) Model

Bratman [141] has developed a theory of practical reasoning that includes intention as a distinct mental state; distinct from the mental states of belief and desire. Bratman's work has inspired the Belief-Desire-Intention (BDI) Model [141]. The BDI model is a software model developed for programming intelligent agents which is inspired from folk psychological studies of mind and human behaviour. The term intentional systems refers to systems whose behaviour can be attributed to system mental attitudes such as beliefs, preferences, and intentions, which play different roles in determining an agent's behaviour. Such attitudes are categorized into: 1) cognitive, such as beliefs and knowledge, 2) conative, such as intention, commitment and plans, and 3) affective, such as desire, goals, and preferences [141]. A BDI model can be envisioned as having four main components :

1. Beliefs: represent the informational state of the agent; in other words, its beliefs about the world. Using the term belief rather than knowledge recognizes the fact that what an agent believes may not necessarily be true and may change in the future.

2. Desires: represent the motivational state of the agent. They represent objectives or situations that the agent would like to accomplish or bring about.

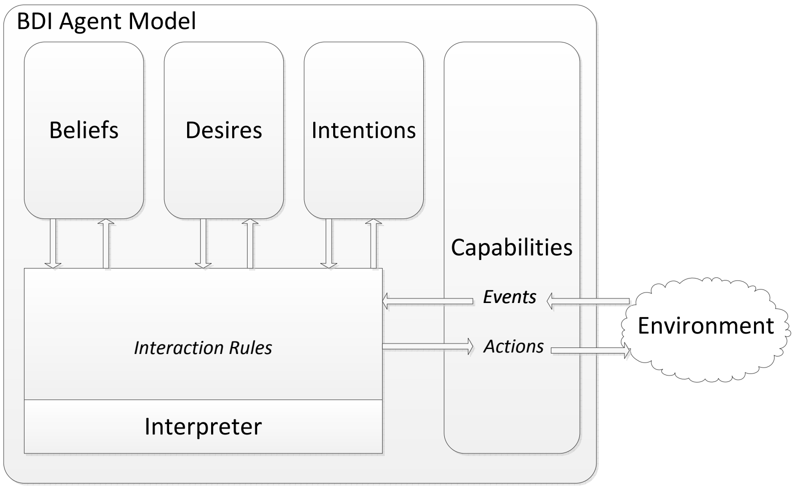


Figure 4.1: The BDI solver model.

- Goals: A goal is a desire that has been adopted for active pursuit by the agent. Usage of the term goals adds the further restriction that the set of active desires must be consistent.

3. Intentions: represent the deliberative state of the agent, *i.e.*, what the agent has decided to do. Intentions are desires to which the agent has to some extent committed to.

   - Plans: are a sequence of actions that an agent can perform to achieve one or more of its intentions. Plans may include other plans, *i.e.*, sub-plans.

4. Events: are triggers for the agent's reactive operation. An event may update beliefs, trigger plans, or modify goals. Events may be generated externally and transmitted to sensors or systems.

One of the attractive features of a BDI model is the ability of a BDI agent to continuously reason about beliefs, goals, and intentions and act accordingly. This model represents both present uncertainties, due to limitations in perception, and future uncertainties, due to dynamism. BDI agents are able to balance the time spent on deliberating about plans and executing those plans. However, the BDI model does not explicitly describe mechanisms for interaction with other agents and integration into a multi-agent system.

4.3 Extended Hybrid Architecture for Sensor Management

Due to the nature of the pervasive surveillance application, the sensor management system is expected to make decisions and compromises regarding alternate sensing strategies under time and resource availability constraints. Accordingly, SMF has to support various functional and non-functional capabilities to be able to address the system requirements. Traditional coordination architectures fall short in achieving the required merits to meet the various system requirements, such as structured control with a high degree of flexility, scalability, and low complexity. With a specific application in-mind, the combination of different architectures in a tailored manner results in a hybrid system that can benefit from the various architectural advantages and avoid their limitations. This customized hybrid architecture can lend itself to application-specific system requirements and characteristics. This has instigated the idea behind the proposed architecture. This section introduces the proposed E-HASM to address the SM challenges in pervasive surveillance.

E-HASM is a multi-layer architecture for SMFs designed for pervasive surveillance applications. The proposed approach is based on the layered organizational design framework discussed in Chapter 3 which implements the design concepts of the service-oriented architecture and offers system extendibility, modularity, and reusability. The proposed architecture aims to combine the advantages of the holonic, federated, and market-based architectures. Usually, a phenomenon of interest is localized in terms of proximity to a subset of sensors in the physical environments. To efficiently manage the system, E-HASM utilizes this property by using localized subsystems of sensor nodes forming a holarchy.

The main coordination architecture of the proposed approach is the holonic paradigm. As discussed in Section 2.3.6.5.1, the "whole" vs "part" concept of the holonic paradigm allows autonomy, flexibility, and fault tolerance. Authority and control are highly distributed among holons belonging to different levels of the holarchy to increase autonomy. The holonic architecture can offer a high degree of scalability and reliability by accounting for them in the design. All of these merits makes the holonic paradigm a suitable match for the SMF. However, holonic systems can grow significantly and become extremely complex which can lead to unpredictable overall system performance. Since the success rate of the overall system depends on the combined success rate of the various holons, a structured organization is needed to achieve effective coordination between the holons and define the flow of information and control commands so as to derive predictable performance.

E-HASM offers a multi-layered management approach that defines the interaction between different groups of holons. E-HASM consists of autonomous, self-reliant, and recursive holons that interact differently according to the management level of operation. The peer holons can be organized to form either a federated or a market based structure. As shown in Figure 4.2, the E-HASM approach divides the system into five main levels: the decision support level, the system management level, the macro-management level, the micro-management level, and the sensor level. Each of these levels is considered a holon in itself and is also composed of a set of holons that perform some functional tasks.

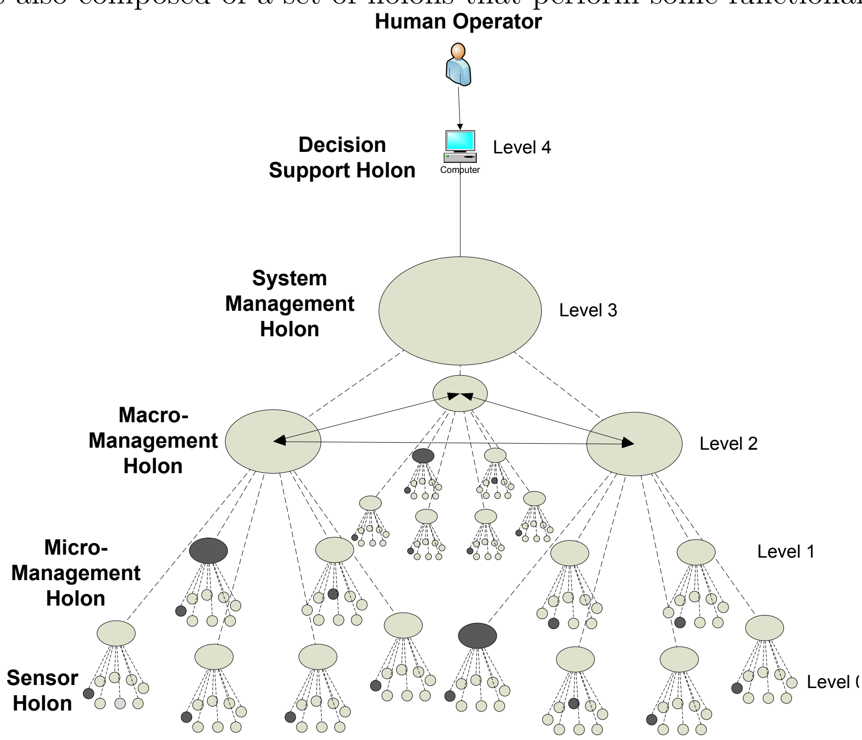


Figure 4.2: Extended Hybrid Architecture for Sensor Management coordination structure.

This multi-layer approach allows E-HASM to increase the sensor system scalability by dividing the system operational complexity over different layers. The proposed breakdown of the different levels of E-HASM allows a more efficient scalable system with the structured control needed for pervasive surveillance applications. From Figure 4.2, level 0 is compromised of sensor holons; each is responsible for the autonomous operation of the sensor. The sensor holons in level 1 form a federated architecture. The localized federated architecture allows an organized interaction and structured control of the resources, in addition to rapid response to real-time environmental stimuli. The delegate of each federation is denoted by the dark gray node. On the other hand, the peer holons in level

2 form a market-based architecture. Since the number of holons decreases going up the chain of command between different levels, the market-based architecture in level 2 offers efficient resource management and role adoption with relatively low communication overhead. The localized collaboration of holons allows for timely operation. It should be noted that in Figure 4.2 the dashed lines represent a breakdown of the holon contents and not a communication link.

Each holon in E-HASM is designed as an intelligent entity using the BDI model. Such intelligent holons possess the capabilities of localized reasoning and planning based on their short-term and long-term objectives. The set of beliefs of each holon represents the perception of its surrounding environment and it is continuously updated and modified over time,*e.g.*, location, energy level, or environmental events. The set of desires are represented by the holon objectives and goals. In the pervasive surveillance application, the desires of the sensor holons can, for example, be detecting any abnormal behavior in the VOI. The intentions provide the plans of action that should be taken by each holon, such as scanning the VOI for abnormalities.

In recent years, a number of research projects have considered applying the holonic paradigm to the sensor management problem [15, 22, 78, 121]. The holonic sensor management algorithms proposed in the literature lack considerations for non-functional merits, *e.g.*, scalability, flexibility, and structured characteristics. Furthermore, the networking aspects are not considered. The work reported in this chapter aims to address these issues and provide a flexible sensor management solution. Moreover, this work shows how using the BDI model to design the various holons allows for the autonomy of different system subcomponents, as well as, localized reasoning and distributed decision-making.

4.3.1 E-HASM Design Details

In the following, a top-bottom approach is adopted in discussing the design considerations of the E-HASM holons: decision support holon, system management holon, macro-management holon, micro-management holon, and sensor holon.

4.3.1.1 Level 4: The Decision Support Holon (DSH)

The Decision Support Holon (DSH) resides on the human operator side of the system. The main aim of the DSH is to provide a computer-aided decision for the human operator. It should be noted that the actual decision is taken by the human operator. The DSH consists of four main holons: decision assistant holon (DAH), human-machine interface holon (HMIH), system holon (SYSH), and the control and coordination holon (CCH). Figure 4.3 shows the architectural design of the decision support holon. The dashed lines show the flow of control commands within the SYSH, while the solid lines show the flow of information attributes.

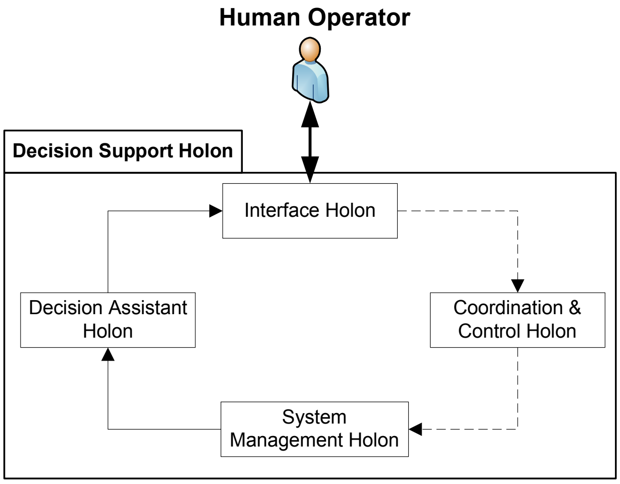


Figure 4.3: Decision Support Holon (DSH) design structure.

The Decision Assistant Holon (DAH) analyzes the current state of the system and accordingly rationalizes the appropriate action. The Human-Machine Interface Holon (HMIH) aims to facilitate the interaction of the human operator and the system and provides a Graphical User Interface (GUI) for ease of use. The Control and Coordination Holon (CCH) is the holon responsible for carrying out the human operator's actionable decisions. The CCH analyzes the strategic goals and breaks them down into tactical goals. Finally, tactical tasks are passed to the system holon to be executed.

4.3.1.2 Level 3: The System Management Holon (SYS-MH)

The System Management Holon (SYS-MH) is responsible for the operation of the whole system. Figure 4.4 shows the architectural design of the system level holon. The SYS-MH is composed of four main holons: the control and coordination holon, the task management holons, the macro-management holon, and the fusion holon. The dashed lines show the flow of control commands within the SYS-MH, while the solid lines show the flow of information attributes.

The control and coordination holon acts as the brain of the system and interfaces with the decision support holon. The control and coordination holon is responsible for

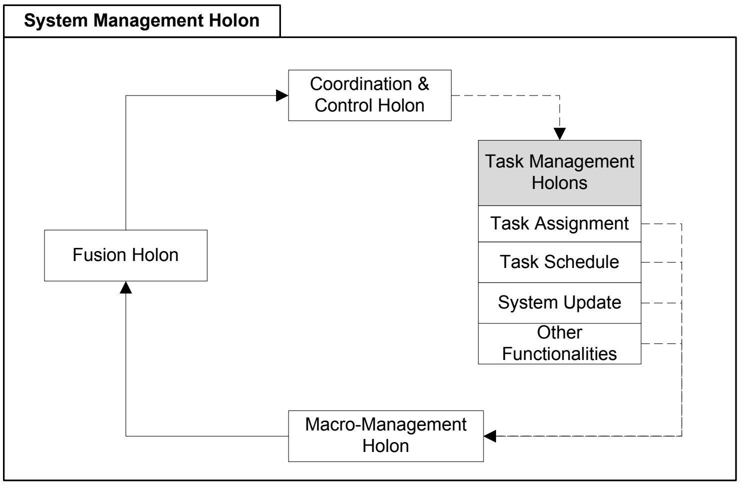


Figure 4.4: System management holon (SYS-MH) design structure.

analyzing the tactical goals received from the DSH and breaking it down into tactical tasks. These tactical tasks are, accordingly, passed to the task management holons to be further processed and scheduled. The macro-management holon allocates the tactical tasks to the appropriate sub-system holon. Finally, the fusion holon is responsible for fusing the observations reported by the macro-management holon. These observations are further processed to form information attributes that can be passed to the DSH.

4.3.1.3 Level 2: The Macro-Management Holon (mMH)

The macro-manager (mMH) divides the system into a small number of sets, where each sub-system represents a specific set of sensors in the system, *e.g.*, based on the geographical area. These sub-systems interact with each other using the market-based paradigm to assign or delegate tasks.

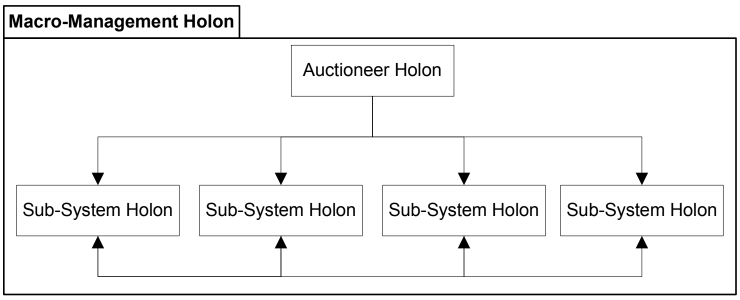


Figure 4.5: Macro-Management Holon (mMH) design structure.

The market-based architecture appears to be a suitable match for the interaction between the mMH sub-systems in task assignment. This is attributed to the higher operation level of the mMH which is comprised of a relatively small number of μMH. The limited number of buyers and sellers in the market results in less communication overhead, thus saving energy, and increasing the probability of reaching optimal or sub-optimal solutions in a distributed manner. Using a market-based approach in this manner to achieve task allocation and decision-making can result in fast sub-optimal solutions, reliable and flexible control, and the ability to handle applications that have a natural spatial distribution. Figure 4.5 shows the simplified architectural design of the market sub-system holon. A simplified market-based architecture was implemented for demonstration purposes.

4.3.1.4 Level 1: The Micro-Management Holon (μMH)

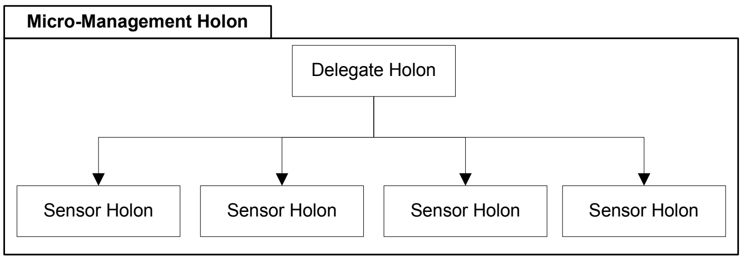


Figure 4.6: Micro-Management Holon (μMH) design structure.

The macro-management sub-system is further divided into smaller clusters. Each cluster is a small group of sensor holons that are in close proximity to each other. Each cluster forms a federation. The operation of these federations is managed by a decision-making holon, *i.e.*, delegate holon, as shown in Figure 4.6. The sensor holons communicate solely with the delegate to report sensory observation and to receive the assigned task. The delegates of different federations form the mMH and communicate with each other either directly or through the auctioneer.

Figure 4.7 shows the design of the delegate holon. The delegate analyzes the assigned tasks and allocates them to various sensor holons. Moreover, the delegate holon is responsible for fusing the sensory observations of the sensor holons in its federation. Furthermore, the delegate manages and coordinates the collaboration of the sensors in a cooperative manner, such as cueing and handoff.

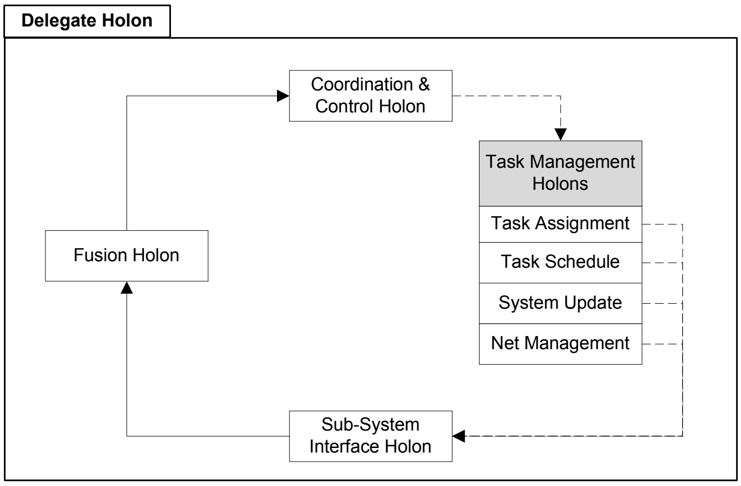


Figure 4.7: Delegate Holon design structure.

4.3.1.5 Level 0: The Sensor Holon (SENSH)

The sensor holon is responsible for the management of a single sensor operation. It is composed of the control and coordination holon, the task management holons, the basic fusion holon, and a sensor physical interface holon to interface with the sensor hardware. The control and coordination holon interfaces with the delegate holon, analyzes the assigned task, and manages the operation of the other holons on the same sensor. As the task management holons at this level of operation only handles local tasks only locally, the task assignment holon is absent since it is unnecessary. In addition, the mode holon may also be present, controlling the operating mode of the sensor to decrease energy consumption and increase the survivability rate. The sensor interface holon controls the operations of the sensor hardware, *e.g.*, transducers, actuators, and others, and converts the sensor signal into normalized measurements. Finally, the basic fusion holon is an optional holon and is responsible for low-level measurement processing so as to provide the delegate with a more refined quality of measurement and a reduction in communication overhead.

It is also assumed that the sensors are capable of cooperative tracking functional property in the form of cueing or handoff to increase the quality of surveillance. Cueing is the process of using the detections or tracks from a sensor to point another sensor towards the same target, while, the handoff includes transferring the surveillance responsibility of the target. Figure 4.9 shows the cueing and the handoff operations between two sensors.

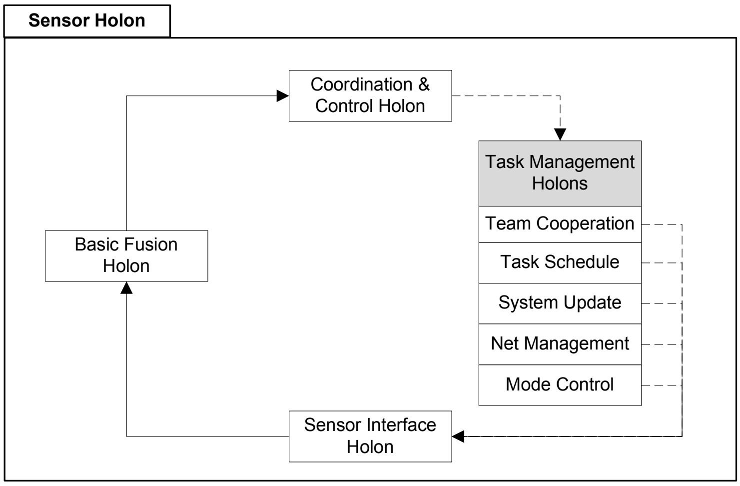
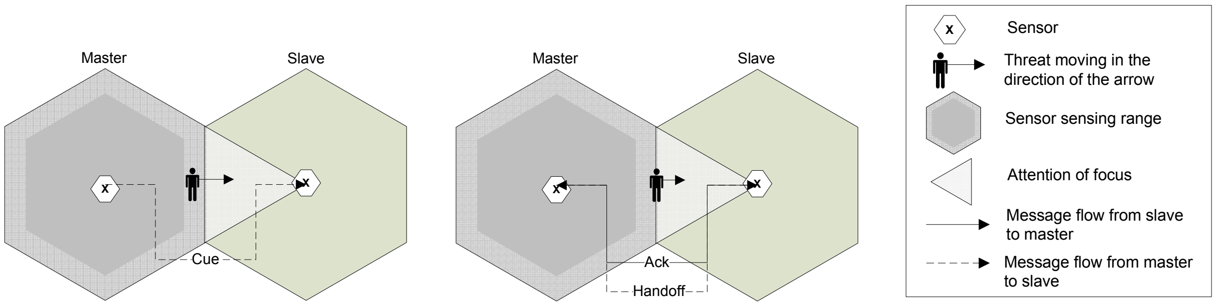


Figure 4.8: Sensor Holon design structure.



(a) Cueing (b) Handoff (c) Key

Figure 4.9: Sensor cooperation using cueing and handoff of targets.

4.3.2 Comments and Network Considerations

After describing the design details of the E-HASM architecture, this section reflects on system characteristics and advantages. The proposed E-HASM is built using the holonic paradigm and therefore inherits its autonomy, flexibility, and scalability characteristics. Furthermore, the E-HASM design was based on the multi-layered organization design framework presented in Chapter 3 and offers an extendable, reusable system that can lend itself to multiple services and functionalities.

In addition, the implementation of the holons as intelligent agents with beliefs, desires, and intentions captures the uncertainty about the environment and allows rapid adaptation of its operations in accordance with its adopted intentions. The mMH market-based approach balances between the local and the global utility in a fast optimal/sub-optimal manner. Moreover, the proposed E-HASM maintains the structured characteristics needed for efficient control by the federated control structure embedded into the system. This structure is highly necessary for seamless interaction with the human-in-the-loop and for the surveillance problem. Furthermore, localized reasoning decreases the number of communication messages transmitted or forwarded by the sensor nodes as well as the required communication signal strength which is based on distance between nodes, and thus increases network lifetime significantly.

A sensory system may consist of large number of sensor nodes that may be spread over a large geographical area. However, a physical phenomenon is usually localized within a certain area in VOI. Taking this fact into consideration, E-HASM utilizes that phenomenon proximity to achieve efficient sensor management. The operation of the SMF is divided into numerous sub-systems based on the proximity of each set of nodes, thereby, providing a fast response time to the phenomenon and limiting the communication overhead of the subsystem. Such an approach increases scalability, reduces energy consumption, provides localized operation, allows autonomy of different sub-systems, and has many other advantages. A cluster-based network topology is recommended for such systems. In this work, the process of cluster head selection is assumed to be performed in an energy-aware distributed manner.

The main advantage of the proposed E-HASM over the work proposed in [121] is that the E-HASM is not only divided into layers but also that the system is viewed from the perspective of the functional tasks offered. This allows the seamless extendibility of the functionality of the system. Furthermore, peer sensor holons can form a federated structure that allows efficient control of the resources needed to perform the required function in a localized manner without the overhead of passing it up the chain of command between different layers. The federated μMH allows the SENSHs to use their collective knowledge to avoid false detection. In addition, higher control levels can be designed with more flexible architectures allowing seamless system growth and fault tolerance.

4.4 Sensor Management Evaluation Metrics

This section provides the mathematical formulation of the quality metrics used to study and compare the performance of the E-HASM. In the literature, the most popular SMF evaluation metric used in tracking missions is the tracking error [40, 97, 108, 112, 113] that is presented in the form of Root Mean Square Error (RMSE). Although the RMSE gives a good indication of the accuracy of the system at hand, it fails to reflect the performance of the surveillance system and its management.

Quality of Surveillance (QoSv) is a newly used notion that can evaluate the performance of a surveillance system. In the literature, QoSv metrics were previously used when studying partial coverage in WSNs with the aim of finding the smallest number of awake sensors that can achieve system objectives [142, 143]. In this work, the QoSv metric is defined in a more general manner that can reflect overall system performance regardless of WSN coverage. We define the QoSv as a quantitative metric that represents the effectiveness of the surveillance system. The main objective of pervasive surveillance systems is to detect abnormal phenomena in a timely manner and successfully track it for the duration of its existence in the VOI. Thus, QoSv is quantified by the target detection quality and the tracking quality of the system, and both are mathematically formulated in the following.

Let Ω be the set of all sensors in the system, $\Omega = \{s_0, s_1, s_2 .....s_{n_s-1}\}$, where s_i denotes the sensor with label i, ordered in sequence, and n_s is a constant that denotes the total number of sensors in the system. Moreover, let β_k be the set of all targets in the system at time k, $\beta_k = \{t_{0,k}, t_{1,k}, t_{2,k} .....t_{n_k-1,k}\}$, where $t_{i,k}$ denotes the target with label i at time k, and n_k is the total number of targets in the system at time step k that varies at every time step, thus, n_k is dynamic.

Target $T_{i,k}$ is said to be engaged/detected if and only if there exists a set of sensor $\alpha_{j,k} \subset \Omega$ such that $T_{i,k}$ is observable by $\alpha_{j,k}$, that to say, $T_{i,k}$ is in the field of view of sensors $\alpha_{j,k}$ at time k. The set $\alpha_{j,k}$ is the superset of sensor $s_y \in \Omega$ where $T_{i,k}$ is in the field of view of s_y at time k, given that i, j, and y are labels. And let $O(T_{i,k}, \alpha_{j,k})$ be a binary variable that is set to 1 if the target $T_{i,k}$ is engaged by set of sensors $\alpha_{i,k}$ at time k, and is reset to zero otherwise. This binary variable denotes the detection status of target $T_{i,k}$ at time k.

For all targets at time k to be engaged,

$$\sum_{\forall i} \sum_{\forall j} O(T_{i,k}, \alpha_{j,k}) = n_k \tag{4.1}$$

for a given time k.

Thus, for all the targets to be engaged for the duration of the surveillance,

$$\forall\ k,\ \sum_{\forall i} \sum_{\forall j} O(T_{i,k}, \alpha_{j,k}) = \sum_{\forall k} n_k = N \tag{4.2}$$

However, due to the systematic or random deviation of the sensor nodes as well as the environmental characteristics, sensor observations can exhibit errors. The Detection

Quality (DQ) evaluates the sensor ability to correctly detect threats; this is given by the Detection Success Ratio (DSR) and the Detection Rate (DR) metrics. The DSR is an indicator of the ratio of the number of targets that were successfully detected to the total number of targets detected and is given by

$$DSR = \frac{\varphi}{\varphi + \varrho} \times 100\% \tag{4.3}$$

Where φ stands for the number of targets that were truly detected; *i.e.*, true detections, where $\varphi \leq N$ and ϱ stands for number of false detections. While, the Detection Rate (DR) indicates ability of the system to detect threats, we can also get an indication of the system DR by using the miss rate. The miss rate represents the failure of the system to detect a threat; thus, as the DR increases the miss rate decreases and vice versa, hence, $DR \propto \frac{1}{Misses}$. We will refer to the miss rate as misses and it is given by

$$Misses = \frac{\phi}{\tau_{ST}} \tag{4.4}$$

where ϕ is the number of undetected threats, and can be given by $N - \varphi$ and τ is a finite time horizon. In this work, it is assumed to be the total simulation time and is denoted by τ_{ST}.

When Target T_i exists within the VOI for several time units, the association between the target T_i and its track measurements for the duration of time in which it is in the volume-of-interest is called track continuity.

Let $\zeta^k_{i,j}$ be the fused measurement of set of sensors α_j for the target T_i at time unit k,

To have track continuity, an association function must exist between target T_i, the detection status, and the sensory measurements of the target T_i for each time units it exists within the VOI.

For a given target T_i at time unit k

$$T_{i,k} \ \underrightarrow{O(T_{i,k}, \alpha_{j,k})} \ \zeta^k_{i,j} \ : \ A(T_{i,k}) \tag{4.5}$$

For a given target T_i at time unit k

$$A(T_{i,k}) = \sum_{\forall j} O(T_{i,k}, \alpha_{j,k}) * \zeta^k_{i,j} \tag{4.6}$$

The track continuity ratio of target T_i which is denoted as $C(T_i)$, is the ratio of time units in which the association function of target T_i exists $G(T_i)$ and the overall time in which target T_i was present in the VOI, which is denoted by $K(T_i)$. It is assumed that $\zeta_{i,j}^k > 0$ iif $O(T_{i,k}, \alpha_{j,k}) > 0$, thus,

for a given target T_i

$$\exists A(T_{i,k}) \ : \ G(T_{i,k}) = \sum_{\forall j} O(T_{i,k}, \alpha_{j,k}) \ > \ 0 \tag{4.7}$$

Consequently, for a given target T_i

$$C(T_i) = \frac{(\sum_{\forall k} G(T_{i,k}))}{K(T_i)} = \frac{(\sum_{\forall k} \sum_{\forall j} O(T_{i,k}, \alpha_{j,k}))}{K(T_i)} \tag{4.8}$$

Accordingly, the average track continuity ratio C_{avg} for all targets within the environment provides an evaluation metric of the performance of the entire system, and it can be denoted

$$C_{avg} = \frac{(\sum_{i=1}^{N} C(T_i))}{N} \tag{4.9}$$

N is the total number of targets that were present in the system during the whole time of surveillance, such that

$$N = \bigcup_{\forall k} n_k \tag{4.10}$$

Accordingly, the Tracking Quality (TQ) is a function of the average track continuity ratio over the course of system lifetime and the normalized root mean square tracking error Err. Thus, the TQ for threat t is given by

$$TQ(t) = \int_{\forall k} \sum_{\forall s} [C_{avg} * (1 - Err_s^k(t))] \tag{4.11}$$

where k is the time unit over the course of the system lifetime, s is the tracking sensors, and $(Err_s^k(t))$ is the normalized root mean square tracking error and is computed by

$$Err_s^k(t) = \frac{\sqrt{E[\ ||\zeta_{pos}^k(t) - Z_s^k|(t)||^2]}}{\zeta_{maxpos}^k(t) - \zeta_{minpos}^k(t)} \tag{4.12}$$

where $\zeta_{pos}^k(t)$ is the actual position of target t at time k and $Z_s^k(t)$ is the observed position of target t by sensor s at time k. Under the assumption that a sensor only needs to know the threat cell on the grid to determine its exact location, it is conceivable to ignore the contribution of $Err_s^k(t)$ to the $TQ(t)$ in the simulation carried out in this thesis.

4.5 Simulation Setup and Results Discussion

The performance of the E-HASM is demonstrated in this section. The E-HASM approach is compared to the most popular centralized approach. The proposed approach is tested in a pervasive surveillance application context. In the rest of this section, the simulation platform is described, then simulation setup is illustrated, followed by simulation results and a discussion of the analysis.

4.5.1 Jadex Platform

Jadex [144] is an agent-oriented reasoning engine for the implementation of rational agents. It simplifies the implementation of multi-agent systems through a middle-ware that complies with the Foundation of Intelligent Physical Agents (FIPA) specifications and through a set of graphical tools that support the debugging and deployment phases. One main advantage of Jadex is that no new programming language is introduced. Instead, Jadex agents can be programmed using XML and Java programming languages in state-of-the art object-oriented Integrated Development Environments (IDEs) such as eclipse [145]. Another important aspect concerns the middleware independence of Jadex. As Jadex is loosely coupled with its underlying middleware, Jadex can be used in different scenarios on top of agent platforms and enterprise systems.

Jadex offers a communication architecture based on the Agent Communication Language (ACL). The communication architecture offers flexible and efficient messaging, where Jadex creates and manages a queue of incoming ACL messages that are private to each agent. Moreover, the Jadex standalone platform is a multi-agent development environment based on the joint intention theory [146]. Jadex is a Belief-Desire-Intention (BDI) reasoning engine for intelligent agents. The term reasoning engine means that it can be used together with different kinds of middleware providing basic agent services such as communication infrastructure and management facilities. Figure 4.10 shows the Jadex Platform.

Jadex rational agents have an explicit representation of their environment in the form of some beliefs about their world model and of their objectives in the form of goals. Rationality indicates that the agent will always perform the most promising actions (based on the knowledge about itself and the world) to achieve its objectives. As it usually does not know all of the effects of an action in advance, it has to deliberate about the available options. For example, a game playing agent may choose between a safe action or a risky action that has a higher reward in case of success.

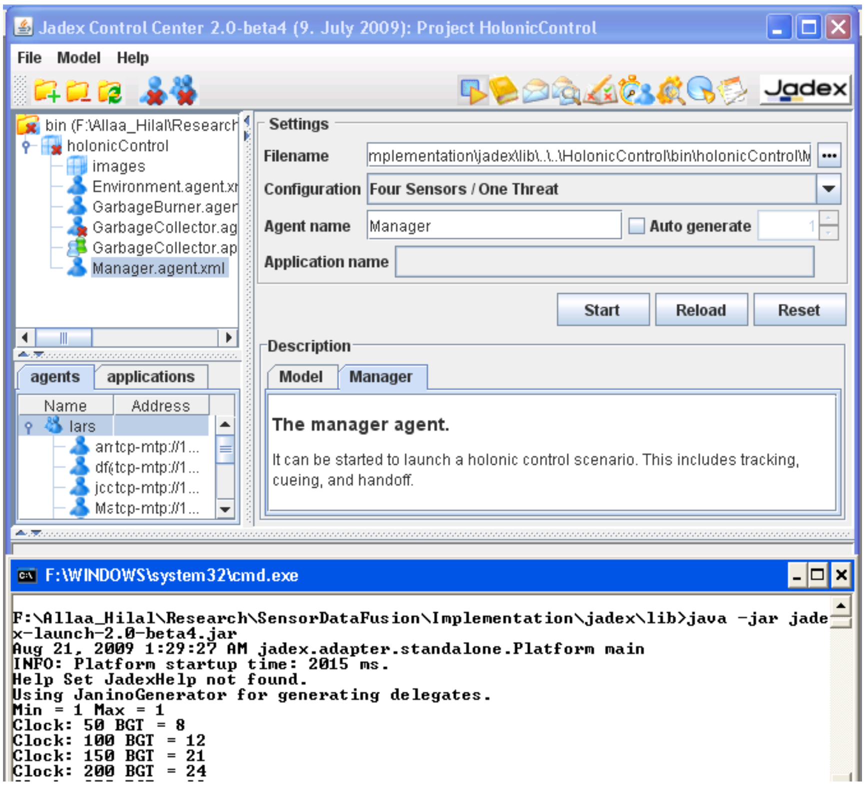


Figure 4.10: Jadex Platform.

4.5.2 Simulation Setup

The airport concourse is represented by a square area divided by a mesh grid into cells, monitored by numerous sensors. Each sensor has a sensing range of the 3×3 grid units. The sensors are static and are represented in the graphical user interface by a yellowish round object. Passengers enter and leave the airport concourse randomly. Impulsive bursts of passengers arrival and departure are also randomly generated to simulate the real world scenario. The passengers are considered targets to the threats in the environment. The number of targets injected into the environment varies between 50 to 200 targets for the duration of the simulation. Moreover, the injected targets depart the environment at random times. These benign targets are represented in the simulation by white and black images.

The threat is represented as an intelligent mobile agent with sets of beliefs, desires and intentions. The number of threats vary from 1 to 12 threats. The threats do not depart the scene for the duration of the simulation. The threats move all around the concourse. The

Table 4.1: Simulation environment setting.

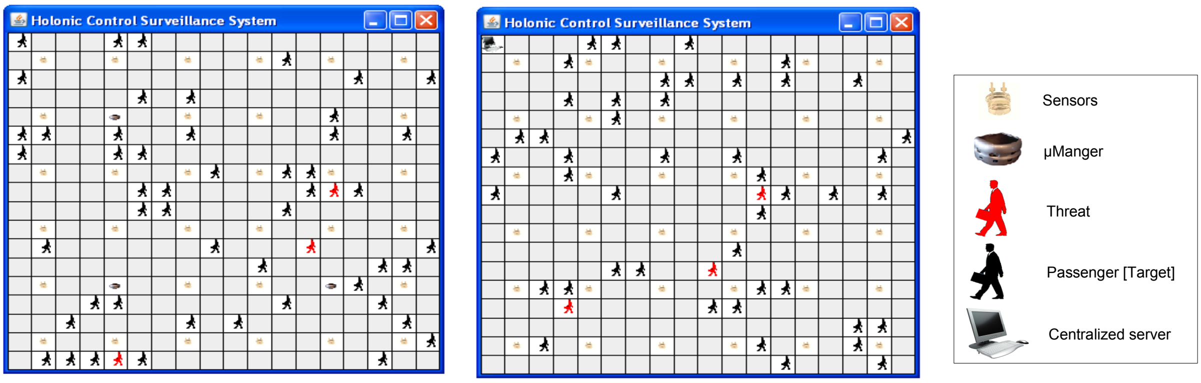
Parameter	**Value**
Area	6×6 to 18×18 grid
# Sensors	4 to 36
# Threats	1 to 12
# Targets	50 - 300
Target motion	preset pattern random change in direction
Direction	4 direction
Simulation time	1000 sec

motion of the threat is set to a pre-specified pattern, however, a random motion pattern is invoked arbitrarily. The simulation is carried out for 1000 seconds. Table 4.1 shows the simulation configuration parameters used.

Two different approaches, E-HASM and a centralized approach were implemented for comparison. Figure 4.11 shows a snapshot of the implemented graphical user interface for the two approaches. The E-HASM is composed of a group of smart sensors nodes and a group of delegate nodes as shown in Figure 4.11(a). The centralized system shown in Figure 4.11(b) is composed of a group of sensors and a centralized processing unit represented on the top left side of the simulation environment.

In a centralized approach, the central unit collects data from the sensors and processes all the collected data to formulate global knowledge about the state of the environment. This allows the central server to compute the global optimal decision or action of each node. The centralized approach is quite popular for pervasive surveillance applications because of its simplicity, structured control, and near-optimal solutions [37,40,72,87,97,110,112,113, 117]. The centralized approach implemented in this work is an adaptation of the research proposed in [37]. The centralized unit is assumed to be 10 times faster than the delegate nodes. All the nodes within the system communicate via wireless channels over a broadcast network with limited bandwidth. Both the delegate nodes and the centralized server have limited queuing space, however, the queue size of the centralized server is larger than that of the delegate.

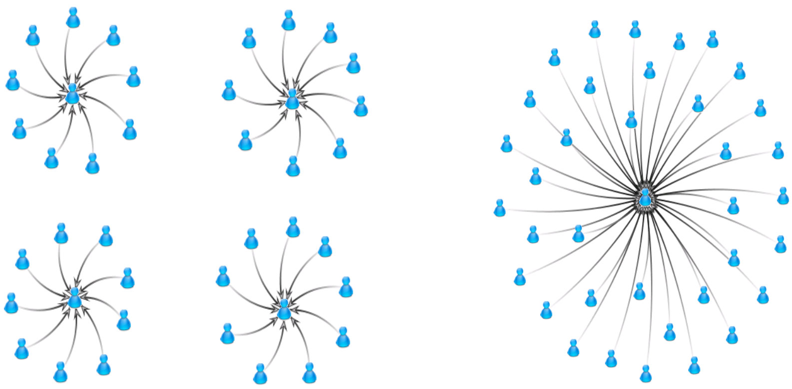
The communication between the nodes is done using ACL message passing. Figure 4.12 shows the directed graph of the communication messages plotted by the Jadex command center. These directed graphs are plotted for an 18x18 environment size with 36 sensors, and 4 delegates for E-HASM or 1 centralized processing unit. The human-like icon represents agents in the system. Figure 4.12(a) shows that the communication is localized



(a) The E-HASM GUI (b) The Centralized GUI (c) Key

Figure 4.11: The airport concourse surveillance scenario implemented using Jadex Standalone Platform.

between the delegate nodes and the follower sensor nodes. Please note that although delegate holons can communicate with each other, this inter-delegate communication is rarely used. Therefore, delegate intercommunication is not plotted in Figure 4.12(a) to increase the visibility of the diagram. Figure 4.12(b) shows that all the sensors actually communicate directly with the centralized unit.



(a) E-HASM comm. (b) Centralized comm.

Figure 4.12: The directed graph of the communication messages plotted by the Jadex command center.

A global tracking mission of all threats is used as the main mission of the SMF. It is assumed that a sensor only needs to determine the cell on the grid in which the threat resides to determine the exact location of the threat.

4.5.3 Results and Discussion

Six different sets of experiments were conducted to compare the performance of E-HASM to the single-layer centralized approach, as shown in Figure 4.13.

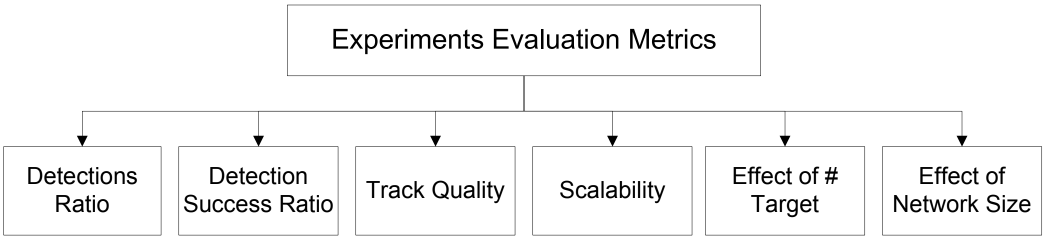


Figure 4.13: A summary of the experiments used to evaluate the performance of the proposed E-HASM.

4.5.3.1 Detection Rate

This experiment is carried out over a 6×6 grid environment with a varying number of threats; from 1 to 12, and a number of passengers that ranges from 150 to 200. The sensory system main objective is to secure the VOI by detecting and tracking threats throughout the environment for the duration of their existence. It should be noted that the task of cueing and handoff is not being considered in these simulation runs. The miss rate is used to indicate the detection rate based on Equation 4.4, *i.e.*, the miss rate is inversely proportional to the detection rate.

Figure 4.14 plots number of misses made by both the E-HASM and the centralized architecture over a varying number of threats. The trendlines are superimposed over the simulation results. From Figure 4.14, it can be deduced that the E-HASM yields a lower number of misses when compared to the centralized approach for all values of threats in the experiment. In fact, the average number of misses recorded by E-HASM is less than one over the whole experiment with a maximum of 3 misses. On the other hand, the centralized approach has an exponentially increasing number of misses as the number of threats increases. This is attributed to the fact that the increasing number of threats results in a significant increase in the communication overhead between the centralized server and the sensor nodes. The increase in the volume of communicated data incurs queueing delays, thus, resulting in delayed logging and actuation. However, the E-HASM benefits from the localized control of the architecture and does not suffer from a hike in data communication as the number of threats increases.

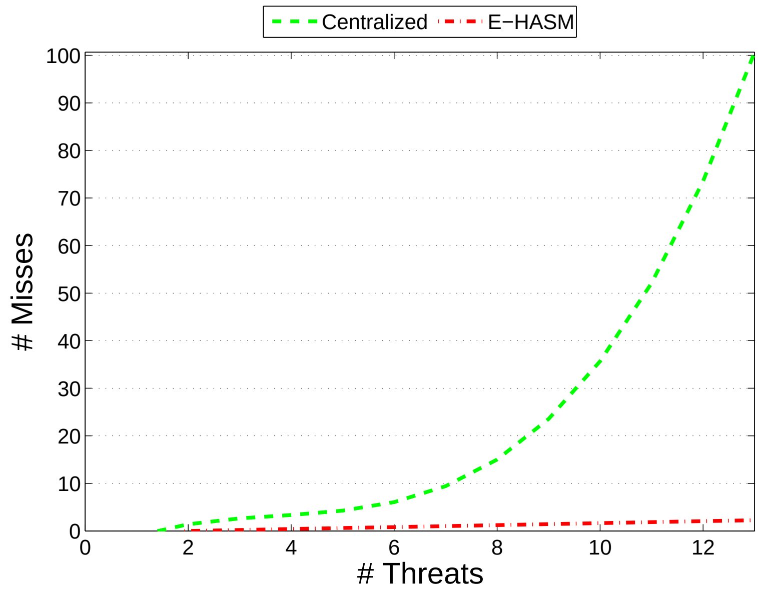


Figure 4.14: The number of misses for the E-HASM and the centralized architecture.

4.5.3.2 Detection Success Ratio

Using a similar simulation environment as that described in Section 4.5.3.1, the detection success ratio for both the E-HASM and the centralized architecture over a varying number of threats is investigated and plotted in Figure 4.15. From Figure 4.15, it can be noticed that the E-HASM yields a higher success rate percentage over the simulation time when compared to the centralized architecture. The centralized approach results in an exponentially decreasing detection success rate as the number of threats increases. Similarly, the exponential decrease in the success rate witnessed by the centralized system is attributed to the communication and processing overhead that burdens the centralized system as the number of threats increases.

4.5.3.3 Tracking Quality

Figure 4.16 plots the tracking quality versus the number of threats for both the E-HASM and the centralized architectures. The size of the simulation environment is an 18x18 grid with the number of threats varying from 1 to 40. Passengers randomly enter or leave the simulation environment with 50 passengers waiting in the concourse at any instant in time. Cooperative tracking between sensors is utilized to keep a close monitoring of high threat level targets. The sensors detect and keep track of the movement of threats in addition

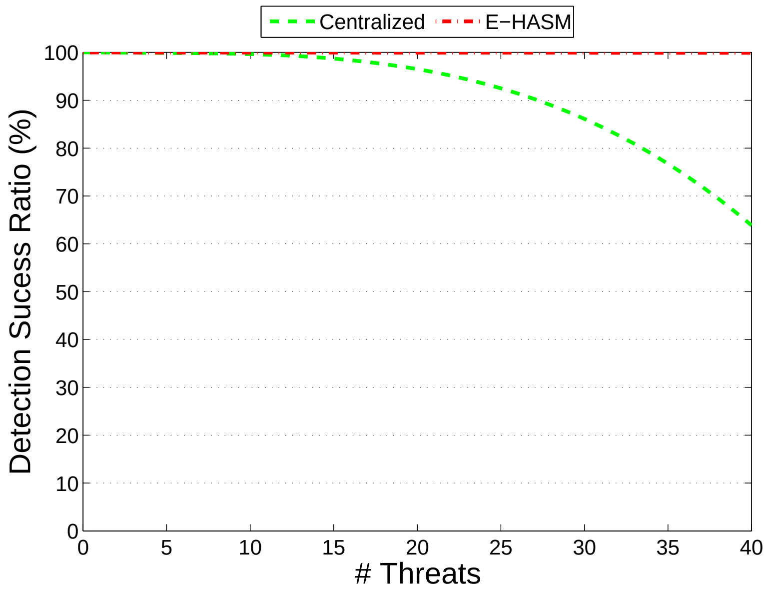


Figure 4.15: The detection success rate for the E-HASM and the centralized architecture.

to cueing the delegate node whenever a threat is about to move out of the range of the sensor. The delegate node subsequently locates and cues the sensor that monitors the area where the threat is headed.

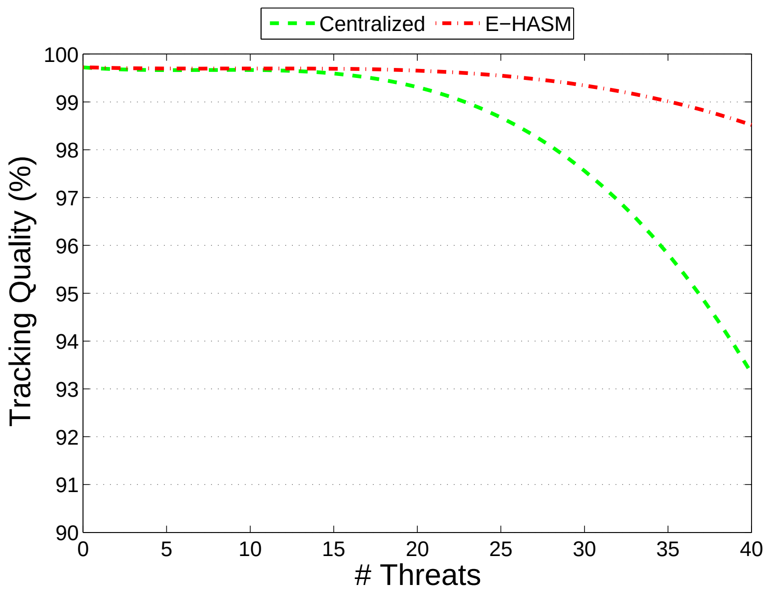


Figure 4.16: The tracking quality of the E-HASM and the centralized architecture.

From Figure 4.16, it can be noted that the performance of the E-HASM and the centralized approach are almost identical for low number of threats. This observation is attributed to the fact that the E-HASM does not benefit from localized control operation for the case of only one threat in the environment. However, for large number of threats, it can be deduced that the E-HASM offers higher tracking quality as defined by Equation 4.11 than the centralized approach. Moreover, the decrease in tracking quality with an increasing number of threats is higher for the centralized approach when compared to the E-HASM approach. This is attributed to the communication and processing overhead of the centralized architecture.

4.5.3.4 Scalability

Scalability is the ability of the system to handle a growing workload in a graceful manner and is a highly desirable feature in pervasive surveillance applications. Figure 4.17 plots the number of sensors needed to achieved a tracking quality of 99.99% with a growing number of threats for both the E-HASM and the centralized architectures. Figure 4.17 shows that the number of sensors required by E-HASM to achieve a tracking quality of 99.99% increases linearly with the number of threats. On the other hand, the number of sensors needed in the centralized approach to achieve the same tracking quality increases almost exponentially with the number of threats. This is attributed to the increased communication overhead of the centralized approach as the number of threats increase which leads to packet losses and delays that compromise the tracking quality of the centralized system. Additional sensors are added to the centralized approach to introduce redundancy which increases the tracking quality to reach 99.99%. It should be noted that the centralized approach requires 8 times the number of sensors needed by the E-HASM to track 12 threats at a tracking quality of 99.99%. These results prove that the proposed E-HASM scales well with the increasing number of threats, unlike the centralized approach.

4.5.3.5 Effect of the Number of Targets

This experiment is carried out over an 18×18 grid environment with 12 threats and number of targets varying from 50 to 400 passengers entering or leaving the environment randomly. In this experiment, the sensors cooperate to increase the continuity of the tracking of the movement of the threats through cueing.

Figure 4.18 plots the effect of increasing the number of targets on tracking quality for both the E-HASM and the centralized architecture. From Figure 4.18, it can be deduced

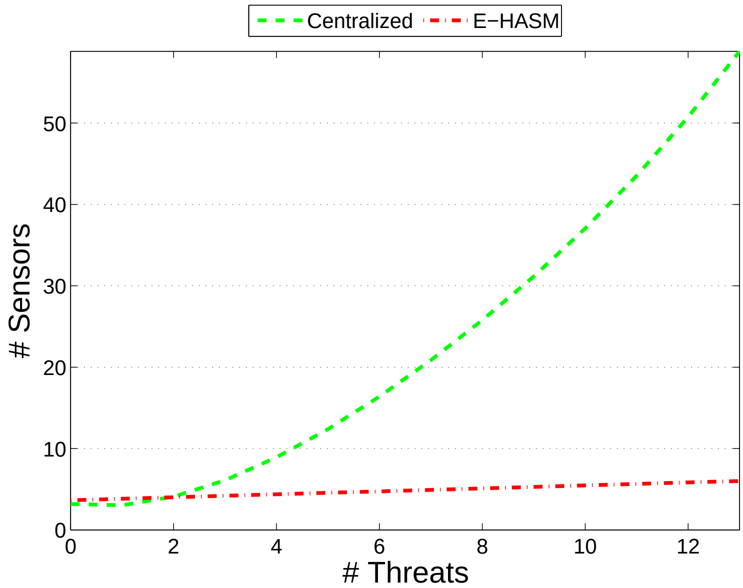


Figure 4.17: Number of sensors required by E-HASM and centralized architecture to track a growing number of threats with a tracking quality of 99.99%.

that the E-HASM yields a higher tracking quality when compared to the centralized approach for large number of targets in the environment. It can be noted that an increasing number of targets results in a decreasing tracking quality for the centralized approach. This is a result of the additional communication overhead incurred by the centralized approach as a result of the sensors communicating the target findings to the central server along with the additional target detection and evaluation procedures. On the other hand, the E-HASM architecture yields a near-constant tracking quality. This is attributed to the distributed processing and localized threat evaluation by each sensor node in the E-HASM approach.

4.5.3.6 Effect of Network size

This experiment is carried out over a varying grid area size with 12 threats and 50 passengers. As the area size increase, the number of sensors needed to monitor the area increases, *e.g.*, an area of 6x6 needs 4 sensor to provide full coverage in the surveillance scenario, while an area of 27x27 needs 81 sensors to monitor it. Figure 4.19 plots the effect of increasing the network size on tracking quality for both the E-HASM and the centralized architecture. From Figure 4.19, it can be noted that the increasing area size results in a decrease in the

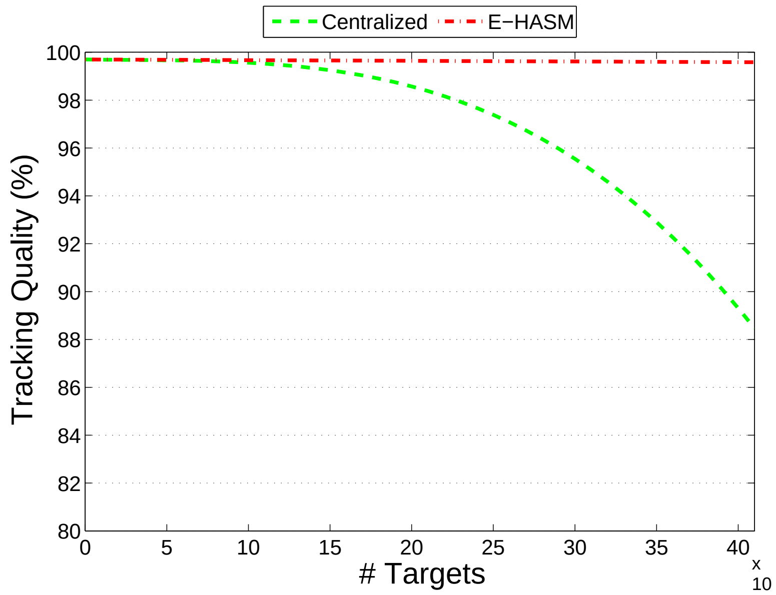


Figure 4.18: The effect of increasing the number of targets on the tracking quality for the E-HASM and the centralized architecture.

tracking quality for both approach. However, the E-HASM maintains linear performance as the grid size increases, while the tracking quality of the centralized approach decreases in a faster manner as the size of the VOI increases. This is attributed to the localized operation of the E-HASM system which results in distributed processing and minimizes the communication overhead.

4.6 Summary

Pervasive surveillance systems need intelligent management to control the large number of sensor nodes and process the large amount of data. Therefore, a sensor management architecture is vital component in the design of SMF to efficiently coordinates the flow of information and control commands between system components. This chapter introduces the Extended Hybrid Architecture for Sensor Management (E-HASM). E-HASM combines the advantages of the holonic, federated, and market-based architectures in a multi-layered approach to guarantee scalability while offering a structured system with localized control. The E-HASM subcomponents are modelled as intelligent nodes using the BDI model which increase the local autonomy of subsystems. Moreover, this work formulate mathematically the Quality of Surveillance (QoSv) evaluation metric in a general manner and uses it to

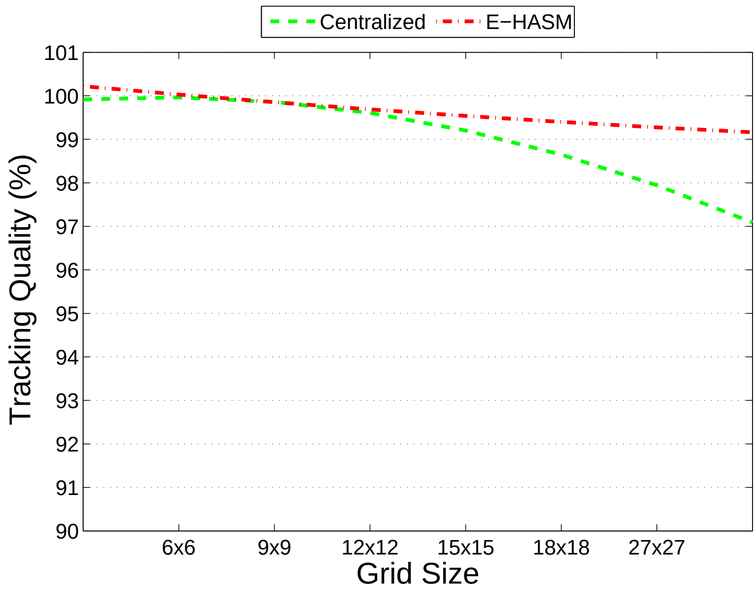


Figure 4.19: The effect of increasing the network size on track continuity for the E-HASM and the centralized architecture.

investigate and compare the performance of the proposed architecture to the popular centralized one in a target tracking mission using simulation. The E-HASM is implemented using the Jadex standalone platform. The results illustrate the scalability of the E-HASM and the superior performance of the E-HASM to the centralized approach in all the evaluation metrics used. However, this comes with the expense of higher management complexity. The main contribution of this chapter is as follows:

- Propose the E-HASM architecture that combines the holonic, federated, and market-based architectures in a complementary manner,
- Present the design details of E-HASM based on the Layered SM organizational design framework [147] and the design principles of the service-oriented architecture [126],
- Model the E-HASM subcomponents as intelligent nodes using the BDI model and define the cooperative interaction between them,
- Formulate mathematically the Quality of Surveillance (QoSv) evaluation metric in a general manner,
- Compare the performance of the proposed architecture to the popular centralized approach in a target tracking mission using simulation,

- Investigate the scalability of the proposed approach via simulation,

The proposed E-HASM can provide energy savings when compared to the centralized architecture due to reduced communication overhead and the localized structure. However, the limited power reserves of the sensor nodes is a precious resource that must be intelligently managed. In the following chapter, an autonomous energy-aware reasoning performed in a distributed manner on-board the sensor nodes is proposed to efficiently manage sensor energy resources and thereby prolong the lifetime of such networks.

Chapter 5

Energy-Aware Decision Making: A BDI Model

Power is a scarce commodity in sensor networks, hence, it is imperative that the network resources are managed so as to prolong the lifetime of the network as much as possible. Since a sensor node is expected to sense as well forward/route information from other sensors, its failure due to power shortage denies the network of its sensing capability and affects other sensors' ability to transport their data. This chapter introduces an energy-aware team-theoretic formulation based on the Belief-Desire-Intention model. Section 5.1 provides an introduction to the proposed work. Section 5.2 briefly discusses the state-of-the art of energy-aware sensor management. The proposed sensor operation and characteristics are presented in Section 5.3, while, the energy consumption model used is introduced in Section 5.4. The novel energy-aware sensor management approach is proposed in Section 5.5. Section 5.6 discusses the experimental work conducted to test and validate the proposed energy-aware sensor management scheme. Section 5.7 concludes the chapter.

5.1 Introduction

Sensor nodes operate on limited energy budgets where replenishment of power resources might not be possible. When a sensor node energy is depleted or falls below a certain threshold, the sensor will fail to monitor and communicate any abnormal phenomenon in its sensing range. Thus, the nodes limited energy supply is a critical resource that needs to be efficiently utilized. Energy-aware Sensor Management can prolong the lifetime of the network and conserve scarce energy resources. The sensor management is expected to make decisions that drive the performance of the whole network to reach its objectives while handling the overwhelming amounts of information collected. Furthermore, the network is expected to adapt to the dynamics of its environment despite, and often as a result of, its limited resources. Indeed, resource scarcity makes the collective and collaborative behaviour of sensor nodes a driving factor to the overall system performance.

This chapter focuses on developing an autonomous energy-aware SM that thrives to maximize the lifetime of the sensor network. A team-theoretic formulation of smart sensor nodes based on the Belief-Desire-Intention (BDI) model is proposed as a mechanism for effective collective decision-making. The proposed formulation draws upon the initial design of the components of the E-HASM introduced in Chapter 4. A novel team-theoretic formulation is developed that manages the sensor network in an energy-ware manner using the following 5 measures: (i) adaptive sleeping, (ii) active sensing, (iii) dynamic sensing range, (iv) multi-modality, and (v) constrained communication. The proposed formulation is designed using the design principle of the multi-layered SM organizational design framework discussed in Chapter 3.

5.2 Related Work

The research community has devised various ways to effectively manage the sensor networks energy budget over the different protocol layers; a comprehensive study of the state-of-the-art energy-aware schemes can be found in [148].

A significant number of research projects has focused on developing sensor sleeping policies as a strategy for energy conservation. Several schemes have modelled the problem as a Partially Observable Markov Decision Processes (POMDP) to devise sleep polices using centralized sensor scheduling techniques [149–155]. The works in [156–158] considered the design of sensor sleeping protocols via wakeup mechanisms. These schemes suffer from high computational cost that prohibits them from running on-board of a sensor node. Moreover, the centralized approach limits the system scalability and presents a processing bottleneck. Other schemes that are proposed in the literature to schedule the nodes sleeping strategies depend on the routing information and network coverage, while neglecting the environment and threat dynamics [97, 102–104].

Numerous research work have focused on developing energy efficient active sensing policies. Most of these research efforts focus an information-theoretic approach to decide on the frequency by which sensor measurements are acquired [159–161]. Approaches, such as Markov Decision Processes and Monte-Carlo Optimization, have been used to derive a policy for active sensing. However, such approaches are computationally expensive to run on-board a sensor. Moreover, information-theoretic schemes depend on the history of sensor measurement in devising the active sensing policy and ignore the environmental characteristics and dynamics.

Adjusting the sensing radius dynamically has been discussed in the literature to address multiple objectives: increase network coverage, decrease energy consumption, and minimize the number of active nodes [162, 163]. Dynamic adjustment of the sensing range can balance the trade-off between the incomplete network coverage, that may result in undetected threats, and redundant coverage of the VOI that wastes the system resources. The problem of the dynamic sensing range adjustment has been investigated from both an optimization [163] and an algorithmic [162] point of views. Another strategy that has been investigated by the research community to reduce the energy consumption is constraining the sensor communication [105, 106, 164–166], where the sensor network has been modelled as a constrained optimization problem. However, these schemes ignored the target and environment dynamics, as well as, the sensor changing status. Therefore, it is clear that there is a need for an energy-aware SM that can make decisions on alternate realtime sensing strategies in a highly dynamic environment and can be practically placed on-board of the sensor node.

5.3 Sensor Characteristics and Operation

The operation of sensor nodes plays an important factor in the effectiveness of the overall system performance. This section discusses the assumptions of the sensor nodes characteristics and operations. A smart sensor node typically comprises of four main building units: a processing unit, a communication unit, a transducer (sensing unit), and an actuation unit, as shown in Figure 5.1.

In this work, a sensor node is assumed to be able to control its sensing range within certain bounds, *i.e.*, decrease or increase the sensing range to a certain threshold; $T_{\eta_{min}} \leq \eta_i \leq T_{\eta_{max}}$; where $T_{\eta_{min}}$ and $T_{\eta_{max}}$ are the minimum and maximum sensing ranges of a sensor node, and η_i is the current sensing range of a sensor node i. It is assumed that, for the sensing range $\eta_i < T_{\eta_{max}}$, the sensor is highly informative, *i.e.*, there is no degradation in the quality of sensed measurements within the range $T_{\eta_{min}} \leq \eta_i \leq T_{\eta_{max}}$. The sensing range is directly proportional to the power consumed in the sensing process, hence, the

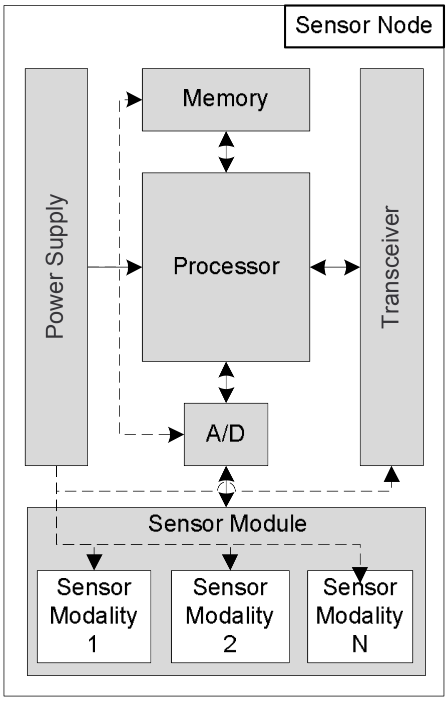


Figure 5.1: Sensor nodes architecture.

larger the sensing range the greater power consumed by the sensing process.

Moreover, the sensor nodes are assumed to have more than one modality for operation; each of these modalities provides a different quality of measurements about the threats in the environment. At higher sensing resolution modalities, the sensor node consumes more power than at lower resolution modalities. In addition, the sensor nodes are capable of active sensing by dynamically changing the frequency by which it is acquiring the sensor measurements.

The sensor nodes have four modes of operation; active/sensing, idle/listening, transmitting/receiving, and sleeping. A sensor node must be in one of these four modes at any given time. Each of these modes consumes different power level. Figure 5.2 illustrates the sensor state transition diagram. When a sensor is in sleep mode, it is assumed that the sensor can not be waken-up externally. The sleep time has to elapse before the sensor is allowed to wake-up. It is assumed that the transmitter and receiver circuits are symmetric in terms of energy, *i.e.*, both consume equal amounts of energy when active. Moreover, the sensor is able to estimate the location of any detected threat within a certain error probability.

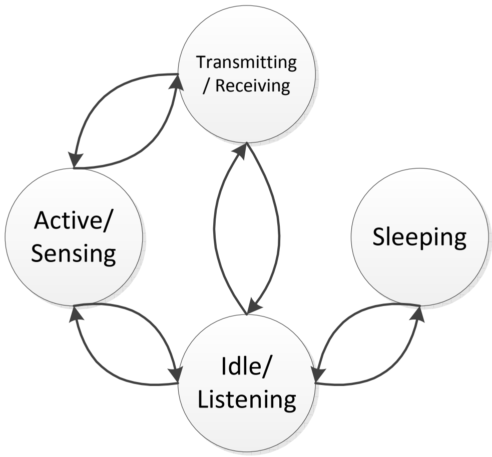


Figure 5.2: Sensor states.

5.4 Energy Consumption Model

Sensor networks are usually battery-operated, hence, it is always required to optimize the battery utilization to extend the lifetime of these equipments as much as possible. If there is no limitation on the energy reserve, the sensor network would collect every possible measurement to maximize the situation-awareness. However, the limited energy budget dictates that the sensor should only collect the measurements that contribute in achieving higher situation-awareness. As a result, sensor nodes are required to operate under the lowest energy consumption needed to achieve the required performance.

Smart sensor nodes are typically compromised of four main building units as shown in Figure 5.1. The operation of each of these units consumes a portion of the energy reserve, thus, affecting the sensor lifetime. Moreover, as discussed in Section 5.3, the smart sensor node has various sensing modalities, sensing frequencies, sensing ranges, and operation modes. Each of these sensor settings consumes different energy costs to operate. This section will provide the adopted energy consumption model for each of these sensor building units.

According to the work in [167–169], each of the sensor components dissipates different energy levels in the different operation states as well as during the state transition as explained in the following:

- Sensing Acquisition: The sensing component transforms physical stimuli into a digital sensor measurement. Sources of sensor power consumption in the sensing acquisition component are: signal sampling and conversion of physical signals to electrical signals, signal conditioning, and analog-to-digital conversion (ADC). Let I_{sense} be the total current required for sensing activity and T_{sense} be the time duration of sensing. The total energy dissipation for the sensing activity, $E_{Sensing}$, for b-bits packet per sensing cycle given the supply voltage, V_{sup}, is given by

$$E_{Sensing}(b) = b * V_{sup} * I_{sense} * T_{sense} \; . \tag{5.1}$$

- Sensor Logging: Logging consumes energy in the form of reading a b-bits packet and writing it into memory. The energy consumption of a single logging process in a sensor node is formulated as

$$E_{Logging}(b) = E_{write} * E_{read} = \frac{b * V_{sup}}{8} * (I_{write} * T_{write} + I_{read} * T_{read}) \; , \tag{5.2}$$

  where E_{write} is energy consumed in writing data, E_{read} is energy consumed in reading b-bits packet data, I_{write} and I_{read} are the currents for writing and reading one byte of data, respectively. T_{write} and T_{read} are the time for writing and reading one byte of data, respectively.

- Micro-controller processing: The energy consumed by the micro-controller for processing and data aggregation is attributed to two components: energy loss as a result of switching, E_{switch}, and energy loss due to leakage current, E_{leak}. Leakage energy occurs when a sub-threshold leakage current flows between the power source and the ground [167]. Total energy dissipated in data processing and aggregation of b-bits packet, $E_{Process}$, per processing cycle is given by

$$E_{Process}(b, N_{cyc}) = E_{switching} + E_{leakage} \; , \tag{5.3}$$

$$E_{switching} = b * N_{cyc} * Cp_{avg} * V_{sup}^2 \; , \tag{5.4}$$

$$E_{leakage} = b * V_{sup} * \left(I_0 * e^{\frac{V_{sup}}{n_p * V_t}} \right) * \left(\frac{N_{cyc}}{f} \right) \; , \tag{5.5}$$

  where N_{cyc} is the number of clock cycles per task, Cp_{avg} is the average capacitance switched per clock cycle, I_0 is the leakage current, n_p is the constant which depends on the processor, V_t is the thermal voltage, V_{sup} is the voltage of the supply power source, and f is the sensor frequency.

- Radio Transmission and Receiving: Communication with neighbouring sensor nodes is enabled by radio communication. According to [167], the energy dissipation due to transmitting b-bits packet for a distance d_{ij} is formulated as

$$E^k_{Comm}(b, d_{ij}) = b * E_{elec} + \left[b * d^n_{ij} * E_{amp}\right]_{tx} , \quad (5.6)$$

where E_{elec} is the energy dissipated due to transmit or receive electronics, E_{amp} is the energy dissipated by the power amplifier, and n is the distance based path loss exponent.

- Actuation: Energy dissipation for actuation, $E^k_{Actuate}$, is hard to estimate in general because it is highly application-dependent. A popular form of actuation can be in the form of motion. The energy dissipation as a result of actuation for duration, $T_{actuate}$, given the current consumed by the actuation circuit, $I_{actuate}$, is evaluated by

$$E^k_{Actuate}(b, d_{ij}) = V_{sup} * I_{actuate} * T_{actuate} . \quad (5.7)$$

- Sleep, Idle, and Transient Energy: Radio and micro-controller units support different operating modes including active, idle, and sleep. Transitions between operating modes involve significant energy dissipation [167]. When a sensor node is in idle state, it will listen to the channel for a duration of T_{idle} per round, then becomes active for a duration of T_A, and then sleeps for T_S. Let T_{tranON} and $T_{tranOFF}$ be the times required for sleep-to-idle and idle-to-sleep transitions, respectively, and the current I_A and I_S are the currents for active and sleeping modes. Hence, the total energy dissipation from the sensor node per round is evaluated by

$$T_{cycle} = \frac{T_{tranON} + T_A + T_{tranOFF}}{T_{tranON} + T_A + T_{tranOFF} + T_S} , \quad (5.8)$$

$$E_{Transient} = T_A * V_{sup} * \left[T_{cycle} * I_A + (1 - T_{cycle}) * I_S\right] . \quad (5.9)$$

- Initialization: Cluster formation entails a number of messages to be exchanged between the sensor nodes and the cluster head to establish the membership. The energy dissipated in the system initialization and the cluster formation is ignored in this work.

According to the discussion above, the overall sensor node energy consumption can be modelled as a linear combination of the energy consumed in each component using the following relationship

$$E_{sensor}^{k+1} = E_{sensor}^{k} - [E_{Process}^{k} + E_{Comm}^{k}(m,d) + E_{Sensing}^{k} + E_{Logging}^{k} + E_{Actuate}^{k} + E_{Initialize} + E_{Transient}^{k} + \alpha^{k}] \,, \tag{5.10}$$

where E_{sensor}^{k+1} is the sensor energy at time $k+1$, E_{Sleep}^{k} is the energy dissipated by the sensor when it is in sleeping mode, and finally $E_{Initialize}$ is the energy dissipated by the sensor in the network startup phase and cluster formation. It is assumed that the sensor loses no energy while it is in the sleep mode, thus, $E_{Sleep} = 0$.

5.5 Energy-Aware Sensor Management Approach

Managing heterogeneous sensors involves making decisions and compromises regarding the alternate sensing strategies under time and resource availability constraints. The decision-making strategy defines the methodology used by the system entities to self-govern and cooperate to achieve the system goals. The E-HASM architecture, proposed in Chapter 4, is based on the collective performance of autonomous sensors. Each sensor is responsible for independent reasoning and decision-making that affects its state and the overall system. The collective outcome of these decisions affects the overall mission objective. The sensor has to reason about its current state and its available actions that affect the environment, its energy reserve, and the overall network survivability.

Network survivability has become a topic of serious concern to the WSN research community. Due to the criticality of the WSNs applications, the drainage of the energy reserve of a sensor node will result in the unavailability of the node monitoring capabilities. Such unavailability may result in partial coverage to the dynamic scene which may degrade the overall system accuracy and performance. However, low energy use of the sensor resources may prolong the network lifetime, but will affect the quality of the network services, and as a result will degrade the overall situation awareness process. Thus, energy-aware decisions should be taken to manage the sensing resources in a manner that not only prolongs the sensor network lifetime but also improves the process of situation-awareness. In the following sections, the design of an energy aware sensor management is introduced.

5.5.1 Energy Savings Index Calculation

An energy-aware sensor management approach selects sensing strategies that best achieve the system objectives while minimizing the energy consumption. The decision-making process can be viewed as an optimization problem over the spectrum of available decisions. The sensor manager processes a large number of local and global parameters in realtime to adjust the sensing strategies based on the evolving environment dynamics, rendering the problem quite dynamic. As a result, the sensing strategies have to be frequently reconsidered throughout the system lifetime. Due to the limited resources of the sensor nodes, any operations that need to be performed in realtime on-board the node has to be kept computationally inexpensive, in terms of both processing and power consumption. Consequently, this section proposes an efficient sensor design-making process to manage the sensors energy reserves using a heuristics to model the problem. Such heuristic technique can provide a cost-efficient decision-making approach that is sub-optimal in terms of the quality of the solution while achieving significant energy savings for the sensor node.

In order to properly explain the proposed algorithm, several metrics that are needed to model the problem at hand will be introduced. This work formulates a heuristic metric called Energy Savings Index (ESI) to provide an estimation of the sensor node status and its need/ability to conserve energy. The ESI is computed locally on-board of the sensor at realtime. As the energy reserve decreases, ESI has to increase to indicate the higher need to save energy. Thus, ESI depends on the current energy reserve, as well as, the initial sensor energy. The ratio between the current energy reserve to the initial sensor energy is called energy index, ϕ, and is defined as

$$\phi_t^s = \frac{\zeta_t^s}{\zeta_0^s} \, , \tag{5.11}$$

where ζ_t^s and ζ_0^s are the available energy reserve at time t and the initial sensor energy for sensor s, respectively. We will also define the energy rate at time instance t, Δ_t, as the difference between the sensor energy level at time t and that at time $t - \delta$, where δ is a small time difference. The energy rate is given by

$$\Delta_t = \| \frac{\zeta_t - \zeta_{t-\delta}}{\delta} \| \, . \tag{5.12}$$

Context awareness is a key aspect of intelligent energy-aware SM since the sensor managers need to adapt to the dynamically changing surrounding environment by discarding the current sensing strategy once it becomes energy-inefficient. Accordingly, the current environment dynamics together with the sensor energy index play an important role in the sensor future health. In this work, the dynamism index, ψ, is used to reflect the environment dynamics. Knowing that σ_t is a sensor observation at time t such that $\sigma_t = 0$ if the measurement is considered normal and $\sigma_t > 0$ otherwise, the dynamism index is formulated as

$$\psi_t = \begin{cases} \psi_{t-\delta} \times (1.0 + (0.25 \times \sigma_t)) & \text{if } \sigma_t > 0 \quad : 0 < \psi \leq 1 \\ \psi_{t-\delta} \times 0.75 & \text{if } \sigma_t = 0 \quad : 0 < \psi \leq 1 \end{cases} \tag{5.13}$$

Another parameter needed to properly model the surrounding environment is the criticality level, which refers to the perception of environmental elements of interest, *e.g.*, threats, with respect to time and space and the need to closely monitor the changes inflected by such elements on the environment. The critically is inversely tied with the ESI. In this work, the criticality level refers to the estimated threat level of the VOI. The criticality level, ρ, and is given by

$$\rho_t = \begin{cases} \rho_{t-\delta} \times (1.0 + (0.25 \times \sigma_t)) & \text{if } \sigma_t > 1, \quad : 0 < \rho \leq 1 \\ \rho_{t-\delta} \times 0.75 & \text{if } \sigma_t \leq 1 \quad : 0 < \rho \leq 1 \end{cases} \tag{5.14}$$

From the discussion above, the ESI at time t, Ω_t, is represented as

$$\Omega_t = \lambda * (exp(-c * (\phi_t * (\psi + \rho))) \ , \tag{5.15}$$

where λ is a variable called the delegate factor and it is equal to 1 throughout this chapter, while c is a scalar constant. Figure 5.3 plots several ESI curves under varying dynamism and threat levels versus different energy reserve levels. As it can be seen from Figure 5.3, the ESI increases with decreasing the sensor energy level, the dynamism, and threat level. Using the ESI, the sensor node can estimate its need and ability to save energy, and thereby decide on alternate energy-saving strategies. In the following, the ESI is used to formulate the operation of the various energy-saving strategies proposed in this work.

5.5.1.1 Adaptive Sleep

This work proposes an adaptive sleep algorithm that dynamically evaluates the sensor node probability of going into sleep at the current time together with the sleep interval based on the environment state and sensor health. The proposed algorithm is asynchronous in nature, *i.e.*, it allows any given node to independently enter/exit sleep mode without any inter-node communication. Any sleeping node can not be forced by external sources out of the sleep mode and can only exit the sleep mode once its sleep timer expires. As a result, the sleep interval algorithm has to take into account all the available information on the network dynamics, threat level, and energy level while calculating such interval. It should be noted that the node is able to communicate with its active neighbours whenever it is in the active state.

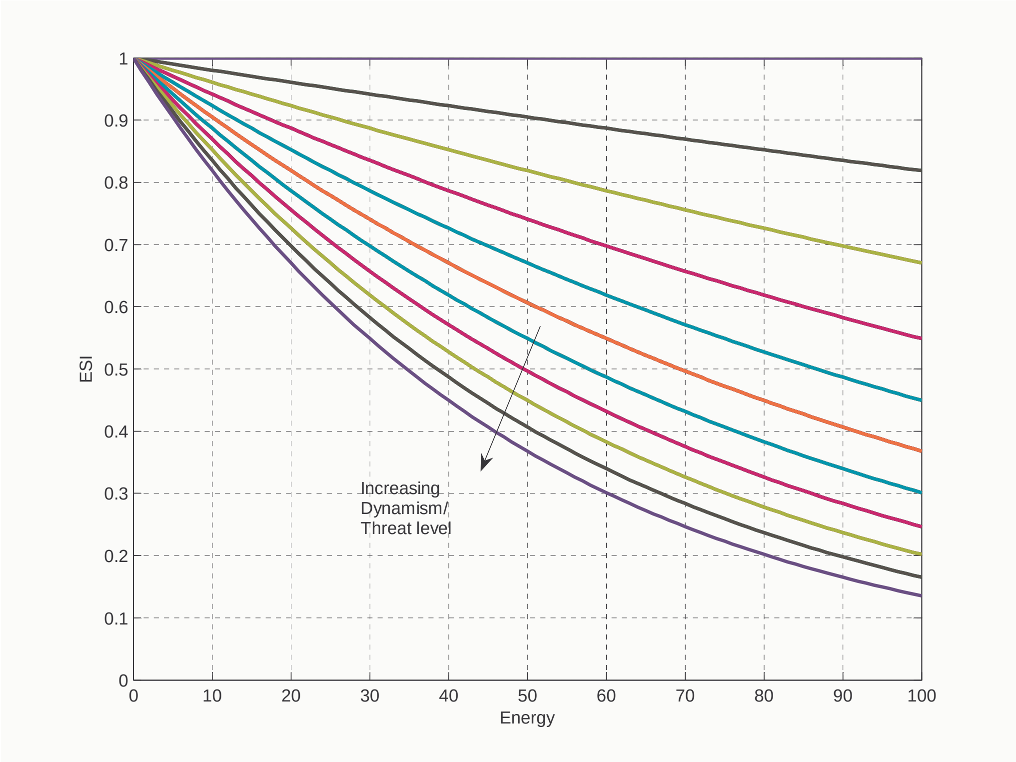


Figure 5.3: Energy saving index over varying dynamism and threat levels versus energy reserve.

The ESI equation in (5.15) is used to derive the probability of the sensor entering the sleep mode. Equation (5.16) formulates the probability of a sensor node going into sleep at time t, $P_t(slp)$

$$P_t(slp) = P_t(slp|\Omega) * P_{t-1}(slp \neq 1) \,, \qquad (5.16)$$

where $P_t(slp|\Omega)$ is the probability of entering the sleep mode given a certain ESI and $P_{t-1}(slp \neq 1)$ is the probability that the sensor was not in sleep mode at time $t-1$.

Using Equation (5.15), the sleep interval at time t, τ_t^{slp}, can be computed as

$$\tau_t^{slp} = C_{slp} * \tau_{max}^{slp} * \Omega^2 \qquad : \qquad \tau_{min}^{slp} \leq \tau_t^{slp} \leq \tau_{min}^{slp} \,, \qquad (5.17)$$

where τ_{min}^{slp} and τ_{max}^{slp} are the minimum and maximum allowable sleep intervals. Setting minimum and maximum sleep intervals is important to guarantee that the energy savings from entering and exiting the sleep mode is much greater than that wasted in during the state transition. C_{slp} is a scalar constant of value empirically determined to be equal to 2. Figure 5.4 plots the sleep interval curve versus the increasing ESI.

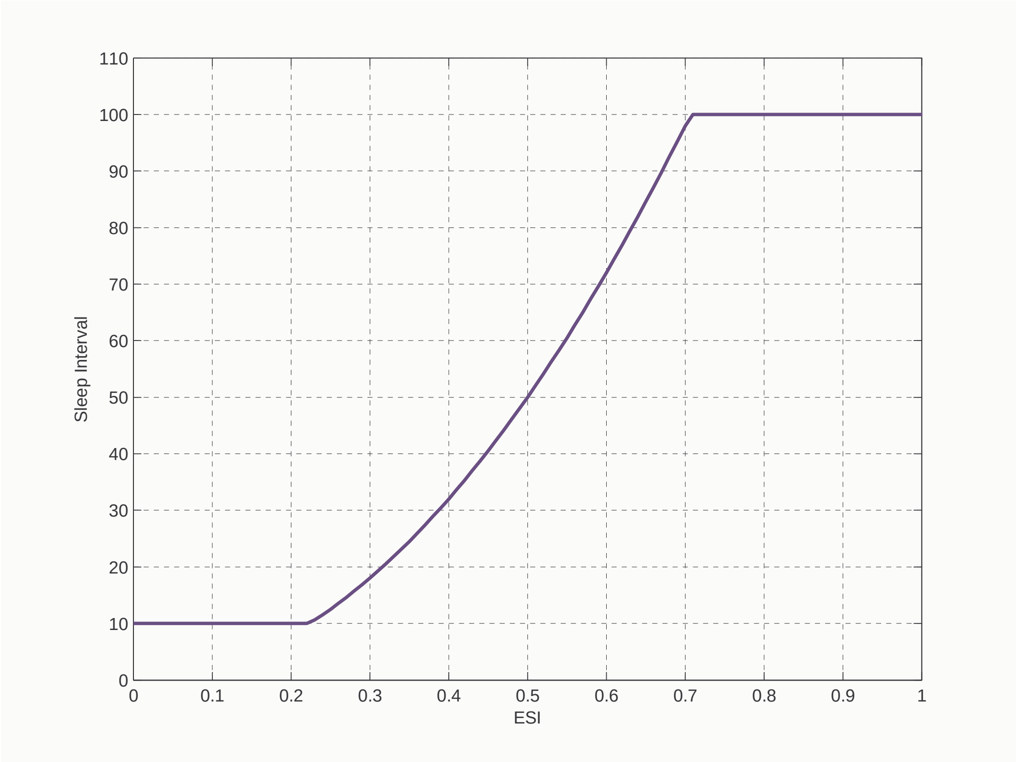


Figure 5.4: The sleep interval in time units versus the ESI.

5.5.1.2 Active Sensing

Active sensing is a form of dynamic sensor management for data generation and collection in which information collected from the environment through sensing is used to guide the sampling process [160]. The sampled data generally has strong spatial and/or temporal correlation [148], hence, the sensors resources might end up being wasted collecting redundant information or insignificant ones. Therefore, controlling the data sampling frequency can result in significant energy savings. Accordingly, active sensing can be defined as the process of adjusting the time intervals between successive sensing instances such that the sensor collects the minimum number of data samples that contains the highest volume of information. The environment dynamics, the threat level, and the sensor energy level are crucial factors in the choice of the sensing interval. This work formulates the node sensing interval at time t, τ_t^{sense}, as

$$\tau_t^{sense} = \tau_{t-\delta}^{sense} + (((0.4 \times (2 \times \Omega)^2)) \times \tau_{max}^{sense}) - C_a \quad : \quad \tau_{min}^{sense} \leq \tau_t^{sense} \leq \tau_{min}^{sense} \;, \quad (5.18)$$

where δ is a small time interval, C_a is a scalar constant, and τ_{min}^{sense} and τ_{max}^{sense} are the minimum and maximum allowable time intervals between successive sensing operations, respectively. The minimum and maximum time intervals include the activation time of the transducers circuit and the time needed to record the measurement itself. A plot of the active sensing interval is given in Figure 5.5 versus ESI. From Figure 5.5, it can be noticed that the active sensing interval increases with the ESI.

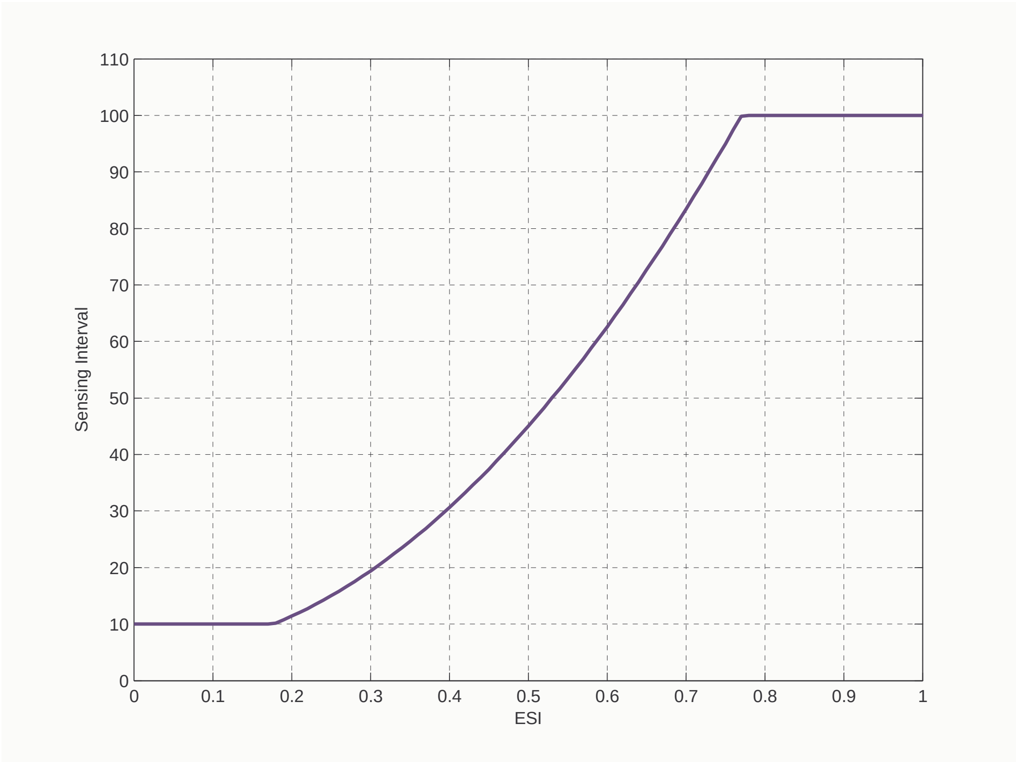


Figure 5.5: The active sensing interval in time units versus the ESI.

5.5.1.3 Dynamic Sensing Range

Dynamic sensing range is the ability of the sensor node to change its sensing radius. This property depends on the transducers type and operation. The sensor nodes can adjust their sensing range within certain bounds without affecting the quality of the collected sensor observations. The sensing range has direct impact on the network coverage and energy consumption, *i.e.*, as the sensor range increases, the network coverage and the sensor nodes energy consumption increase. In this work, we aim to autonomously adjust the node sensing range under the environment dynamics, threat level, and the nodes energy reserve constraints. The node sensing range at time t, η_t, is computed as

$$\eta_t = \eta_{t-\delta} - (((0.4 * (2 * \Omega)^2))) * \eta_{max}) + C_b : \eta_{min} \leq \eta_t \leq \eta_{min} \ , \qquad (5.19)$$

where δ is a small time interval, C_b is a scalar constant, η_{min} and η_{max} are the minimum and maximum sensing range, respectively. The dynamic sensing range versus ESI is plotted in Figure 5.6 which demonstrated the direct relationship between the sensing range and ESI.

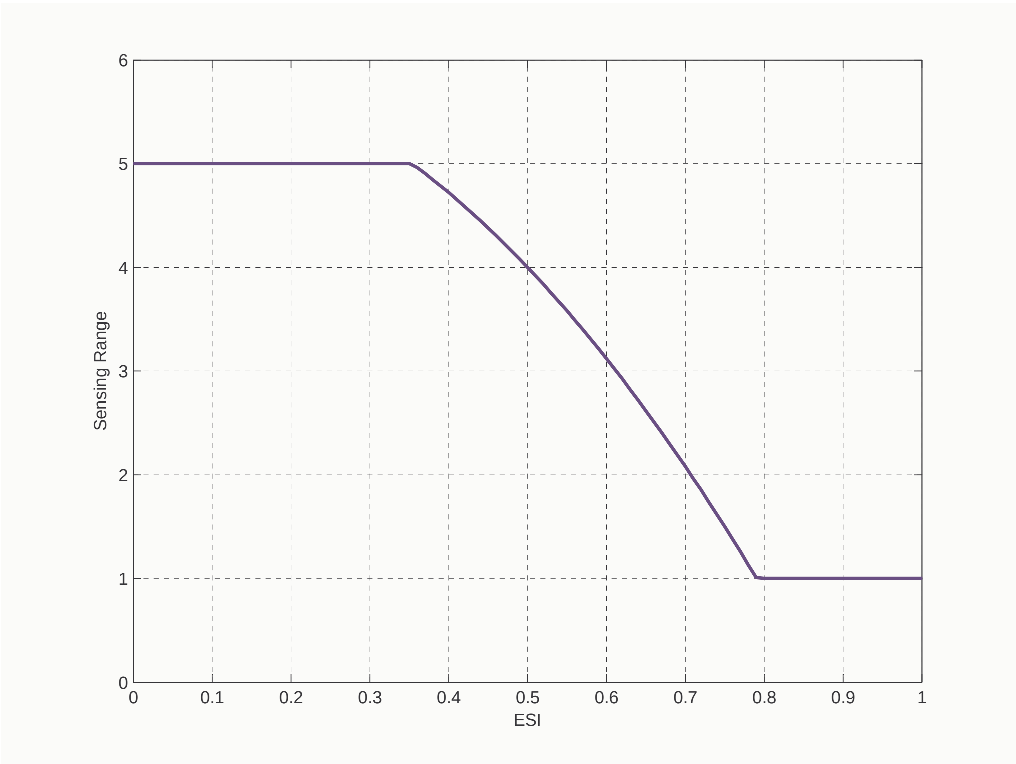


Figure 5.6: The sensing range versus the ESI.

5.5.1.4 Multi-Modality

Smart sensor nodes are usually characterized by multiple sensing modalities, where each of these modalities provides a different quality of measurements about the threats in the environment. However, higher resolution modalities result in higher power consumption, which is not affordable in sensor nodes. Selecting a specific modality to be used throughout the life of the system may result in either quickly draining the system reserve or missing some important information that are not captured by that modality. Therefore, this works proposes an adaptive multi-modality scheme that increases the modality level in response to the increase in the environment dynamics and/or the threat level. Representing such multi-modality selection scheme at the individual node level is one of the strengths of this work.

ALGORITHM: Multi-modality selection
Inputs: currentModality, setAvaliableModalities, ModalityThreshold
ESI, threatLevel, dynamismLevel
Outputs: newModality
If current-Modality is not the minimum modality
& ESI $\leq$ ModalityThreshold & dynamismLevel is low & threatLevel is low
{
$newModality = currentModality - 1$
$ModalityThreshold = ModalityThreshold * 0.75$
}
If threatLevel high or dynamismLevel is high
{
Activate higher sensing modalities
$newModality = \frac{threatLevel}{maxThreatLevel} * maxModality$
$newModality = newModality > currentModality ? newModality : currentModality$
$ModalityThreshold = ModalityThreshold * 1.25$
}

Table 5.1: Multi-modality selection algorithm.

Table 5.1 shows the multi-modality selection algorithm. The proposed algorithm bases its decisions on the dynamic environment information, the threat level, the node energy level, and the set of available modalities. The algorithms activates lower modalities depending on lower environment dynamics and lower threat levels. On the other hand, it engages higher modalities when there is a need for collecting higher quality observations, *e.g.*, when the threat level is high or at high environmental dynamism levels. The modality threshold parameter is dynamically changed over time to reduce the time where higher modalities are deployed as much as possible.

5.5.1.5 Constrained Communication

A large percentage of the energy consumed in sensor nodes occurs during the data communication phase compared to the energy consumed during processing. The energy needed to transmit 1 KB over a 100m distance is approximately equivalent to the energy necessary to carryout 3 million instructions at a speed of 100 million instructions per second (MIPS) [170]. In a low dynamic environment, the sampled data might contain redundant or insignificant information, thus, there might be no need to communicate such information to the delegate. Nevertheless, if the sampled data contain the same information for a long period of time, it might be important to notify the delegate of the persistence of the measurements. On the other hand, in a highly dynamic environment, changes happen more frequently and communicating such information might be critical to the success of the mission. As a result, this work proposes a constrained communication algorithm which provides an on-demand communication in highly-dynamic environments and an on-demand/periodic combined communication with fused information in case of low environmental dynamism. Figure 5.7 illustrates the idea behind the proposed constrained communication scheme. Table 5.2 lists the pseudocode for the constrained communication algorithm.

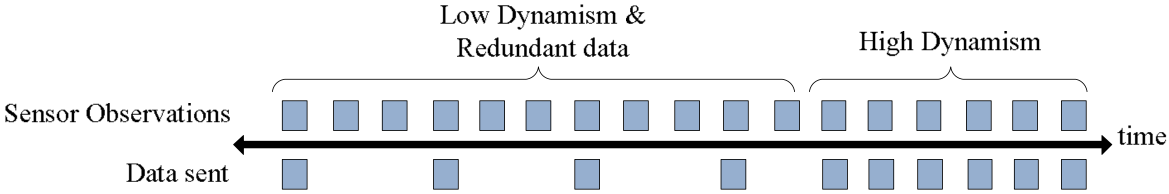


Figure 5.7: The proposed constrained communication concept.

5.5.2 Modal Logics Formulation

This section provides the energy efficient SM design modelled in the Modal Logics formal framework [171]. Section 5.5.2.1 provides a brief introduction of the modal logics language and operators. Section 5.5.2.2 formulates the proposed energy-aware SM using modal logics and Section 5.5.2.3 provides the joint responsibility formulation of the sensor nodes.

5.5.2.1 Modal Logics Framework

Modal logics is a formal logic primarily developed in the 1960s that extends the classical propositional and predicate logic to include operators expressing modality. Modal logic studies reasoning that involves the use of the expressions "necessarily" and "possibly". A formal modal logic represents modalities using modal operators. This section gives an overview of the Modal Logics formal framework in which the model of the SM problem will be expressed. A complete formal definition of the modal logics language syntax and semantics can be found in [171].

The operators of the modal logics language have the following meanings: The operator *true* is a logical constant for truth. Knowledge is the strongest individual informational attitude and always corresponds to facts. In order to represent knowledge in the Modal Logics language, $Know(i, \kappa)$ is used to denote that an agent i knows proposition κ. While, $B_x(i, \kappa)$

ALGORITHM: Constrained Communications

Inputs: constrainedComm, counter, commThreshold, threatLevel, dynamismLevel

Outputs: constrainedComm

```
If constrainedComm is not activated & dynamismLevel is low & threatLevel is low
  {
    Activate constrainedComm
    Set counter to zero
    Reset commTimer
    Send sensor information to delegate
    While sensing the environment
      {
        Fuse observation information
        Increment counter
        If counter ≤ commThreshold or commTimer expires
          {
            Send fused information to delegate
            Set counter to zero
            Reset commTimer
          }
        If threatLevel is high or dynamismLevel is high
          {
            Deactivate constrainedComm
            Communicate to the delegate on-demand
            break
          }
      }
  }
```

Table 5.2: Constrained communication algorithm.

and $Goal(i, \kappa)$ mean that agent i has a belief or a goal of κ, respectively. $Intend(i, \alpha, \kappa)$ denotes that agent i has adopted intention α to achieve goal κ. The $=$ operator is the first-order equality. The $\in$ operator relates an agent to groups of agents; it has the expected set-theoretic interpretation, *i.e.*, $(i \in g)$ means that the agent denoted by i is a member of the group denoted by g. The $(Agts\ \alpha\ g)$ operator means that the group denoted by g are precisely the agents required to perform the actions in the action sequence denoted by α. The A operator is a path quantifier: $A\,\kappa$ means that κ is a path formula that is satisfied in all the futures that could arise from the current state. The operators $\neg$ (NOT), $\vee$ (OR), and $\wedge$ (AND) have the classical logic semantics, as does the universal quantifier $\forall$.

Other operators include: $Happens\ \alpha$ is a path formula that means that the action α happens next, $\alpha; \alpha'$ means the action α is immediately followed by α', $\alpha|\alpha'$ means either α or α' happens next, $\alpha?$ is a test action, which occurs if α is *true* in the current state, α^* means the action α is iterated, $\alpha\ \mu\ \beta$ means α is satisfied until β becomes satisfied, $\Diamond\alpha$ means α is eventually satisfied, $\Box\alpha$ means α is always satisfied.

5.5.2.2 Modal Logics Energy-Aware SM Formulation

Modal logics has been acknowledged as a formal framework for representing a cooperative problem solving model [172]. In this section, the logic used to design the intelligent reasoning in each sensor is formally formatted in the Modal Logics language. Individual sensor nodes are designed to have five different informational attitudes: knowledge, beliefs, goals, commitments, and intentions. The key mental states that control the agents behaviours are intentions that define local behaviour based on selected goals.

It is assumed that there is a finite set of sensor nodes that cover the VOI uniformly. These sensors need to achieve a number of conflicting objectives using multiple intention plans. Let i be any sensor node and g is the group of all sensor nodes, then

$$\forall\, i\ \in\ g\,. \tag{5.20}$$

Since any sensory system should be able to collect information about the state of the environment, the sensors are capable of performing environment monitoring through scan actions. The scan action is denoted by α and it can be only carried out by members of the group g,

$$Agts\ \alpha\ g\,. \tag{5.21}$$

Each sensor node has an indication of its energy level; let ν represents the local knowledge of sensor i that its current energy level ζ is greater than 0,

$$\nu := \Diamond(know(i,\zeta) > 0)\ . \tag{5.22}$$

Moreover, by performing the scan action α, the sensor node can establish a belief state about the presence of abnormality within the VOI. Let ϱ represents the belief state of sensor i that an abnormal event, χ, might exist in the environment,

$$\varrho := \Diamond(B_x(i,\chi_\alpha))\ . \tag{5.23}$$

Let the abnormality evaluation action be denoted by Γ. Using action Γ, the sensor node can estimate the belief state, ρ, about the presence of a threat within the VOI as

$$\rho := \Diamond(B_x(i,\chi_\Gamma))\ . \tag{5.24}$$

In a surveillance system, the main system goal is to secure the VOI, which can be denoted by Ψ. To achieve $Goal(i,\Psi)$, an intention plan has to be adopted that defines the sensor actions under various outcome, which can be given by

$$Goal(i,\Psi) \Rightarrow Intend(i,S,\Psi)\ . \tag{5.25}$$

Accordingly, sensor i carries out $Intend(i,S,\Psi)$ plan which provides a sequence of actions to achieve $Goal(i,\Psi)$. The plan is carried out if the sensor node has not exhausted all of its energy reserve. The sensor node will perform the scan action α followed by formation of belief ϱ. If the presence of abnormality belief ϱ is *true*, then sensor i performs the abnormality evaluation action Γ to form a belief about the presence of a threat ρ such that if ρ is *true*, the cue action to the delegate node ς is performed,

$$Intend(i,S,\Psi)\ :=\ (\Box\,\nu\ \wedge((\alpha\ ;\ (\varrho\ ?\ \Gamma))\ ;\ \rho\ ?\ \varsigma))^* \tag{5.26}$$

On the other hand, sensor nodes, being battery-powered, have a limited lifetime. To prolong the nodes lifetime, an energy-aware sensor has to reason on various energy conserving strategies. The goal to conserve energy is denoted by ϑ such that $Goal(i,\vartheta)$ is achieved by an intention plan given by

$$Goal(i,\vartheta) \Rightarrow (\Box\,\nu\ \wedge((B_x(i,ESI)\ ;\ (M_x(ESI \to (\gamma,\ \varpi,\ \iota,\ o,\ \upsilon)) \Rightarrow\ Intend(i,\Lambda_\vartheta,\vartheta)))))^* \tag{5.27}$$

For sensor i to achieve $Goal(i,\vartheta)$, the node energy reserve has to be greater than zero, then the node formulates its belief about the state of the environment and sensor status using the ESI, $Bx(i, ESI)$. Based on that belief, the sensor node activates a meta-reasoning process M_x to decide which energy conserving sub-goal it will adopt, denoted by Λ_ϑ

$$\Lambda_\vartheta \in \{\gamma,\ \varpi,\ \iota,\ o,\ \upsilon\} \tag{5.28}$$

where $\{\gamma,\ \varpi,\ \iota,\ o,\ \upsilon\}$ denotes the adaptive sleep, active sensing, dynamic range, multi-modality, and constrained communications algorithms, respectively.

Reasoning about which and when each goal is adopted is expressed by the goal to manage the sensor operations and denoted by Υ. Similar to the previous goals, to achieve $Goal(i, \Upsilon)$, the sensor i should have sufficient battery power to operate. Subsequently, the sensor node activates a meta-reasoning process, M_x, to reason between securing the VOI and energy conserving goals followed by activating the Λ_Υ plan and carries out the logging action L

$$Goal(i, \Upsilon) \Rightarrow (\Box\, \nu\ \wedge ((M_x(\psi\ ,\ \vartheta) \Rightarrow\ Intend(i, \Lambda_\Upsilon, \Upsilon)));\ L))^* \tag{5.29}$$

$$\Lambda_\vartheta \in \{\psi\ ,\ \vartheta\} \tag{5.30}$$

5.5.2.3 Joint Responsibility Formulation

In a WSN with constrained resources, sensor nodes have to collectively work to maximize the system success in achieving its goals. The mental state of individual sensor nodes is defined by their adopted intentions based on their commitment to achieving a joint goal with specific motivation. The authors of [146,173] have developed the theory of joint intentions that models the cooperative behaviour of a multi-agent system with mutual beliefs and goals as well as joint intentions and commitments in achieving a system objectives.

Intelligent agents engaged in a cooperative activity based on their mutual beliefs can adopt joint intentions and joint commitments to the overall system objective. Nevertheless, each agent still has its own individual commitments to specific local goals. The mutual beliefs, $M\text{-}B_x$, and mutual goals, *M-Goal*, shape the social convention by which joint intentions result in joint commitments. A Joint commitment, *J-Commit*, defines the conditions under which such commitment can be dropped, and also describes how the agent should behave towards its fellow team members. Therefore, the joint commitment, *J-Commit*, is defined by

$$(J\text{-}Commit\ a\, b\, y\, pre\, c)\ , \tag{5.31}$$

where a is the team of agents, b is the goal to be achieved, y is the motivation for goal b, pre is the precondition that has to be initially satisfied, and c is the convention indicating a termination condition.

Using the joint intention theory, the collective performance of the sensor nodes in the proposed energy-aware SM is modelled. Since the main objective of the sensory system is securing the VOI, a team of sensors g has a joint persistent goal to achieve goal ψ, thus having a mutual goal ($M\text{-}Goal(g, \Psi)$), by jointly adopting the intention plan S.

$$M\text{-}Goal(g, \Psi) \Rightarrow J\text{-}Intend(g, S, \Psi) \tag{5.32}$$

The adopted intention plan of individual sensors ($J\text{-}Intend(g, S, \Psi)$) results in a joint commitment to achieve the mutual goal ($M\text{-}Goal(g, \Psi)$):

$$\begin{aligned} J\text{-}Intend(g, S, \Psi) \ &:= \ (M\text{-}B_x\ g\ (Agts\ \alpha\ g)) \ \wedge \ (J\text{-}Commit\ g\ S \\ &\Diamond(Happens(M\text{-}B_x\ g\ (Does\ S))\ ?\ \Psi)\ (\nu\ \wedge\ \varrho\ \wedge \rho)\ (\neg\nu)) \end{aligned} \tag{5.33}$$

5.5.3 Meta-reasoning and BDI formulation

A sensor may have multiple conflicting local objectives, *e.g.*, monitoring the VOI and increasing its lifetime. Each of these objectives entails a list of plans that the sensor has to choose from. In such case, the sensor needs to decide on what to reason on, *i.e.*, the sensor needs to use meta-reasoning techniques to decide on a reasoning mode. The term "meta-reasoning" denotes that the system is able to reason about its own operation. Meta-reasoning allows adaptability in the sensor behaviour and decisions to accommodate both the dynamic environment changes as well as the changes in its reasoning about operation itself. Figure 5.8 illustrates the meta-reasoning model.

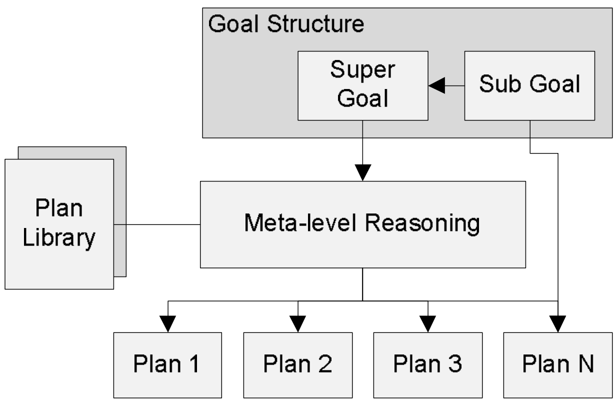


Figure 5.8: The meta-reasoning model.

Because of the limited sensor node resources, the sensor node has to change its mode of operation using on-board deliberations on available commitments. The sensors use meta-reasoning to decide and modify their current commitments based on realtime variations in the environment and the current sensors health. The goal of meta-level control is to improve the quality of decisions by determining what and how much reasoning is needed. Although meta-level control allows agents to dynamically adapt to the changes, it could also interfere with ground-level performance. Thus, identifying the decision points that require meta-level control is of importance to the performance of resource limited nodes.

Figure 5.9 illustrates the sensor goals and commitments that manage the sensor node operations and highlights the decision points where meta-control is needed. Jadex provides an architectural framework for deciding how goals interact and how an agent can autonomously decide which goals to pursue. This process is called goal deliberation. The current release of Jadex includes a goal deliberation strategy called "Easy Deliberation", which is designed to allow the specification of the relationships between goals based on goal cardinalities [174].

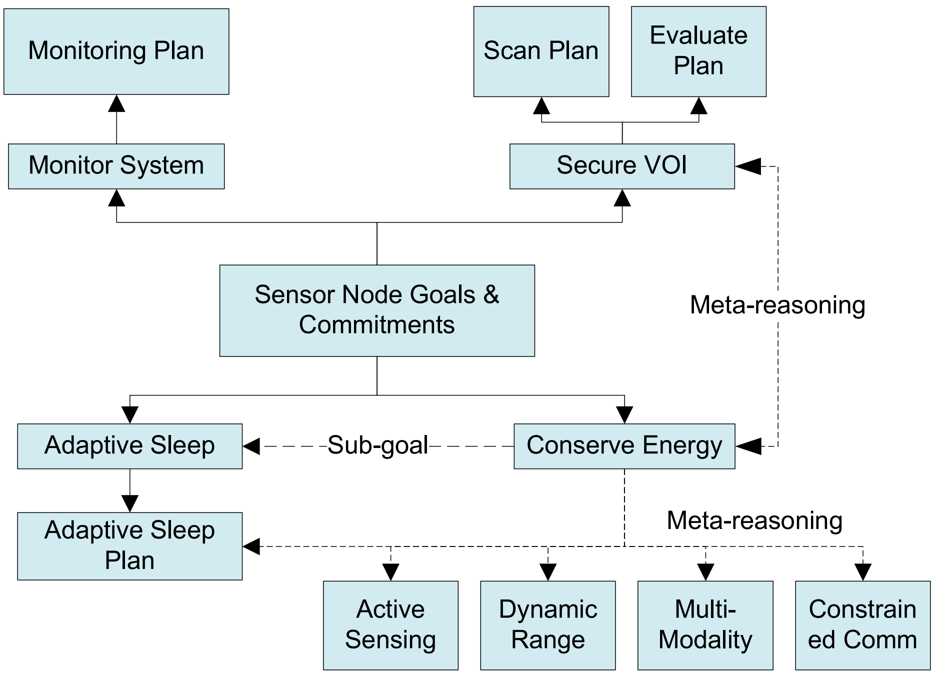


Figure 5.9: The Energy-Aware SM goals and commitments.

5.6 Simulation Setup and Results Discussion

The simulations presented in this section aim to quantify the performance of the proposed approach. The scenario adopted in the experiments performed models the problem of an airport surveillance and implemented on the Jadex platform. The rest of this section explains the simulation setup and discusses the simulation results.

5.6.1 Simulation Setup

The layout of the airport used in these experiments is presented in Figure 5.10. The airport halls are virtually divided by the sensors during the initialization phase into mesh grid cells. Each sensor has an initial sensing range of the 3×3 grid cells. The sensors are stationary with heterogenous modalities and are represented in the graphical user interface by a gray round object and the delegates by black ones. Each sensor is equipped with a battery of 2000 power units. The passengers enter and leave the airport randomly. Impulsive bursts of passenger arrivals and departures are also randomly generated to simulate the real world. Moreover, the injected targets depart the environment in random times. These benign targets are represented in the simulation by white and black human-like images.

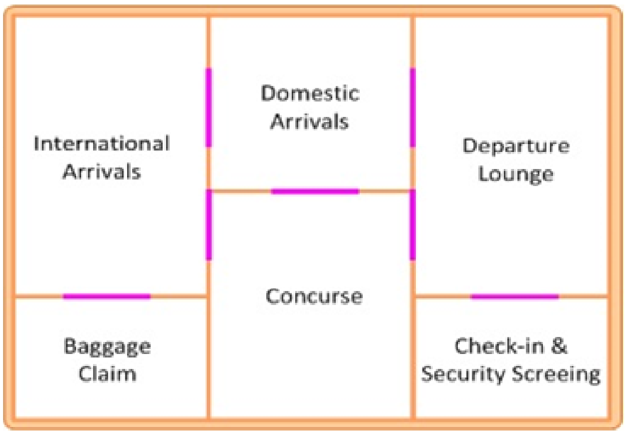


Figure 5.10: An international airport simplified plan.

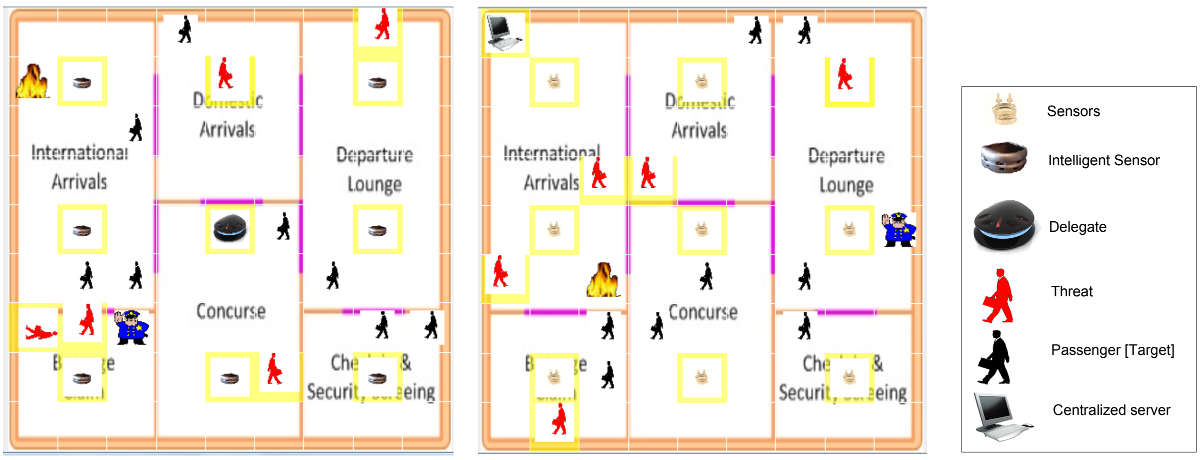
The human threats are represented as intelligent mobile agents with sets of beliefs, desires, and intentions. The detection and tracking of human threats are the focus of the system. The number of threats vary between 1 and 20 threats. The threats do not depart the scene for the duration of the simulation and they move all around the airport. The motion of the threat is set to a pre-specified pattern, however, a random motion pattern is invoked arbitrarily. The simulation is carried out until all sensors run out of energy and the surveillance system fails. Table 5.3 lists the simulation configuration parameters used.

Three different approaches were implemented for comparison; the proposed energy-aware approach denoted by EC-HASM, E-HASM, and centralized. Figure 5.11 shows a

Table 5.3: Simulation environment setting.

Parameter	Value
Area	9×9 to 36×36 grid
# Sensors	6 to 144
Battery power	2000 power units
Danger levels	1 levels (Human Threats)
# Threats	1 to 20
Target motion	preset pattern (progressive scan) random change in direction
Direction	4 direction

snapshot of the graphical user interface for the implemented approaches. The EC-HASM and E-HASM are composed of a group of smart sensor nodes and a group of delegate nodes. The centralized system shown in Figure 5.11(b) is composed of a group of sensors and a centralized processing unit represented on the top left side of the simulation environment. The processing speed of the centralized unit is 10 times faster than that of delegate nodes in the EC-HASM and E-HASM. A global surveillance of all threats within the VOI is the main mission of the system. Similar to Chapter 4, it is assumed that the sensor only needs to know the cell on the grid in which the threat resides to determine the exact location on the threat. Moreover, it is assumed that by detecting an entity within the VOI, the sensor can identify its threat level.



(a) The Proposed SMF GUI (b) The Centralized GUI (c) Key

Figure 5.11: The airport surveillance scenario implemented on Jadex Standalone Platform.

5.6.2 Simulation Results

The results of the proposed energy-aware algorithm is represented in this section. Various experiments were executed to evaluate the performance of the proposed technique with respect to varying network size, number of threats, threat agility, environment dynamism, tracking quality, and energy consumption.

5.6.2.1 Impact of Network size

This set of experiments were performed to evaluate the systems performance with respect to varying network sizes. The network size varies from 9×9 grid cells monitored by 9 sensors and 1 delegate to 36×36 grid cells monitored by 144 sensors and 18 delegates. The threats within the VOI are set to 5 threats and their agility is set such that they move in a progressive scan manner with no sudden changes in direction or location. The environment dynamism is set to the maximum value, *i.e.*, the changes in the environment happens fast.

A WSN needs a certain number of sensor nodes to be considered functional and able to perform its tasks. However, the number of sensor nodes needed is highly dependent on the application requirements and network topology. In this thesis, it is assumed that the network is considered alive and is able to function with at least one operational sensor. Thus, the network lifetime, in this work, denotes the lifetime of the network from the start of the initialization phase until the last sensor to die in the network.

Figure 5.12 plots the overall network lifetime versus the varying grid sizes for the different schemes tested. The results show that the overall network lifetime increases as the network size increases for all three approaches studied. However, the network lifetime for the EC-HASM increases with a larger slope than that of the E-HASM and the centralized approaches. Moreover, it can be noted that the EC-HASM network lifetime is, in the worst case, $10\times$ larger than the overall network lifetime for the centralized SM approach. On the other hand, the network lifetime of the E-HASM is only double that of the centralized on average. This is attributed to the adaptive energy-aware operation on the EC-HASM compared to that of the E-HASM and the centralized approaches.

Each sensor node dissipates its energy independently, thus, the sensors energy reserves are consumed at a different rates. When the energy reserve of any sensor node gets depleted, gaps may appear in the sensing coverage of the sensor network. As a result, degradation is witnessed in the overall system ability to detect threats and monitor their behaviour. In this context, the sensor lifetime signifies the lifetime of the first sensor to die in the network. Figure 5.13 plots the sensor lifetime versus the varying grid sizes. Similarly, it

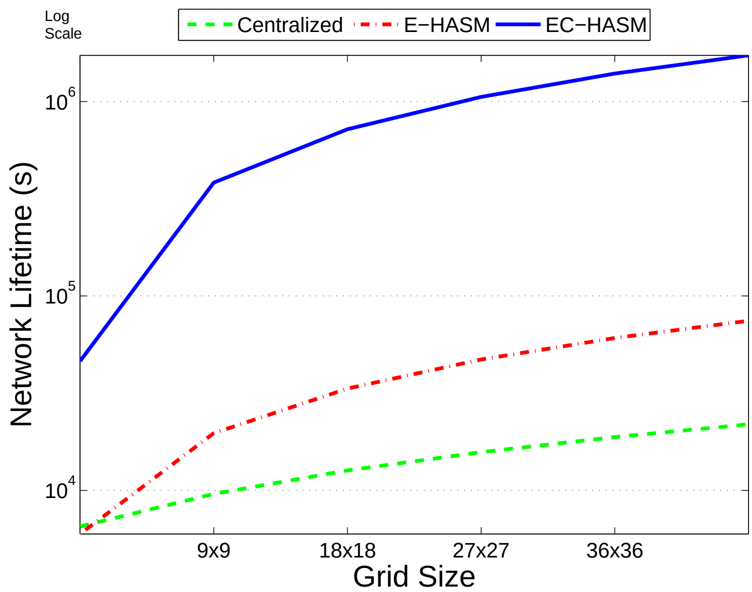


Figure 5.12: The network lifetime over varying network sizes.

can be observed that the sensor lifetime increases as the network size increase in all the three approaches and EC-HASM outperforms the other two techniques tested. Also, the increase in lifetime is more significant for the EC-HASM compared to the E-HASM and centralized SM. This is attributed to the adaptive energy-aware operation of the EC-HASM and the cooperative design of the EC-HASM sensor nodes .

Figure 5.14 shows the ratio of the communication messages exchanged per unit time versus the varying grid size. It can be noted that the communication overhead ratio increases as the network size increases for both the E-HASM and the centralized approaches while remaining almost constant for the EC-HASM approach. Moreover, the EC-HASM has lower communication overhead compared to both the E-HASM and the centralized SM. In the worst case scenario, the communication overhead of the centralized approach is $100\times$ that of the EC-HASM. This is attributed to the reduced communication of the EC-HASM approach which is a result of the distributed processing, the localized decision making, and the constrained communication scheme.

5.6.2.2 Impact of Number of Threats

This set of experiments are carried to investigate the impact of the number of threats on the system performance. The setup is formed using 9×9 grid monitored by 9 sensors and

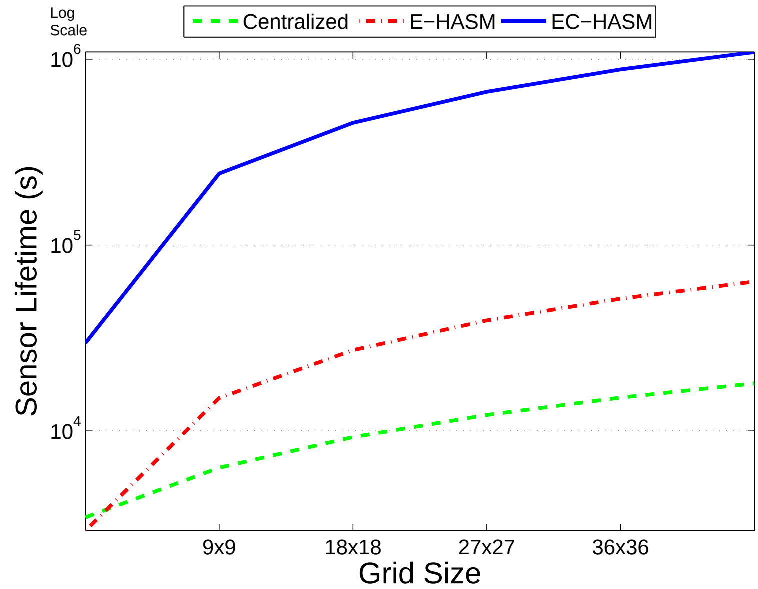


Figure 5.13: The sensor lifetime over varying network sizes.

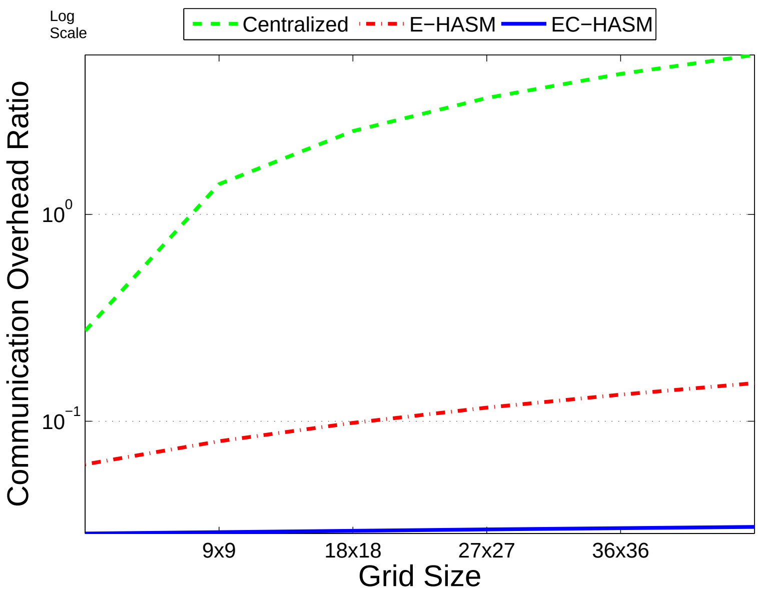


Figure 5.14: The communication overhead over varying network sizes.

1 delegate, the number of threats within the VOI vary between 1 and 20. The threats agility is set such that there is no sudden changes in their movement. The environment dynamism is set to the maximum value.

Figure 5.15 plots the overall network lifetime versus the number of threats. From Figure 5.15, it can be noted that the overall network lifetime remains almost constant with the number of threats for the E-HASM approach while the overall network lifetime slightly decreases for the centralized approach. This is attributed to the distributed nature of the E-HASM design, as well as, the reduced communication overhead of the E-HASM compared to the centralized approach. On the other hand, the lifetime of the EC-HASM tends to decrease with increasing the number of threats. This is attributed to the increasing threat level and environment dynamism as the number of threats increase, which leads the sensor nodes to become active for longer periods of time. Despite that reduction in the network lifetime experienced by the EC-HASM, its network lifetime is 10× that of the centralized in worst-case and 5× that of the E-HASM SM.

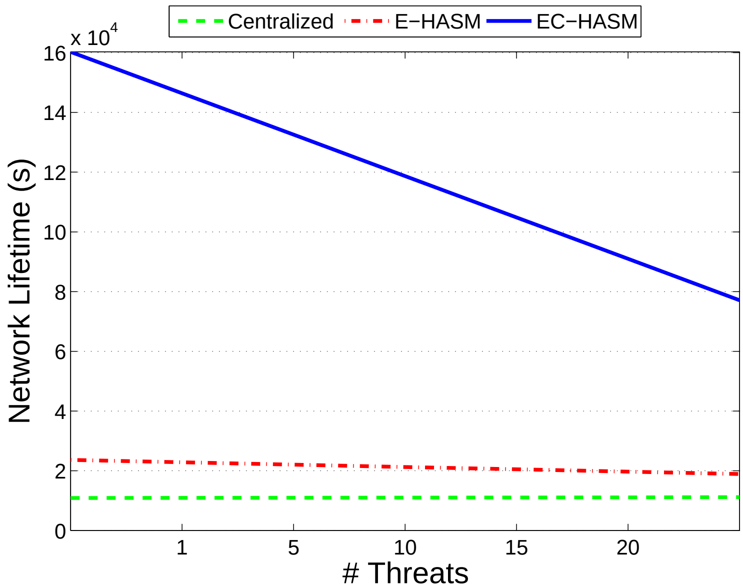


Figure 5.15: The network lifetime versus increasing number of threats.

In Figure 5.16, the sensor lifetime is plotted versus the number of threats. The results show that the EC-HASM, the E-HASM, and the centralized SM approaches exhibit similar trends to the network lifetime plots in Figure 5.15. It should be noted that for the EC-HASM, the sensor lifetime decreases as the number of threats increase. However, the sensor lifetime for the EC-HASM is more than 15× and 8× longer than that of the centralized SM approach in best and worst cases, respectively.

The communication overhead plotted in Figure 5.17 depict the near-linear relationship between the number of threats and the communication messages exchanged for the cen-

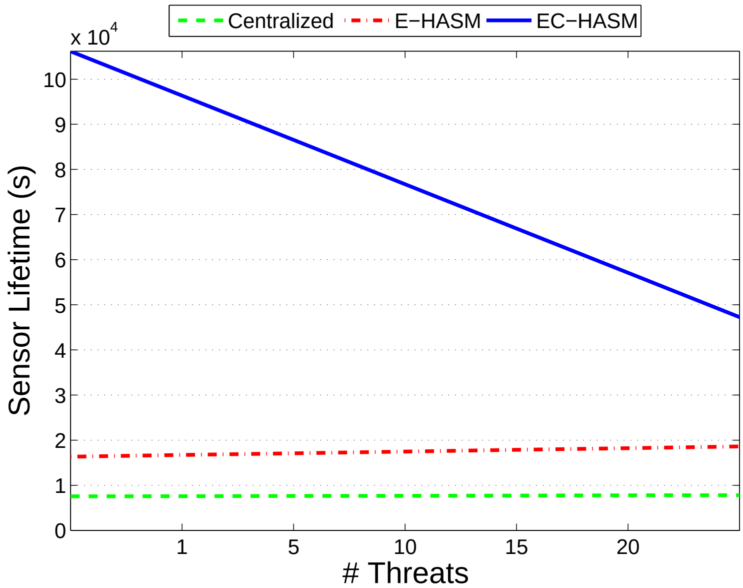


Figure 5.16: The sensor lifetime versus increasing number of threats.

tralized and the E-HASM approaches, with the E-HASM experiencing significantly lower communication overhead compared to that of the centralized approach. This is attributed to the distributed nature, localized operation, and the on-board processing of the E-HASM. On the other hand, the EC-HASM SM yields an even lower communication overhead and remains almost constant as the number of threats increases, mainly because of the reduced communication overhead due to the constrained communication scheme employed in the EC-HASM.

5.6.2.3 Impact of Threat Agility

This set of experiments are carried to investigate the effects of increasing the threat agility levels on the system. The agility in this context refers to how frequent a threat changes its direction while moving throughout the VOI. The setup is formed using 9×9 grid cells monitored by 9 sensors and 1 delegate, the number of threats within the VOI set to 5 threats and the environment dynamism is set to the maximum value.

Figure 5.18 plots the overall network lifetime versus the threat agility. The results in Figure 5.18 show that the overall network lifetime remains almost constant as the threat agility levels increase for the E-HASM and centralized approaches, while the overall network lifetime slightly decreases for the EC-HASM approach. However, the network lifetime of

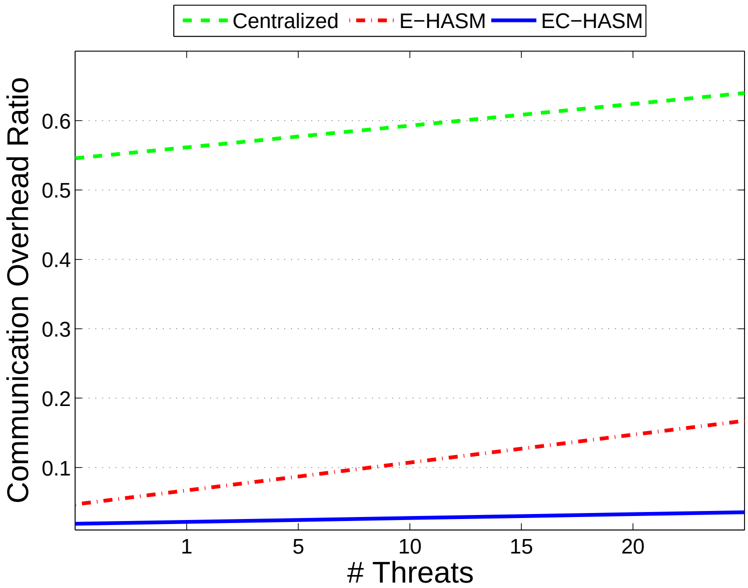


Figure 5.17: The communication overhead versus increasing number of threats.

EC-HASM is on average 15× and 9× that of the centralized and the E-HASM approaches, respectively. Hence, it can be concluded that the EC-HASM scheme is flexible enough to adapt to the environmental changes to prolong the network lifetime by utilizing the environment characteristics.

In Figure 5.19, the sensor lifetime is plotted versus the threat agility. Similar to the trends of the network lifetime graph, Figure 5.19 shows that the sensor lifetime remains almost constant as the threat agility increases for the E-HASM and centralized approaches, while the sensor lifetime decreases for the EC-HASM approach. However, the sensor lifetime of EC-HASM is 9× and 7× that of the centralized and E-HASM approaches in the worst case.

From the plot of the communication overhead versus the the threat agility in Figure 5.20, it can be observed that the average communication overhead for the centralized approach slightly increases as the threat agility level increase. On the other hand, the communication overhead of the E-HASM and the EC-HASM approaches are almost constant as the threat agility increases. Moreover, it should be noted that the communication overhead for EC-HASM is on average 30× and 3.5× less than that of the Centralized and E-HASM schemes, respectively.

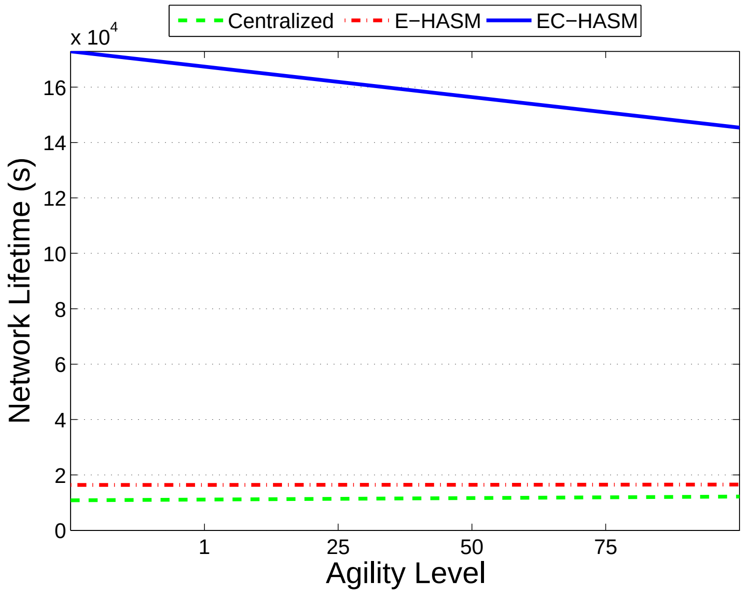


Figure 5.18: The network lifetime versus increasing levels of threat agility.

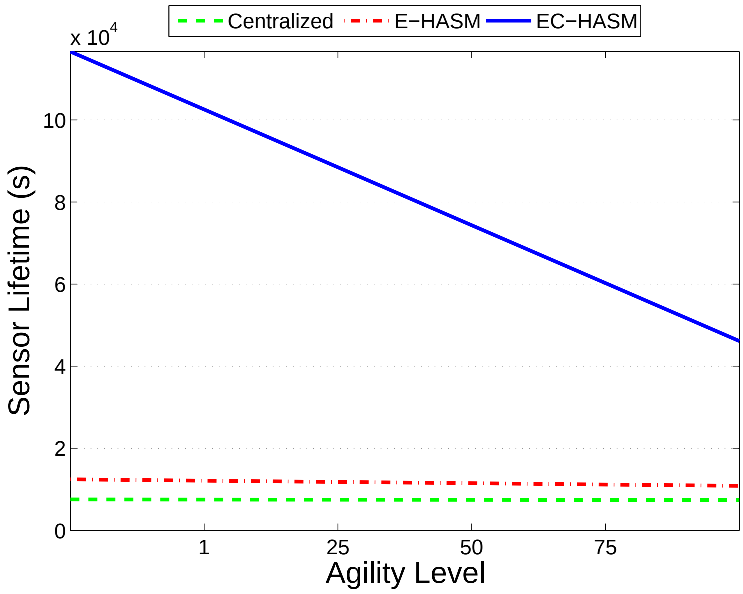


Figure 5.19: The sensor lifetime versus increasing levels of threat agility.

5.6.2.4 Impact of Environment Dynamism

This set of experiments are carried to investigate the effects of increasing the environment dynamism on the system. The dynamism level stands for the frequency by which changes

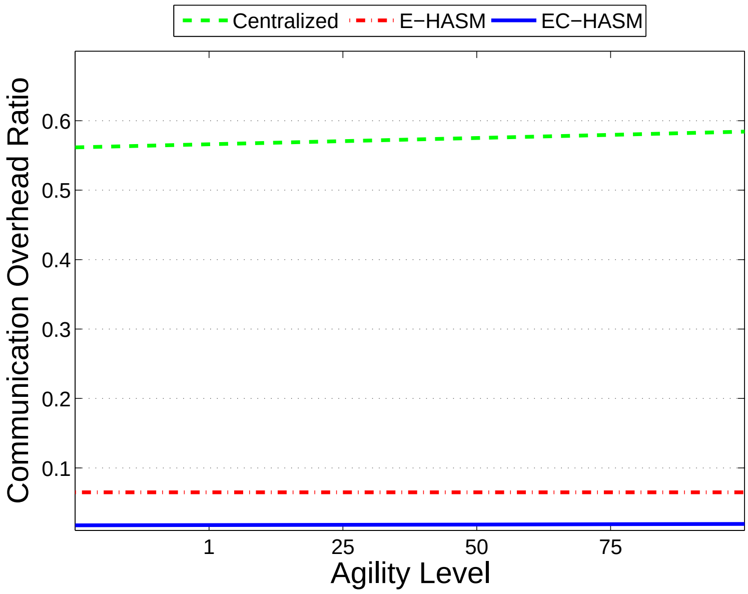


Figure 5.20: The communication overhead versus increasing levels of threat agility.

are inflected on the environment, as well as the speed by which threats and targets moves within the VOI. The setup was formed using 9×9 grid monitored by 9 sensors and 1 delegate, the number of threats within the VOI is 5 threats and the agility level is set to minimum value.

Figure 5.21 plots the overall network lifetime versus the environment dynamism, from which it can be deduced that the overall network lifetime remains almost constant with the increasing environment dynamism for the EC-HASM approach while it exhibits slightly reduction for the E-HASM and the centralized SM approaches. The network lifetime of the EC-HASM is almost $13\times$ and $6\times$ that of the centralized and E-HASM approaches, respectively. This is attributed to the adaptive nature of the EC-HASM to the environment and threat dynamics and the onboard threat evaluation.

In Figure 5.22, the sensor lifetime is plotted versus increasing levels of environment dynamism. From Figure 5.22, it can be noticed that the sensor lifetime exhibits a slight increase with the environment dynamism for the EC-HASM approach while a minor decreases in the sensor lifetime is witnessed in the E-HASM and the centralized SM approaches. The sensor lifetime of the EC-HASM is on average $13\times$ and $7\times$ that of the centralized and E-HASM approaches, respectively. This is attributed to the cooperation between the sensor nodes, the onboard threat evaluation, and t.

The communication overhead for each of the tested schemes is plotted in Figure 5.23

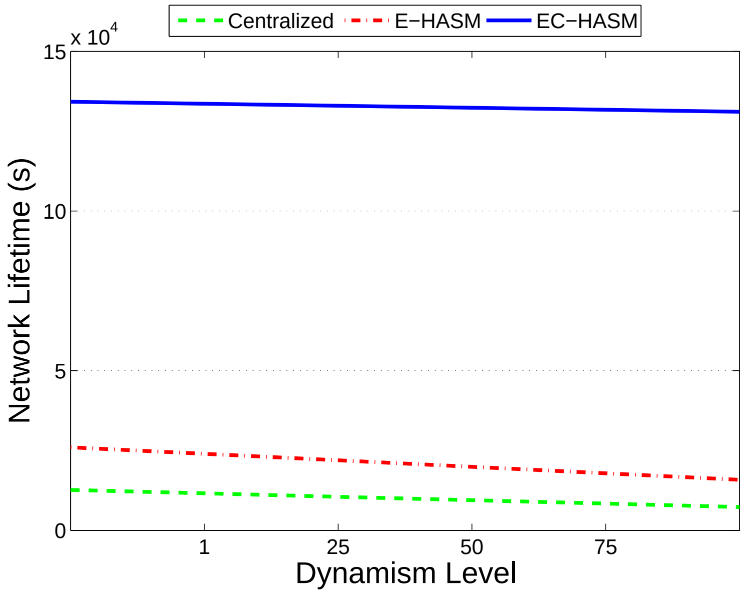


Figure 5.21: The network lifetime versus increasing levels of environment dynamism.

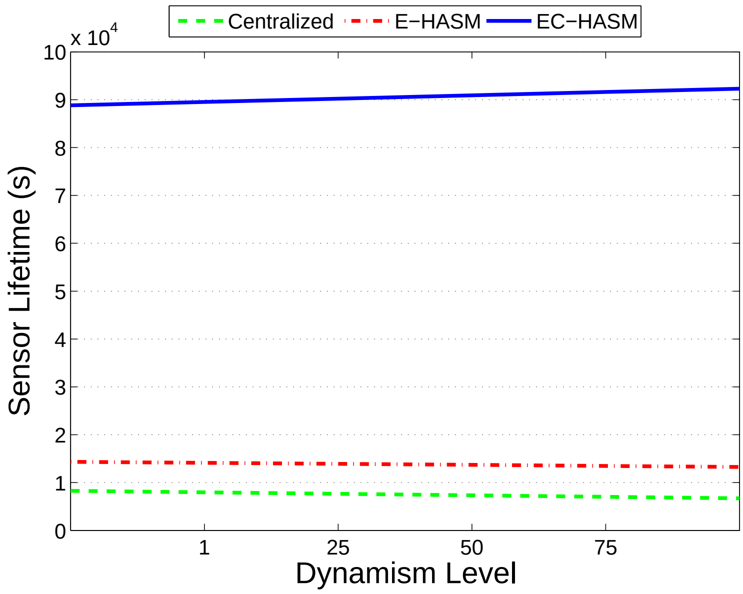


Figure 5.22: The sensor lifetime versus increasing levels of environment dynamism.

versus the environment dynamism. From Figure 5.23, it can be noted that the number of communication messages exchanged in the centralized SM approach increases linearly with the environment dynamism. Moreover, the E-HASM scheme suffers from a minor increase with the dynamism levels. On the other hand, the EC-HASM communication overhead remains constant with the dynamism level. In addition, the EC-HASM has lower communication overhead compared to the E-HASM and the centralized approaches. This is attributed to the constrained communication scheme that is designed to take advantage of the increase environment dynamics and adapt according to the changing environment characteristics.

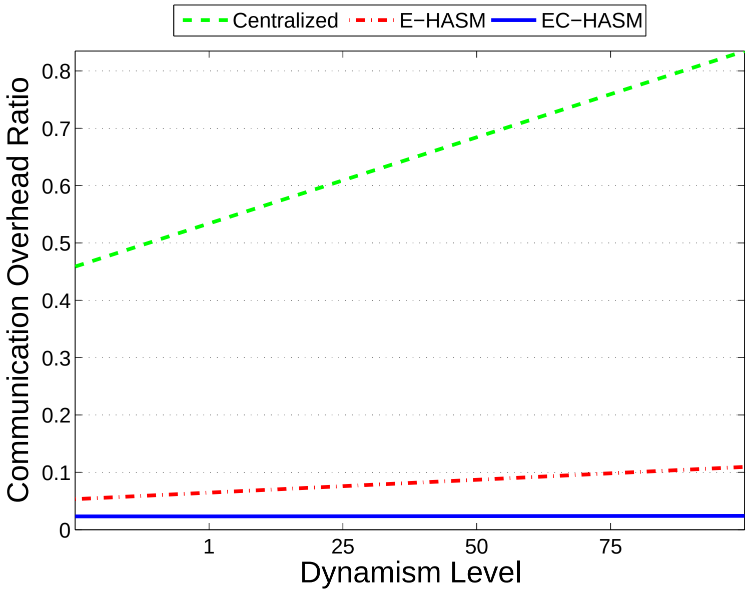


Figure 5.23: The communication overhead versus increasing levels of environment dynamism.

5.6.2.5 Tracking Quality

The tracking quality of the EC-HASM, the E-HASM, and the centralized schemes are plotted in Figure 5.24 versus time. From Figure 5.24, it can be noted that even though the centralized approach provides initially high tracking quality, it fails to maintain such tracking quality and dies relatively quickly. E-HASM shows a better ability to maintain higher tracking quality than the centralized approach, however, the EC-HASM is able to achieve high tracking quality for longer periods of time compared to the other approaches.

Figure 5.25 plots the overall tracking quality of the EC-HASM compared to that of the E-HASM and the centralized schemes versus the network size. From Figure 5.25, it can be deduced that even with increasing the network size, the EC-HASM is still able to achieve

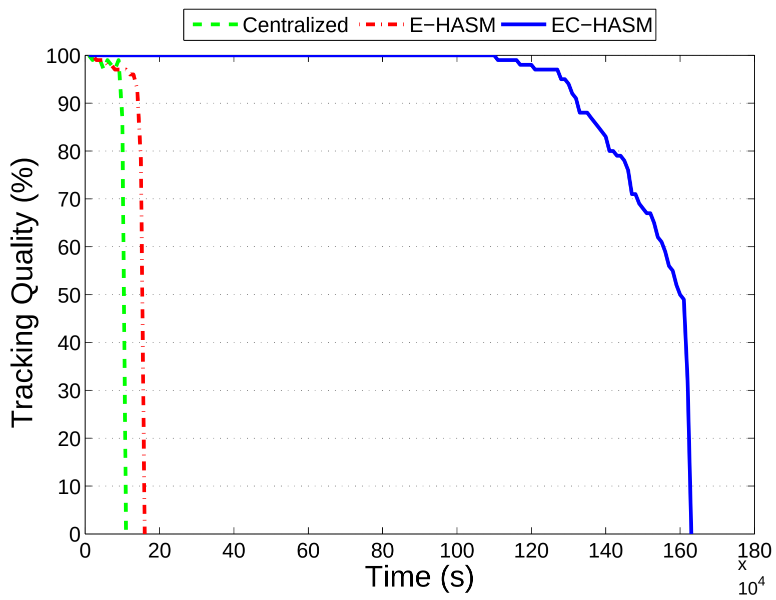


Figure 5.24: Tracking quality of EC-HASM, E-HASM, and centralized SM versus time.

higher tracking quality compared to those of the E-HASM and centralized approaches. This is attributed to the prolonged lifetime of sensors in EC-HASM system that leads to a full network coverage for a long period of time, thus, leading to better tracking.

5.6.2.6 Energy Consumption

The limited sensor resources dictates that the nodes are required to efficiently manage their energy consumption. Figure 5.26 plots the energy dissipation of the EC-HASM compared to that of the E-HASM and the centralized approaches. From Figure 5.26, it can be noted that the centralized approach dissipates energy in a fast linear steep manner. While the E-HASM approach dissipates energy in slower rate than the centralized, the EC-HASM dissipates energy in a significantly slower manner, 12× and 6× slower, than that of the centralized and E-HASM approaches, respectively.

5.7 Summary

With the limited power reserve of the sensor nodes, it is imperative to efficiently manage the sensors resources to prolong the lifetime of such networks. This chapter introduces an autonomous energy-aware SM approach that is carried onboard of the sensor node in

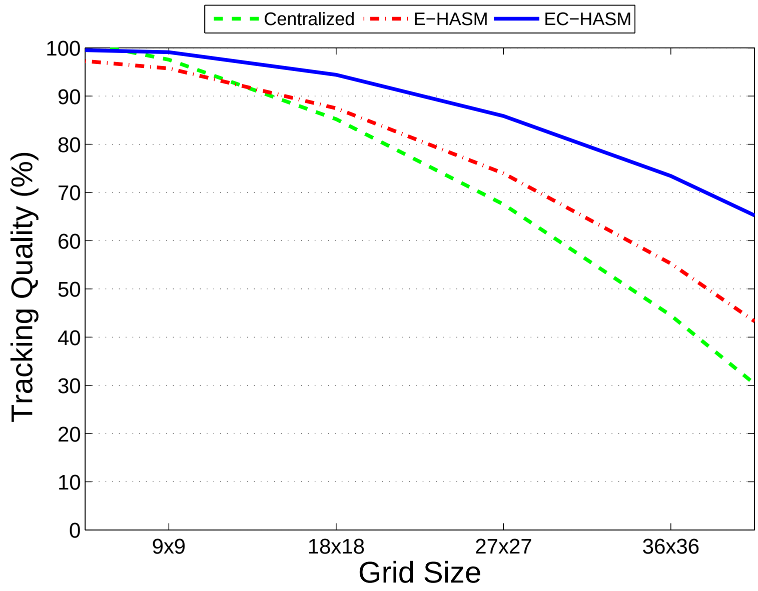


Figure 5.25: Tracking quality of EC-HASM, E-HASM, and centralized SM versus network size.

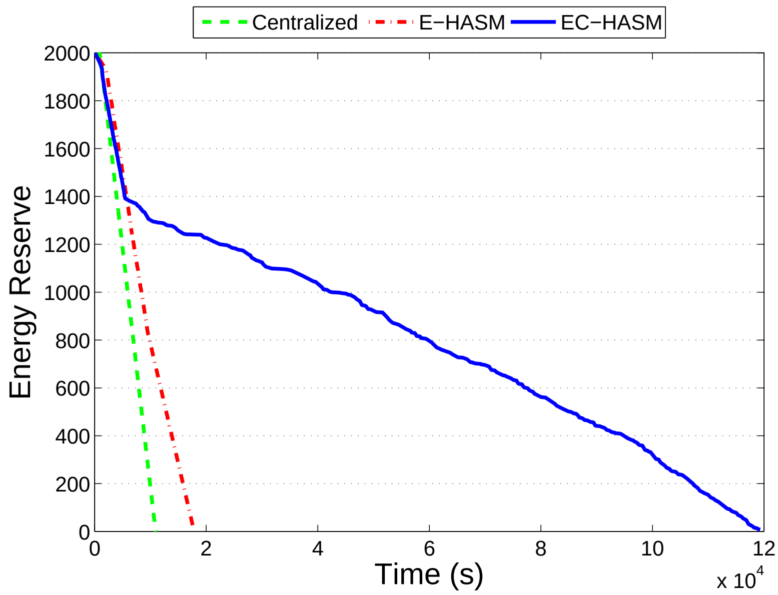


Figure 5.26: The energy consumption of EC-HASM, E-HASM, and centralized SM.

a distributed manner. A team-theoretic formulation of smart sensor nodes based on the Belief-Desire-Intention (BDI) model is proposed as a mechanism for effective collaborative decision-making. The proposed approach draws upon the initial design of the components of the E-HASM introduced in Chapter 4. A novel team-theoretic formulation is developed that manages the sensory system in an energy-ware manner using 5 folds: (i) adaptive sleep, (ii) active sensing, (iii) dynamic sensing range, (iv) multi-modality, and (v) constrained communication algorithms. The results shows the merits of the proposed approach compared to the E-HASM and the centralized schemes in terms of energy consumption, adaptability, and network lifetime. The main contribution of this chapter can be summarized as:

- Design of an autonomous energy-Aware SM using a team-theoretic BDI formulation,
- Distributed reasoning and decision-making scheme that is locally computed on-board of the sensor at realtime,
- A heuristic metric called Energy Saving Index (ESI) to provide an estimation of the sensor node status and its need/ability to conserve energy, as well as, capture the environment dynamics.
- An adaptive sleep algorithm that dynamically evaluates the sensor node probability of sleeping at the realtime and calculates the sleep interval according to the environment state and sensor health.
- An active sensing scheme that controls the frequency by which these sample data are collected providing significant energy saving.
- Dynamic sensing range approach aims to autonomously adjust the node sensing range taking into consideration the environment dynamics, threat level, and the nodes energy reserve.
- An adaptive multi-modality scheme that changes the modality level at the individual node level in response to the increase in the environment dynamics and/or the threat level.
- Constrained communication algorithm that provides an on-demand/periodic combined communication based on the environment dynamism.
- Formal design of the energy-aware SM is presented using the logic modals framework,
- Joint intention modelling for the collective behaviour of the sensor nodes,

- Use of meta-reasoning to decide and modify the sensor adopted commitment based on the variations happening in realtime in the environment as well as the current sensor health.
- Adaptive operation of the sensor node to the environment dynamics, threat level, and the availability of its own resources.

The distributed decision-making process that is proposed in this chapter can be enhanced by defining means of collaborate control to maximize the system utility in reaching its objectives. The following chapter addresses the design of collaborative operation to better manage the system resources.

Chapter 6

Collaboration for Enhanced Sensing

Each individual sensor in a WSN has a partial view of the environment, but collectively the network monitors the entire VOI. Therefore, a WSN that allows the collaborative operation of the sensor nodes can result in an improvement in the system performance. Moreover, a reduction in the variance of the different sensors lifetime can also be achieved simply because the workload can be balanced among the different nodes. This chapter aims to design such a sensor network scheme through proposing a stochastic decision-making scheme using POMDP formulation that represents the delegation decision making. The chapter is organized as follows: Section 6.1 provides an introduction of the proposed work. In Section 6.2, the collaborative and context aware scheme is proposed. The decision-making problem, as well as the SM formulation as a POMDP problem and the optimal policy calculations, are discussed in Section 6.3. Section 6.4 illustrates the performance of the proposed SM and its simulation results. Finally, Section 6.5 concludes the chapter.

6.1 Introduction

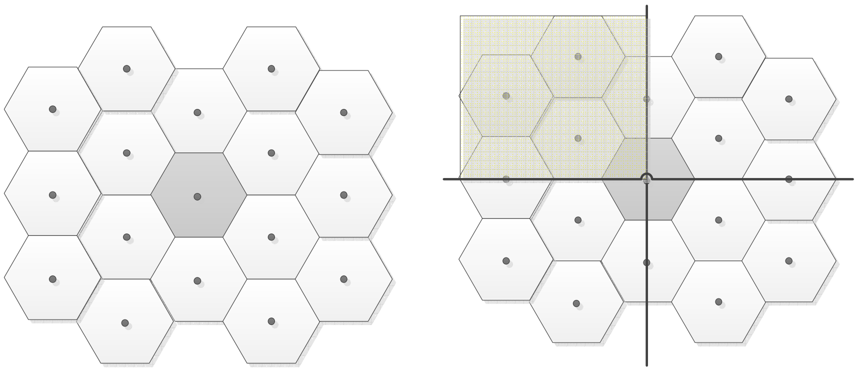
In a smart sensor network, each sensor is responsible for the independent reasoning and decision-making that affects its state and, consequently, the overall system state. Individual sensors form a partial view of the VOI, while combining several sensors views allows the network to build a complete picture of the entire VOI. Therefore, if sensor nodes are able to collaborate together to form a complete view of the dynamic scene, the performance of such a network can improve significantly. By taking into consideration that a phenomenon of interest is usually localized, only a subset of the sensor nodes needs to collaborate to get a complete view of the phenomenon and there is no need to share all the sensors information among the whole network. The E-HASM, proposed earlier in Chapter 4, is structured in a localized manner forming federations among the sensor nodes and the collective outcome of sensors in a delegation affects the overall mission objective.

In this chapter, we introduce a means of collaborative operation in the sensor network to maximize the system ability in reaching its objectives. Since sensor networks are usually battery-operated, then the biggest challenge faced in SM is making decisions regarding local and global sensing strategies under time and energy constraints, considering the large volume of data dealt with. The proposed collaborative scheme for the sensor members of a delegation can enhance the quality of the system performance and reduce the deviation of the sensors lifetime by balancing the workload among the network sensors. The main focus of the newly developed approach is to maximize the information reliability of the sensor sources in a delegation in an energy-efficient manner.

6.2 The Proposed Context-Aware and Collaborative Scheme

The proposed E-HASM architecture models the federations in the form of holarchies where each holarchy is an intelligent entity in itself. Such holarchies achieve their intelligent operation using collaborative behaviour. In pervasive surveillance context, there are various motivations for the sensors of a delegation to collaborate, such as: balancing the workload, reduce the deviation in the sensors lifetime, prolong the lifetime of the network, maximize the network coverage, and improve the information reliability and surveillance quality.

By using the environment statistics collected over all the regions of a delegation, context-aware knowledge can be formulated. Such context-aware knowledge of the environment results in an overall improvement of the collective operation of the sensors and enhanced adaptability to rapidly changing environment. The delegation statistics and environment dynamics can define the collaborative strategies needed to enhance the system performance. Since the phenomena tend to be localized, the delegation can be divided into smaller regions. Each region is formed of a set of sensors that, at least under their maximum sensing settings, have overlapping sensing ranges. The delegation statistics can be collected by fusing the information about the environment dynamics from each region. An example of a delegation is illustrated in Figure 6.1(a) and Figure 6.1(b) depicts a delegation divided into four different regions.



(a) An example of a delegation

(b) An example of delegation division

Figure 6.1: An example of a delegation and its division.

6.2.1 Delegation Dynamism and Threat Level

Each sensor node collects information about its VOI and estimates the dynamism level of the environment as well as the threat level. In this work, the environment dynamism level for each region is computed using a weighted synthesis of its sensor estimates. The weighted average of the dynamism levels ψ of all the sensors in the region R_i is computed as

$$\psi_{Ri} = E[\psi] = \frac{\sum_{j=0}^{N} w_j * \psi_j}{\sum_{j=0}^{N} w_j} , \tag{6.1}$$

where w_j is the weight of the dynamism level of sensor j calculated based on the standard deviation to the mean value of the dynamism level of the region. w_j is formulated as

$$w_j = \frac{1}{\sigma_{Ri}^2} = \frac{N-1}{\sum_{j=0}^{N} (\psi_{mean} - \psi_j)^2} , \tag{6.2}$$

where

$$\psi_{mean} = \frac{\sum_{j=0}^{N} \psi_j}{N} . \tag{6.3}$$

The total dynamism level ψ_D of delegation D is computed using

$$\psi_D = max(\psi_{R_i}) \quad : \forall R_i \in D . \tag{6.4}$$

The threat level defines the criticality of the dynamic scene of the VOI. Similar to the dynamism level, the threat level ρ of each region is R_i can also be computed using the weighted synthesis in which the higher weights are given to the higher threat levels

$$\rho_{Ri} = E[\rho] = \frac{\sum_{j=0}^{N} wr_j * \rho_j}{\sum_{j=0}^{N} wr_j} , \tag{6.5}$$

where wr_j is the weight of the estimated threat level of sensor j calculated based on the standard deviation to the largest value of the threat level of the region and is given by

$$wr_j = \frac{1}{\sigma_{Ri}^2} = \frac{N-1}{\sum_{j=0}^{N}(\rho_{max} - \rho_j)^2} \,. \tag{6.6}$$

The total threat level ψ_D of delegation D is computed using

$$\rho_D = max(\rho_{R_i}) \quad : \forall R_i \in D \,. \tag{6.7}$$

6.2.2 Delegation Health

The limited energy reserve of the battery-operated sensor nodes limits the lifetime of the network, affects the network coverage, and affects the quality of the surveillance process. Therefore, the collective operation of a delegation has to be modified based on the energy reserve available among the member sensors. The delegation health is an indicator of the energy reserves within the delegation. The delegation health is computed using the member sensors' energy index, ϕ, introduced in Section 5.5.1. Since sensors that belong to each region are located in close proximity with partially overlapping sensing ranges, the energy index of a region R_i is calculated as the mean value of the various energy indices of its sensor nodes,

$$\phi_{Ri} = E[\phi] = \frac{\sum_{j=0}^{N} \phi_j}{N} \,. \tag{6.8}$$

The delegate heath represents the percentage of the energy reserve within the delegation to maintain the VOI fully monitored, that is, to achieve full-coverage. Therefore, the delegate health is computed as

$$\phi_{Dh} = min(\phi_{R_i}) \quad : \forall R_i \in D \,. \tag{6.9}$$

6.2.3 Information Reliability Measurement

Sensor nodes that are close in proximity may have overlapping sensing ranges. As a result, several sensors may acquire observations about the same phenomenon happening within their range. The quality and accuracy of these observations may vary between different sensors, due to several factors that include: relative sensor location, noise, transducers type, partial or full occlusion, *etc.* The global knowledge about the sensor sources, properties, surrounding environment, and the nature of any particular credibility model can provide some estimation about the reliability of the sensor nodes as information sources, and hence the accuracy of their observations. The source reliability has been an area of active research for the last decade under the information fusion umbrella, where the belief function of a specific phenomenon is modified based on the estimated reliability of its sensor sources [17, 175].

The majority of sensor management literature is based on an optimistic assumption about the reliability of the underlying models producing the beliefs associated with imperfect data. Nonetheless, different models usually have different reliabilities and are only valid for a specific sensing range. A recent trend in data fusion has addressed this issue mostly by accounting for the reliability of beliefs. This has been accomplished through introducing the notion of a second level of uncertainty, *i.e.*, uncertainty about uncertainty, represented as reliability coefficients. The main challenge arises in the estimation of these coefficients.

Estimating the reliability coefficients of various sensor sources is a challenging task, and the problem has not been widely studied [17]. Most of the approaches used to estimate reliability coefficients that have been proposed rely on domain knowledge and contextual information [176, 177], learning through training [178, 179], possibility theory [180, 181], and expert judgments [182, 183].

The challenges in estimating the reliability coefficients stem from the nature of the factors that affect the reliability sources. The reliability coefficients has to encapsulate contextual information about the sensor during the measurement acquisition, as well as the experts judgement, and the estimated accuracy of the setting by which the sensor has acquired the information. Furthermore, these coefficients have to be recalculated in-between the different sensor measurements whenever the sensor settings or environment dynamics change. As a result, the extensive measurements acquired by a single sensor makes the task quite expensive.

As discussed in Section 5.3, the smart sensor node may have various sensing settings, modalities, ranges, and frequencies, to name a few, by which the sensor can interface with the environment. Every sensor setting affects the quality, reliability, and credibility of the acquired observation in a different manner. The state-of-the-art methodologies for estimating the reliability coefficients in the literature ignore the sensor setting as an affecting parameter in the reliability calculation.

This work proposes a light-weight heuristic approach for estimating the reliability coefficients of the sensor sources that extends the available coefficients estimation techniques to include the impact of sensor settings and estimated environment dynamics. Figure 6.2 illustrates an overview of the proposed reliability estimation process which is modelled as a closed-loop process; such that the sensor management module can tune the sensing transducers to increase the reliability of the acquired information. Moreover, the proposed approach is modular enough to be fused with any of the state-of-the-art models, used to estimate the reliability coefficients, by extending the reliability coefficient calculation to include the sensor and environment considerations. Figure 6.3 shows a high-level diagram of the proposed model.

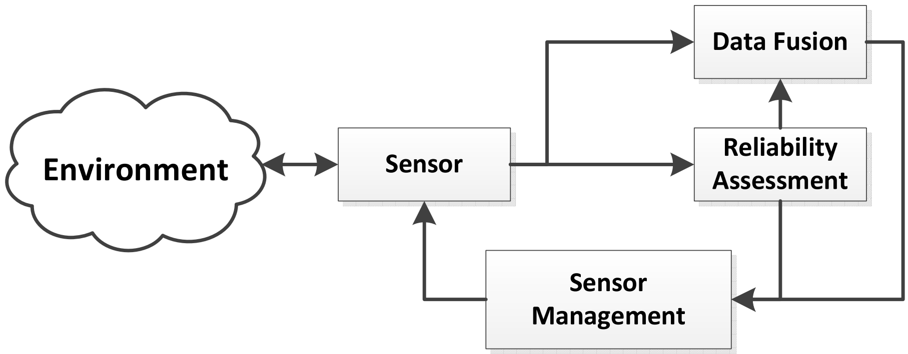


Figure 6.2: Proposed reliability closed loop overview.

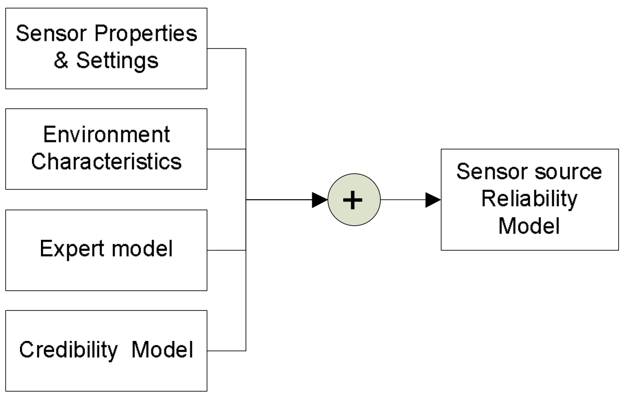


Figure 6.3: The proposed reliability model.

Based on the sensor operation and characteristics model discussed in Section 5.3, the sensor node can control a number of the parameters that define the various sensing settings; modality, sensing range, and sensing frequency. The relationship between these parameters and the source information reliability index is defined as

$$Rel_s \propto \frac{1}{\eta}, \frac{1}{\tau}, M, \frac{1}{\psi}, \tag{6.10}$$

where η is the sensing range, τ is the sensing frequency, M is the sensing modality, and ψ is the environment dynamism level. Therefore, the proposed reliability index is given by

$$Rel_s = e^{-c*(\frac{\eta}{\eta_{max}} * \frac{\tau}{\tau_{max}} * \frac{M_{max}}{M} * \frac{\psi}{\psi_{max}})}, \tag{6.11}$$

such that $0 \leq Rel_s \leq 1$ and c is a scalar constant. Figure 6.4 plots the reliability index versus the dynamism level.

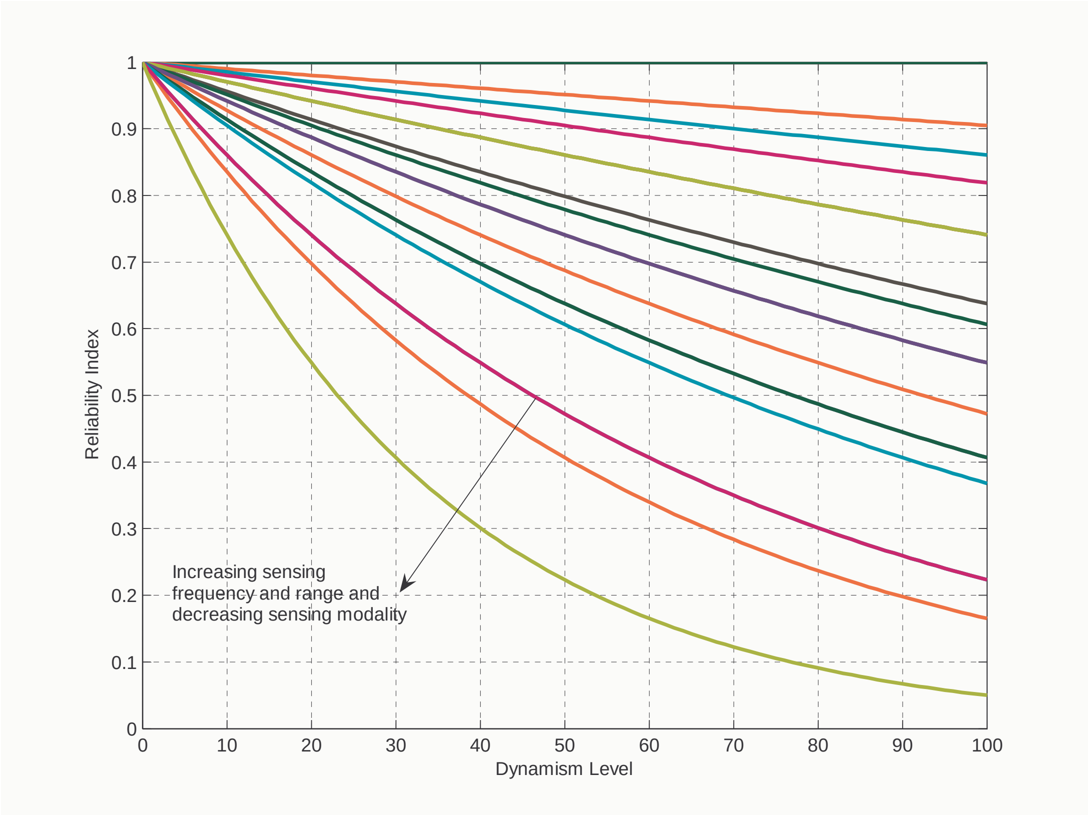


Figure 6.4: The proposed source reliability index versus the dynamism level.

6.2.4 Delegate Factor and Collaborative Algorithm

In Chapter 5, an Energy Savings Index (ESI) is proposed to model the sensor node status and its need/ability to conserve energy. According to the ESI formulation in Equation (5.15), the sensor node modifies its current setting to adapt to the changes in its resources and the environment. In Equation (5.15), the ESI is scaled using variable λ called the delegate factor. The delegate factor is the parameter that weights the ESI formulation and accordingly affects the sensor decision on its alternate sensing strategies. In this Chapter, the delegate node uses the factor λ to tune the sensing operation of the sensor nodes within its delegation, such that $0 < \lambda \leq 1$. Figure 6.5 shows the effects of varying the delegate factor on the ESI.

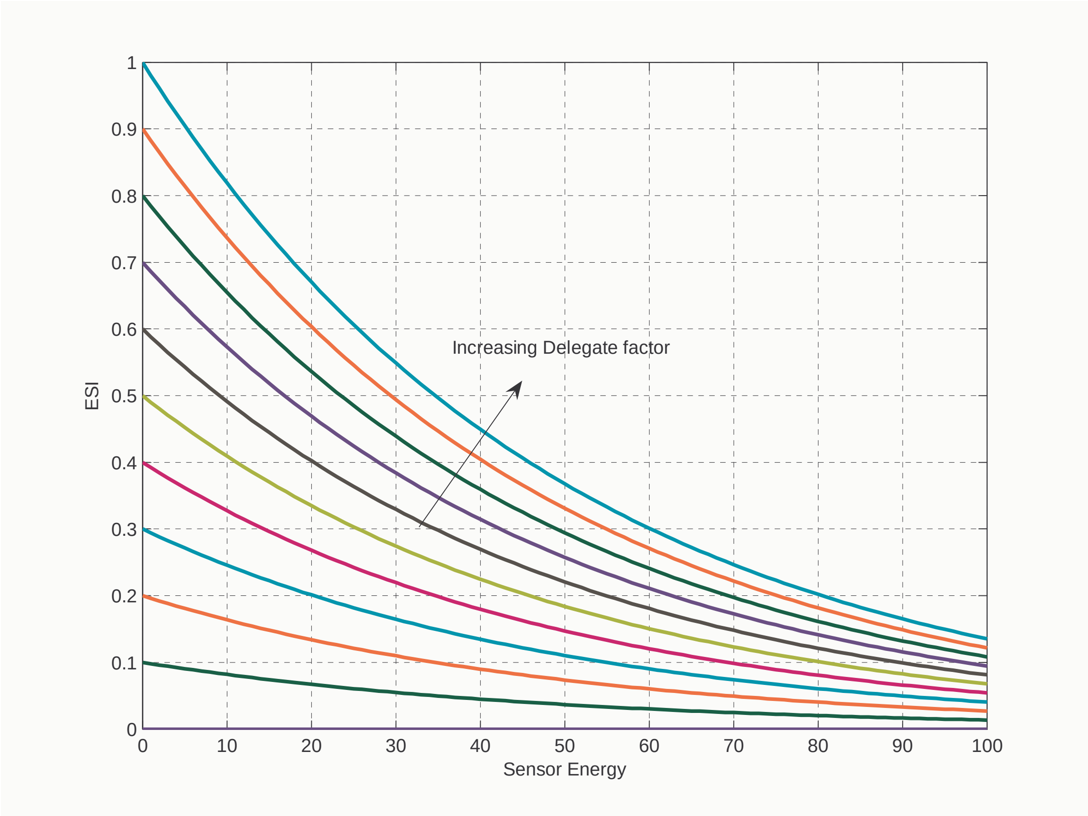


Figure 6.5: The effect of changing the delegate factor on the ESI.

To make decisions on alternate management strategies, the delegate node has to be aware of the status of its sensor members and their estimated environment dynamics. Consequently, each sensor node appends a 16-bits codeword that represents the current sensor setting and its estimated VOI characteristics to every cue message sent from the sensor node to the delegate node. Figure 6.6 shows the proposed 16-bit codeword and Table 6.1 provides an explanation of each parameter in the sensor status codeword. When any given delegate node receives the sensor codeword, it reasons whether to tune/overwrite the sensor current setting and evaluates the estimated gain versus the communication cost. The delegate decision can result in the delegate node sending an acknowledgement packet with the delegate factor λ appended to it, as shown in Figure 6.7(a), or deciding not to change the sensor current settings, as shown in Figure 6.7(b).

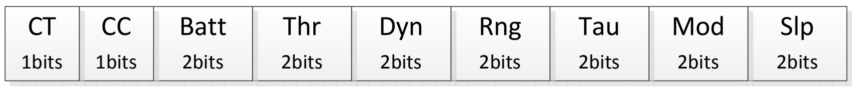
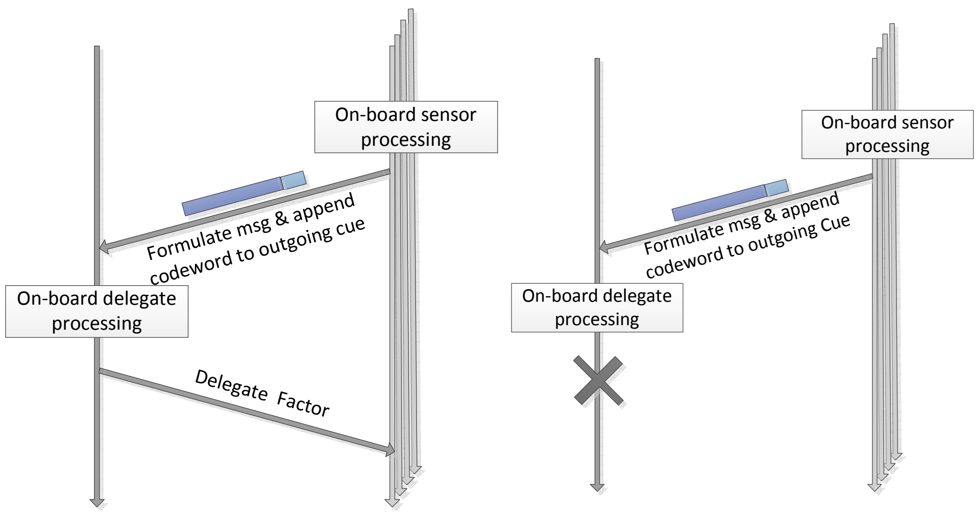


Figure 6.6: Proposed message format between the delegate and sensor nodes.

Table 6.1: An explanation of parameters of the sensor status codeword

Parameter	**# bits**	**Meaning**	**Value**
CT	1 bit	Cooperative Tracking	1: activated, 0: otherwise
CC	1 bit	Constraint communication	1: activated, 0: otherwise
Batt	2bits	Energy reserve	00: dead, 01: low, 10: medium, and 11: high
Thr	2bits	Sensor estimated threat level	01: low, 10: medium, and 11: high
Dyn	2bits	Sensor estimated dynamism level	01: low, 10: medium, and 11: high
Rng	2bits	Sensing Range	01: small, 10: medium, and 11: large
Tau	2bits	Sensing Frequency	01: small, 10: medium, and 11: large
Mod	2bits	Sensing Modality	01: low, 10: medium, and 11: high
Slp	2bits	Sensor entering sleep mode	11: sensor sleeping, otherwise: active



(a) Scenario 1 (b) Scenario 2

Figure 6.7: Proposed communication model.

6.3 Stochastic Decision Making

The sensor management problem can be viewed from higher levels of abstraction as a decision-making problem. The decision-making process produces a final choice that can be regarded as an outcome of a reasoning process leading to the selection of a course of actions among several alternatives [19]. In sensor management systems, the information collected by the sensors is used to design the activities that change how the underlying systems evolve over time [184]. Since the state of each sensor changes over time depending on the performed actions, the sensor management problem is characterized by decisions that are made sequentiality over time. Moreover, the sensor observations may have some degrees of uncertainty [185], thus deeming the decisions made based on these sensor observations non-deterministic. Since each subsequent decision is made based on the previous observations, the outcome of these decisions is also uncertain. It should be noted that the choice of actions, *i.e.*, decisions, is subject to some system constraints. Therefore, to maximize the outcome of each decision and achieve the overall system objective, the problem can be viewed as an optimization decision-making problem under uncertainty.

In such an application, the theory of Partially-Observable Markov Decision Processes (POMDP) has received much attention as a natural framework both for modelling and solving complex structured decision problems [36,186]. POMDPs [187] provide a mathematical framework for modelling decision-making in situations where outcomes are uncertain and under the control of a decision maker. A POMDP is a controlled dynamical process useful in modelling a wide-range of resource control problems [36]. Hence, the POMDPs are a suitable candidate for the decision-making operation in the proposed E-HASM on the delegate-level.

From a problem solving perspective, the system encompasses different sensors that are modelled as a set of utility maximizers that inhabit some kind of POMDP. The current state in a POMDP summarizes the statistical information needed to predict the evolution of future states, thus, satisfying the Markovian property. This assumption is satisfied by the operation of the proposed approach. The current state of the federation, such as the remaining battery charge and threat level, represents sufficient information to predict the future states without referring to previous states. In SM, it has to be noted that actions may affect the evolution of the state of the dynamical system or the nature of the observation acquired. POMDPs model the state evolution dynamics of a stochastic system based on the choice of a certain action from the available set of actions that invoke such evolution. The procedure of choosing such an action is called an action policy. The objective of the work done in this Section is to derive an optimal action policy over the system state distribution that maximizes the system gain.

The proposed mathematical formulation for the POMDP model of the delegate nodes decision-making operation is based on the following assumptions:

- **Sensor nodes operation:** The operation of sensor nodes is an important factor in the effectiveness of the overall system performance. The work in this Chapter adopts the sensor operation model discussed in Section 5.3. It is assumed that when a target is detected, the current location of the target is known by the sensor.

- **Sensor energy consumption model:** Maximizing the battery lifetime of sensor networks is an essential requirement for the operation of such networks because of their dependence on battery power. As a result, sensor node are required to operate under the lowest energy consumption needed to achieve the required performance. This Chapter adopts the sensor energy model in Section 5.4.

- **Sensor motion:** All sensors are assumed to be at fixed locations, thus, there is no energy lost in any sensor movements. However, as a future work, sensor mobility will be considered.

- **Target motion:** Targets are assumed to be mobile in a 2D plane, such that the ground targets move on the ground plane, while any flying targets are assumed to fly at a constant altitude. Moreover, targets are assumed to move in one of four possible directions; $+x$, $-x$, $+y$, and $-y$, at any time instance. In the mathematical formulation used in this work, there is no predefined target mobility model assumed. However, in the simulation and experimentation, different mobility models are adopted.

6.3.1 Problem Formulation using POMDP

In this section, a brief introduction of the POMDP is given and the mathematical formulation of the problem as a POMDP is described. POMDPs are defined as controlled stochastic processes satisfying the Markovian property and assigning reward values to state transitions [188]. A POMDP is a generalization of Markov Decision Processes (MDP) to the situations where the system states are not fully observable. POMDPs are highly complex compared to the MDP, thus rendering exact solutions virtually intractable. To specify a POMDP model, a tuple $(S, A, \Omega, T, P, O, R, b_0)$ needs to be specified, where:

- S is the set of states (the state space) in which the processes evolution takes place,

- A is the set of all possible actions that control the state dynamics,

- Ω is the set of observations (the observation space) which can map to one or more underlying states,
- T is the set of time steps where decisions need to be made,
- $P()$ is the state-transition probability function specifying the next-state distribution given an action taken at a current state,
- $O()$ are observation probabilities,
- $R()$ is the reward function defined on state transition (being in a given state and taking a given action),
- b_0 is an initial probability distribution over the finite set of states.

As shown in Figure 6.8, at each time $t \in T$, the agent does not know the current state $s_t \in S$ but can only know a partial view of it as an observation $o_t \in \Omega$ [188]. This observation is given by the observation function O. In a partially observable environment, observations are probabilistically dependent on the underlying environment state [189]. Therefore, $O \ : \ S \ \times \ A \rightarrow \Delta(\Omega)$ is the probability that observation o_t will be recorded after an agent performs action $a \in A$ and lands in state s_t, is given by

$$O(s_t, a, o_t) = Pr(\Omega^t = o_t | S^t = s_t, A^t = a_t) \ . \tag{6.12}$$

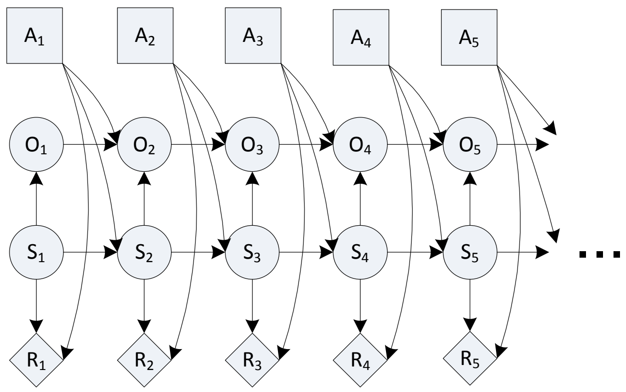


Figure 6.8: POMDP Graphical Model.

The reward is an award received by the system when action a is chosen and results in the transformation of the system state from state s_k to s_{k+1}. The reward function $R(s_k)$ is a tool to specify priorities in achieving the system goals, and weights are used to represent these priorities. Moreover, the rewards function can also be penalized to represent the cost of a certain action performed or states achieved. The reward is normalized between [0,1] using

$$R = \frac{R + C}{R_{max} - R_{min}} \; . \tag{6.13}$$

The theory of POMDP does not actually require the set of states, actions, and observations to be finite. However, in the proposed modelling for the delegate SM problem, the number of states, actions, and observations are finite, while the time horizon in our problem modelling is assumed to be infinite. The uncertainty in our knowledge of the states is due to the stochastic nature of the problem and the probabilities associated with the various sensor observations. Furthermore, the proposed POMDP model is assumed to be stationary.

Generally, the main objective of a POMDP system is to calculate the optimal course of actions in an uncertain environment based on the history of its sensory inputs. This work assumes an infinite horizon discounted sum of rewards model. The system behaviour is therefore determined by its policy, which in its most general form is a mapping from the set of belief states to actions

$$\pi \; : B \; \rightarrow \; A \; . \tag{6.14}$$

The expected policy value is defined as the expected value of system trajectories induced by the policy

$$V^{\pi}(b) = R(b, a) + \gamma \sum_{o'} Pr(o'|b, a) V^{\pi}(b^{a}_{o'}) \; . \tag{6.15}$$

The value function can be represented as a number of piecewise linear and convex hyperplane, as shown in Figure 6.9.

In many application domains, the state space and action space may be very large. This usually arises due to one of two common reasons: discretization of continuous variables into many values or states/actions defined by the joint assignment of several variables [190]. POMDPs with states and actions defined by several variables are often referred to as factored POMDPs because the transition function typically factors into a product of conditional probability distributions. Due to the size of the SM problem, the factored representation of the POMDP is used to model the SM decision-making process. In this work, we propose two models for the POMDP formulation; a sensor-centric and a region-centric model, where the stochastic decision-making process using POMDP is performed on-board of the delegate node. The objective of both models is to derive an action policy

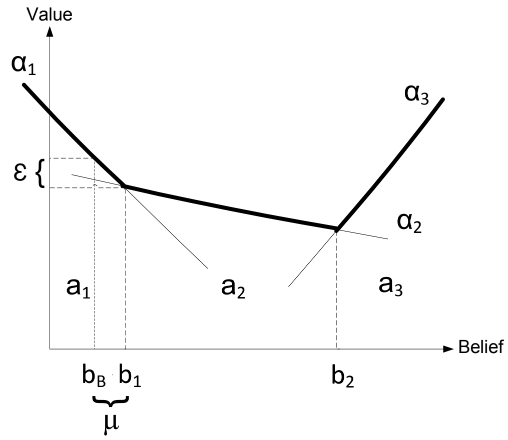


Figure 6.9: Piecewise convex value function.

that can refine the collective operation of the federation of the delegate. In the rest of this section, both models are discussed in more detail.

6.3.1.1 Sensor-Centric Model

In this model, the delegate node is responsible for all computations to derive the action policy based on all the sensor members settings and VOI dynamics. The model allows the delegate to perform sensor-centric rather than delegation-centric computations.

6.3.1.1.1 States: In the surveillance problem, the system state are modelled as a set of observations whose values describe the state of the environment. Hence, the state s can be described as a multi-variant random variable $X = (X_1, ..., X_n)$. The state variables for each sensor i are:

- Sensor-Sleeping (Slp^i): a binary variable that is set to one when the sensor enters the sleep-mode. Based on the sensor decision-making design discussed in Chapter 5, the sensors by default aim to conserve energy and reduce power consumption. It should be noted that this work assumes that the sensor does not experience any energy loss during sleep mode;

- Modality (Mod^i): an integer variable that represents the level of resolution used by the sensor nodes to acquire the observations;

- Active-Sensing (Tao^i): an integer variable that reflects the environmental observations acquisition frequency of the sensor nodes;

- Sensing-Range (Rng^i): an integer variable that models the sensing range of the sensor nodes;
- Constrained-Communication (CC^i): a binary variable that reflects the enabling of the constrained communication algorithm in the sensor on-board decision-making;
- Cued (Q^i): a binary variable that is set to one when the sensor receives a cue message that directs the sensor to a coming threat;
- Dynamism-Level (ψ^i)): an integer variable that indicates the level of environment dynamics computed by the sensor nodes;
- Threat-Level (ρ^i): an integer variable indicating the threat level within the VOI of sensor i. The threat level vary according to the danger imposed on the area under surveillance;
- Information Reliability (Rel^i): an integer variable that models the reliability of measurements acquired by the sensor source;
- Energy Autonomy (ϕ^i): an integer variable that reflects the remaining energy level in the sensor battery;

All of the integer variables above (Mod^i, Tao^i, Rng^i, ψ^i, ρ^i, Rel^i, ϕ^i) are allowed to take only three values, *i.e.*, low, medium and high, to reduce the size of the state space. Thus, the state s_k^i of a single sensor i at time k is goven by

$$s_k^i = [Slp_k^i, Mod_k^i, Tao_k^i, Rng_k^i, CC_k^i, Q_k^i, \psi_k^i, \rho_k^i, Rel_k^i, \phi_k^i] \,. \tag{6.16}$$

Since each region is formed by sensors that are close in proximity and therefore, can collaborate to get a better estimation of the environment and prolong the network lifetime, the region state $s_k^{Rj} \in S$ is represented by the vector

$$s_k^{Rj} = [\vec{Slp}_k, \vec{Mod}_k, \vec{Tao}_k, \vec{Rng}_k, \vec{CC}_k, \vec{Q}_k, \vec{\psi}_k, \vec{\rho}_k, \vec{Rel}_k, \vec{\phi}_k] \,, \tag{6.17}$$

where the vector representation indicates the respective values of the states for all sensors within the specific region j at time k.

6.3.1.1.2 Observation Space: The observation space Ω represents the set of observations that can model the underlying state of the environment. In the sensor-centric model, the delegate node estimates the underlying state of sensor i with partial observability using an acquire set of observations:

- Estimated Reliability ($\ddot{r}^i$): an integer variable representing the estimated information reliability of the sensor source;
- Estimated Threat Level ($\ddot{t}^i$): an integer variable indicating the estimated threat level within the VOI;
- Estimated Dynamism Level (ψ^i)): an integer variable that indicates the level of environment dynamics computed by the sensor nodes.

All the aforementioned variables are limited to only three values, *i.e.*, low, medium, and high, to reduce the problem size.

6.3.1.1.3 Action: All the possible actions that the sensor node can perform are represented in the action space denoted by A. In the proposed POMDP modelling of the delegate decision-making in the pervasive surveillance problem, the set of actions A is composed of:

- Decrease-Tao (Γ^i_τ): is the action by which the sensor i increases the frequency by which it acquires the observations from the environment.
- Increase-Mod (Γ^i_M): is the action by which the sensor i increases the sensing modality by which it observes its sensing range to identify any targets within its vicinity.
- Increase-Rng (Γ^i_R): is the action by which the sensor i extends its sensing range to identify any targets within its vicinity.
- Conserve-Energy (Γ^i_S): is the action by which each sensor switches its operation mode from awake to sleep mode to reduce power consumption.
- Activate-CT (Γ^i_{CT}): is the action by which the sensors are engaged in cooperative tracking. When the cooperative tracking is activated, the sensor tracks the threat within its sensing range and cues the neighbouring nodes when the threat gets out of its sensing range.

Although it can be argued that using the cooperative tracking mode can be beneficial for all threat types, it should be noted that cooperative tracking consumes more energy than the regular tracking and drains the sensor resources faster. The choice of the action policy is of great importance to increase the sensor network lifetime while achieving the required system objective. The set of actions to be take by the sensor is denoted by

$$A = \{\Gamma^i_\tau, \Gamma^i_M, \Gamma^i_R, \Gamma^i_S, \Gamma^i_{CT}\} \ . \tag{6.18}$$

6.3.1.1.4 State and Observation Transition Probability Function: The state transition probability indicate which state is likely to appear after the current state. In other words, the state-transition probability $P(s_{k+1}|s_k, a_k)$ specifies the probability of state $s_k \in S$ to change into state $s_{k+1} \in S$ when action a_k is performed,

$$s_k \ \underrightarrow{a_k} \ s_{k+1} : P(s_{k+1}|s_k, a_k) \ , \tag{6.19}$$

where

$$\forall s, a, \sum_{s_{k+1}} P(s_{k+1}|s_k, a_k) = 1 \ . \tag{6.20}$$

The probability $P()$ can be represented in matrix form where P_a is a $|S|x|S|$ matrix that contains $P_{a,s_{k+1},s_k} = p(s_{k+1}|s_k, a)$.

Since the states in our problem can be decomposed using multiple random variables, it is possible to decompose the probability $P(s_{k+1}|s_k, a_k)$ into a product of probabilities. The independencies between the random variables can be exploited to decrease the size of the representation of the transition function using

$$\begin{aligned} P_{\Gamma^i_\tau}(s_{k+1}|s_k) &= P_{\Gamma^i_\tau}(\vec{Slp}_{k+1}, \vec{Mod}_{k+1}, \vec{Tao}_{k+1}, \vec{Rng}_{k+1}, \vec{CC}_{k+1}, \vec{Q}_{k+1}, \\ &\quad \vec{\psi}_{k+1}, \vec{\rho}_{k+1}, \vec{CT}_{k+1}, \vec{Rel}_{k+1}, \vec{\phi}_{k+1}|s_k) && (6.21) \\ &= P_{\Gamma^i_\tau}(Slp^i_{k+1}|s_k) * P_{\Gamma^i_\tau}(Mod^i_{k+1}|s_k, \vec{Slp}_{k+1}) * ... \\ &* \ P_{\Gamma^i_\tau}(\phi^i_{k+1}|s_k, \vec{Slpi}_{k+1}, \vec{Mod}_{k+1}, \vec{Tao}_{k+1}, \vec{Rng}_{k+1}, \vec{CC}_{k+1}, \vec{Q}_{k+1}, \\ &\quad \vec{\psi}_{k+1}, \vec{\rho}_{k+1}, \vec{CT}_{k+1}, \vec{Rel}_{k+1}) && (6.22) \end{aligned}$$

In the pervasive surveillance problem, the value of the variables in time unit $k+1$ depend only on the variables at time k, hence,

$$\begin{aligned} P_{\Gamma^i_\tau}(s_{k+1}|s_k) &= P_{\Gamma^i_\tau}(Slp^i_{k+1}|s_k) * P_{\Gamma^i_\tau}(Mod^i_{k+1}|s_k, \vec{Slp}_{k+1}) * ... \\ &* \ P_{\Gamma^i_\tau}(\phi^i_{k+1}|s_k, \vec{Slpi}_{k+1}, \vec{Mod}_{k+1}, \vec{Tao}_{k+1}, \vec{Rng}_{k+1}, \vec{CC}_{k+1}, \vec{Q}_{k+1}, \\ &\quad \vec{\psi}_{k+1}, \vec{\rho}_{k+1}, \vec{CT}_{k+1}, \vec{Rel}_{k+1}) \\ &= P_{\Gamma^i_\tau}(Slp^i_{k+1}|s_k) * ... * P_{\Gamma^i_\tau}(\phi^i_{k+1}|s_k) && (6.23) \end{aligned}$$

Similarly, state s_k can be decomposed to give

$$\begin{aligned}
P_{\Gamma^i_\tau}(s_{k+1}|s_k) &= P_{\Gamma^i_\tau}(Slp^i_{k+1}|s_k) * ... * P_{\Gamma^i_\tau}(\phi^i_{k+1}|s_k) \\
&= P_{\Gamma^i_\tau}(Slp^i_{k+1}|\vec{Slp}_k, \vec{Mod}_k, \vec{Tao}_k, \vec{Rng}_k, \vec{CC}_k, \vec{Q}_k, \vec{\psi}_k, \vec{\rho}_k, \vec{CT}_k, \vec{Rel}_k, \vec{\phi}_k) * ... \\
&* \ P_{\Gamma^i_\tau}(\phi^i_{k+1}|\vec{Slp}_k, \vec{Mod}_k, \vec{Tao}_k, \vec{Rng}_k, \vec{CC}_k, \vec{Q}_k, \vec{\psi}_k, \vec{\rho}_k, \vec{CT}_k, \vec{Rel}_k, \vec{\phi}_k) \quad (6.24)
\end{aligned}$$

Given the structure of the problem and the function-specific independencies, the transition function for the action π^i_τ can be represented by defining each probability by the variables it depends on at time k rather than all the variables composing the state s_k. This results in a reduced probability space and a more trackable problem solution,

$$\begin{aligned}
P_{\Gamma^i_\tau}(s_{k+1}|s_k) &= P_{\Gamma^i_\tau}(Slp^i_{k+1}|\vec{Slp}_k, \vec{Mod}_k, \vec{Tao}_k, \vec{Rng}_k, \vec{CC}_k, \vec{Q}_k, \vec{\psi}_k, \vec{\rho}_k, \vec{CT}_k, \vec{Rel}_k, \vec{\phi}_k) * ... \\
&* \ P_{\Gamma^i_\tau}(\phi^i_{k+1}|\vec{Slp}_k, \vec{Mod}_k, \vec{Tao}_k, \vec{Rng}_k, \vec{CC}_k, \vec{Q}_k, \vec{\psi}_k, \vec{\rho}_k, \vec{CT}_k, \vec{Rel}_k, \vec{\phi}_k) \\
&= P_{\Gamma^i_\tau}(Tao^i_{k+1}|\vec{Tao}_k, \vec{Q}_k, \vec{\psi}_k, \vec{\rho}_k, \vec{\phi}_k) * P_{\Gamma^i_\tau}(\phi^i_{k+1}|\vec{Slp}_k, \vec{Mod}_k, \vec{Tao}_k, \vec{Rng}_k, \vec{CC}_k, \vec{\phi}_k) \\
&* \ P_{\Gamma^i_\tau}(Rel^i_{k+1}|\vec{Slp}_k, \vec{Mod}_k, \vec{Tao}_k, \vec{Rng}_k, \vec{CC}_k, \vec{Q}_k, \vec{\psi}_k, \vec{\rho}_k, \vec{CT}_k) \quad (6.25)
\end{aligned}$$

Similarly, the remaining action transition probabilities can be simplified using the function-specific independencies.

Observations are probabilistically dependent only on the underlying environment state [189]. At each time step, the sensor is in an unknown state $s^i_k \in S$ and it executes an action $a_k \in A$ to reach another unknown state $s^i_{k+1} \in S$ and getting an observation $o^i_{k+1} \in \Omega$. Similar to the state transition, the observation transition probability can exploit the independencies between the random variables to decrease the size of the representation of the transition function.

6.3.1.1.5 Immediate Rewards Function: In this work, the $R(s_k)$ is represented by a weighted function of the revenue and the associated cost of being in state s_k and is given by

$$R(s_k) = \alpha * r(s_k) - \frac{1}{\alpha}c(s_k)\,, \quad (6.26)$$

where α is the weighting factor such that $\alpha \geqslant 1$. In the pervasive surveillance problem at hand, the system aims to maximize the detection and tracking of targets that impose threats to the system, and tune the sensor setting to maximize the information reliability. However, being battery-operated forces the sensor nodes to conserve energy whenever possible. Therefore, the rewards function gives higher priority to acquiring highly reliable information at high threat levels compared to that of conserving energy, and vice versa when the threat level is low.

6.3.1.1.6 Overall Reward Function: The main objective of the proposed sensor network surveillance system is to maximize the surveillance quality while increasing the network lifetime. This can correspond to the expected cumulative sum of immediate rewards for all the states reached by the system. The γ-discounted criterion is commonly used in infinite horizon frameworks since it allows a simple characterization of the optimal value function and its associated policies [188]. The γ-discounted criterion is denoted by

$$\forall s \in S, V_{\gamma}^{\pi}(s) = E^{\pi}[\sum_{k=0}^{\infty} \gamma^k R(s_k)|s_0 = s] \,. \tag{6.27}$$

6.3.1.2 Region-Centric Model

In the region-centric model, the delegate node focuses on the environment dynamics, threat level, and overall region autonomy over the individual sensor settings as described in the previous model.

6.3.1.2.1 States: Similar to the previous model, the system state is described as a set of observations whose values describe the state of the environment. So, the state s can be described as a multi-variant random variable $X = (X_1, ..., X_n)$. The state variables for region R_i are:

- Active-Sensors (α^{R_i}): an integer variable representing the ration of the number of active sensors in region R_i to the total number of sensors in that region, such that $\alpha_i \in [none, low, med, high]$;
- Dynamism-Level (ψ^{R_i}): is an integer variable that indicates the level of environment dynamics within region R_i. To simplify the state space, it can take one of three values, *i.e.*, low, medium, and high;
- Threat-Level (ρ^{R_i}): an integer variable indicating the threat level within region R_i. Similarly, it can take one of three values, *i.e.*, low, medium, and high;
- Delegation Threat-Level (ρ^D): an integer variable indicating the combined threat level of the delegation. It can take one of three values, *i.e.*, low, medium, and high;
- Quality of Coverage (Π^{R_i}): an integer variable representing the ratio of area covered by the sensors of region R_i to that of the total area under surveillance in region R_i, such that $\Pi_i \in [low, med, high]$;

- Information Reliability (Rel^{R_i}): an integer variable representing the reliability of measurements acquired by the sensor source, such that $Rel^{R_i} \in [low, med, high]$;
- Energy Autonomy (E^{R_i}): an integer variable indicating the remaining energy level in the sensor operating battery such that $E \in [dead, low, med, high]$;

Since each region is formulated by sensors that are close in proximity and therefore can collaborate to get better estimation of the environment and prolog the network life time. The state of region R_i is given by

$$s_{Rj} = [\alpha, \psi, \rho, \rho^D, \Pi, Rel, E] \tag{6.28}$$

6.3.1.2.2 Observation Space: The observation space of the region-centric model is similar to that of the sensor-centric one presented in Section 6.3.1.1.2.

6.3.1.2.3 Action: All the possible actions that the sensor node can perform is represented in the action space denoted by A. In the proposed POMDP modelling of the delegate decision-making in the pervasive surveillance problem, the set of actions A is composed of:

- Idle ($\Gamma_I^{R_i}$): it is the action in which the delegate decides that there is no need to tune the sensors member performance. Such action can conserve energy and reduce power consumption of both the sensor and the delegate nodes.
- Increase-Cov ($\Gamma_C^{R_i}$): it is the action in which the delegate tunes the sensing range of the sensors in region R_i to extend its coverage.
- Increase-Rel ($\Gamma_{Rel}^{R_i}$): it is the action in which the sensor adjust its settings to acquire information about the VOI with higher reliability.
- Activate-CT (Γ_{CT}^{i}): it is the action in which sensor are engaged in cooperative tracking. When the cooperative tracking is activated, the sensor would track the threat within its sensing range and cue the neighbouring node when its getting out of its sensing range.

Although it can be argued that using the cooperative tracking mode can be beneficial for all threat types, it should be noted that cooperative tracking consumes more energy than the regular tracking and drains the sensor resources faster. The choice of the action policy is of great importance to increase the sensor network lifetime while achieving the required system objective. The set of actions to be take by the sensor is denoted by

$$A = \{\Gamma_I^{R_i}, \Gamma_C^{R_i}, \Gamma_{Rel}^{R_i}, \Gamma_{CT}^{i}\} \tag{6.29}$$

6.3.1.2.4 State and Observation Transition Probability Function: By modelling the problem in to factored POMDP, the state space can be significantly reduced by exploiting the independencies between the random variables in the factored representation. Similar to the state simplification in Section 6.3.1.1.4, the state transition probabilities can be simplified using the function-specific independencies. Also, the observation transition probability can exploit the independencies between the random variables to decrease the size of the representation of the transition function.

6.3.1.2.5 Rewards Function: As discussed earlier, there are two types of rewards associated with the system state; the immediate rewards/cost and the overall rewards. In the region-centric modelling, the system aims to maximize the detection and tracking of targets that impose threat to the system, increase information reliability, and manage the VOI coverage. However, being battery-operated leads the sensor node to conserve energy whenever possible. The immediate rewards function gives higher rewards to increasing the information reliability, as well as that of extending the coverage, when the threat level is high. However, these state have a higher energy consumption cost. The overall rewards is represented as the accumulative γ-discounted criterion.

6.3.2 Optimal policy Approximation

Factored MDPs permit a compact representation of large MDPs when states or actions are naturally defined by joint assignments to a set of variables [190]. While the size of the conditional probability distributions and the local utility functions grows exponentially with the number of parents for each variable, graphical models are typically sparse and the number of parents is often small and bounded. As a result, the factored representation is often exponentially smaller than the original flat representation. This is particularly useful for large MDPs, but we also need efficient algorithms that can exploit the factored representations. Unfortunately, finding the optimal policy of a factored MDP is EXP-hard using both exact and approximate algorithms to find a near optimal policy with an arbitrarily small additive bound on the loss in value [191]. Consequently, the optimization of a POMDP policy is a notoriously hard problem. In general, finding the optimal policy for finite horizon problems is PSPACE-Complete [192]. As a result, most approaches focus on approximations and try to exploit problem-specific structure to simplify the problem at hand.

6.3.2.1 Symbolic Perseus

The proposed modelling for the sensor management problem in both sensor-centric and region-centric models result in a large state space. Therefore, a policy approximation algorithm that can handle such a large state space has to be used to derive the policy for the system. Poupart in [190] has proposed a generic POMDP solver, called Symbolic Perseus, based on the point-based value iteration algorithm [193] and the Algebraic Decision Diagrams (ADDs) [194]. Symbolic Perseus can compactly represents the α-vectors with ADDs by exploiting the problem specific structure to reduce the state space. Symbolic Perseus have been used to solve problems with millions of states [195].

Although Symbolic Perseus can solve POMDPs with state space in the order of millions, the operation of the algorithm is computationally expensive and is definitely beyond the means of any sensor node. In literature, most of the decision-theoretic approaches that have modelled the SM problem as a POMDP, have assumed powerful central server that can run such algorithms [36–39, 69]. Moreover, the state-of-the-art research have ignored the need for real-time operation when making decisions regarding the management strategies. Although, the optimal policy function can be calculated off-line, the process of the belief state updates has to be done in real-time, which is still relatively computationally expensive.

Since the sensor or delegate nodes are characterized with limited energy resources, reducing the computation complexity of on-board processing is a necessity. Therefore, this work adopts an off-line approach to optimal policy approximation. Taking into consideration that both the delegate and the sensor nodes need to make decisions in real-time regarding the delegation operation, this research work proposes the representation of the optimal policy in the form of a Finite-State Controller (FSC) to eliminate the need of continuous belief state updates and relies on the current and next state estimation and the observation state to compute the optimal action to be carried.

6.3.2.2 Finite State Controller

The optimal value function V^* with a infinite horizon can be approximated using a set of consecutive finite horizon value functions $V_0, V_1, ..., V_t$, where $t \to \infty$ that are called α-vectors. These α-vectors define a partition of the belief space, such that, for each partition, there is an optimal action [189,190]. Representing an optimal value function as a finite set of vectors results in the transformation of all the belief states that belong to one region to new belief states located within the same single belief partition, given the optimal action and a resulting observation. In the resulting policy graph or a Finite-State Controller (FSC), which is made up of the set of partitions and belief transitions, the nodes correspond to belief space partitions where the optimal actions attached and transitions are guided by observations [189].

The action to be performed at each internal memory state $n \in N$is selected by the action selection function. Moreover, the transitions between the different internal states need to be defined beforehand, which is referred to as the dynamic of the internal process. A FSC policy graph is represented as a triple (N, a, η), where (N) is a set of controller nodes n, $(a : N \to A)$ is the action selection function that prescribes an action $a(n)$ for each node n, and $(\eta : N \times O \to N)$ is the node transition function that assigns a successor node n' for each node and observation.

6.4 Results and Discussions

The realization of the proposed collaborative scheme involves two main implementation procedures: firstly, the derivation of an optimal action policy, secondly, the integration of the policy as a part of the intelligent operation of the proposed system. Figure 6.10 illustrates the delegate reasoning operation and the interfacing with the environment and the sensor members of a delegation.

To derive an optimal action policy, the two proposed POMDP models have been implemented using SPUDD, which is a script-like language that represents factored structured POMDPs in a format similar to ADDs [190, 196]. An implementation of the Symbolic Perseus algorithm [196] has been used to derive the approximated optimal policy that maximizes the value function. Symbolic Perseus is scalable enough to tackle problems with million of states, however, the sensor-centric model is in the orders of billions with only four sensors in a delegation which prohibits the use of the Symbolic Perseus in solving such a model. To the knowledge of the authors, no POMDP algorithm can solve a

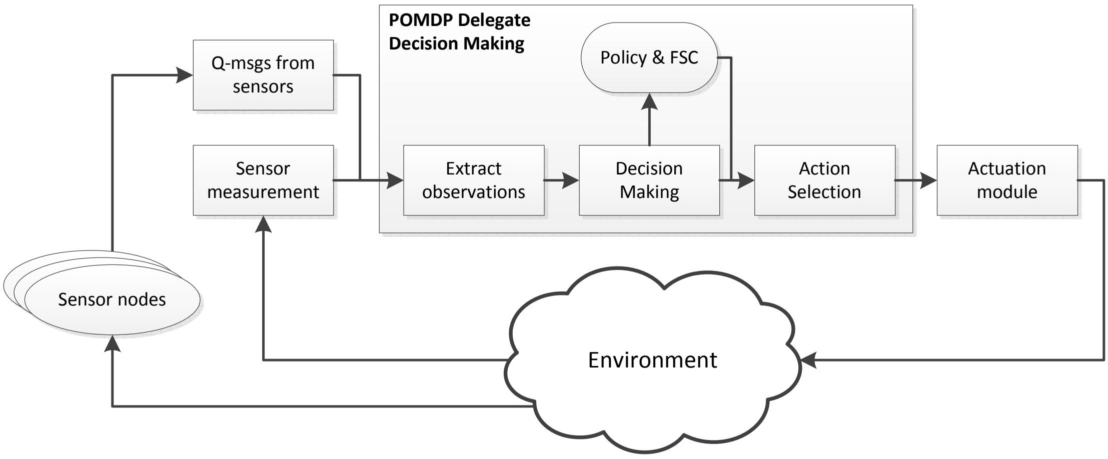


Figure 6.10: An overview for the delegate reasoning process.

Table 6.2: Optimal policy characteristics using Symbolic Perseus

Model	**Initial Value**	**Best Improvement**	**Worst Decline**
Sensor-centric	64.024916	0.005803	-0.030252
Region-centric	79.266446	0.096647	-0.139670

problem with that order in a reasonable runtime. Consequently, this work adopts a simplified version of the sensor-centric model with only one sensor in each region. Although this simplified version can not be used in large-scale application, we had to resort to such implementation to investigate the worthiness of the proposed approach. Table 6.2 lists the policy characteristics extracted from Symbolic Perseus. The proposed sensor-centric model can be beneficial if the number of sensors in each delegation/region is very small (≤ 2).

In the rest of this sub-section, the performance of the proposed SMF employing the context-aware and collaborative scheme using the region-centric model is investigated using five main aspects: network and sensor lifetime, communication overhead, tracking quality, network coverage, and source information reliability. The proposed scheme, referred to as Coop-EHASM, is compared to the centralized, E-HASM, and EC-HASM approaches.

6.4.1 Network and Sensor Lifetime

This set of experiments are carried to investigate the effects of increasing the number of threats on the lifetime of both the network and the sensors. The setup is formed using a grid of 9×9 cells monitored by 9 sensors and 1 delegate, the number of threats within the VOI vary from 1 to 20 with low agility, that is, the threats move in a progressive scan manner with few changes in direction or location.

Figures 6.11 and 6.12 plot the overall network and sensor lifetime versus the number of threats, respectively. The results show that the overall network lifetime for Coop-EHASM, at low number of threats, is lower than that of EC-HASM, whereas, at large number of threats, Coop-EHASM exceeds that of the EC-EHASM. In worst case, the network lifetime of Coop-EHASM and that of EC-HASM are 10× that of the centralized approach. This is attributed to the use of intelligent energy management techniques used in the Coop-EHASM and EC-HASM. At low number of threats, the increased communication overhead of Coop-EHASM slightly decreases the network lifetime, however, at large number of threats, the communication overhead of Coop-EHASM proves to be beneficial and results in a near-constant network lifetime with the increasing number of threats.

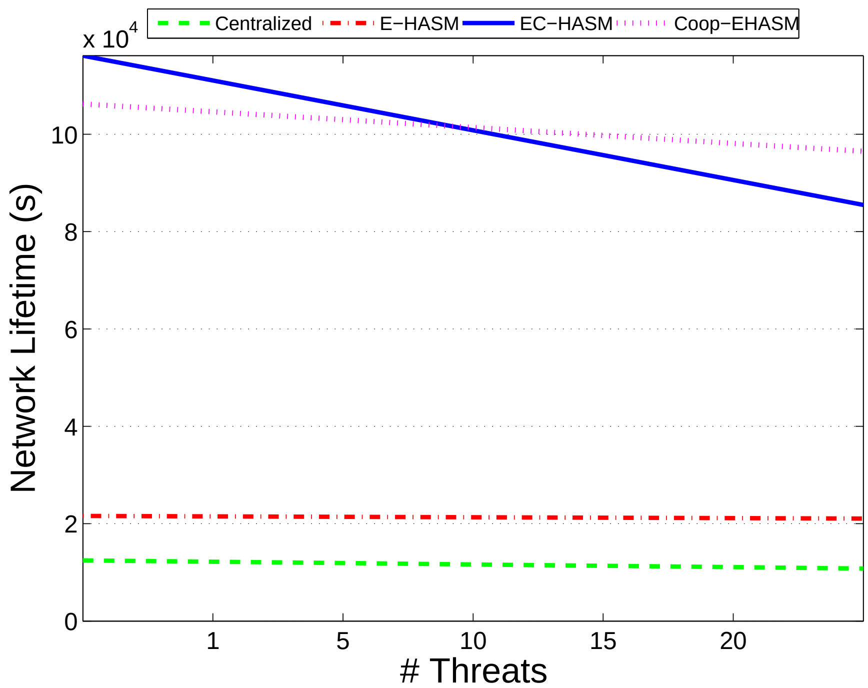


Figure 6.11: The network lifetime over varying number of threats.

Similarly, the sensor lifetime of the Coop-EHASM witnesses a significant decrease with the number of threats because of the fact that as the threat count increases throughout the network, the estimated threat level at each sensor goes higher which results in local reasoning of higher sensor settings. Such a behaviour is attributed to the delegate nodes in Coop-EHASM overriding the energy savings settings of the sensor nodes to increase the coverage and reliability of information observed. In worst case, the sensor lifetime of Coop-EHASM is almost 4× that of the centralized approach because of the use of intelligent energy management techniques, as well as, the reduced communication overhead.

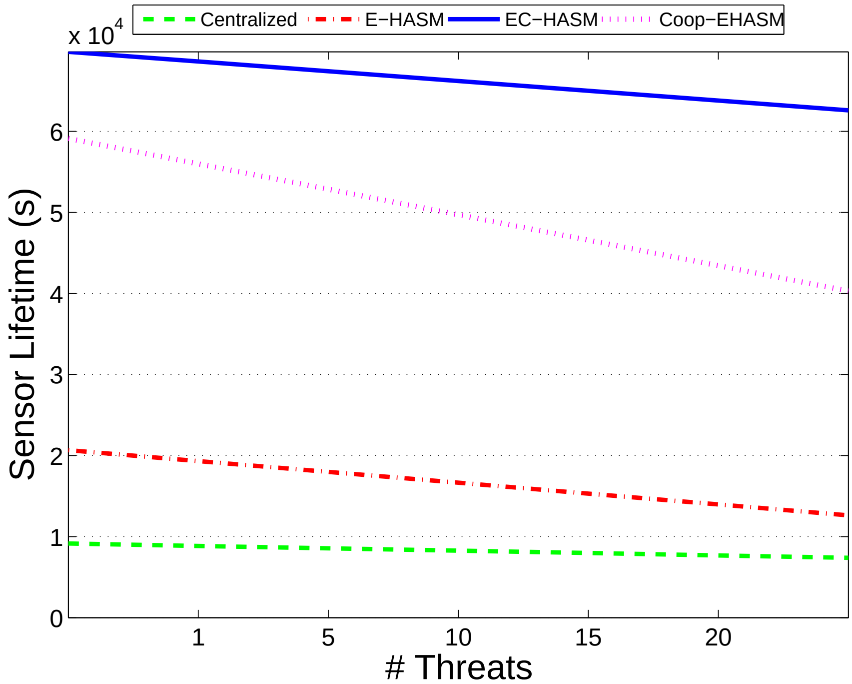


Figure 6.12: The sensor lifetime over varying number of threats.

6.4.2 Communication Overhead

The communication overhead of the Coop-EHASM is plotted in Figure 6.13. From Figure 6.13, it can observed that the communication overhead of Coop-EHASM and EC-HASM tend to be almost equivalent. Although, the number of messages for Coop-EHASM is slightly higher than the EC-HASM system because of the added communication overhead of passing the 16-bits codeword and the λ value between the sensors and the delegate, these extra messages are compensated for by the increased network lifetime of the Coop-EHASM system. It should be noted that the communication overhead of the centralized approach is about 20× that of the Coop-EHASM.

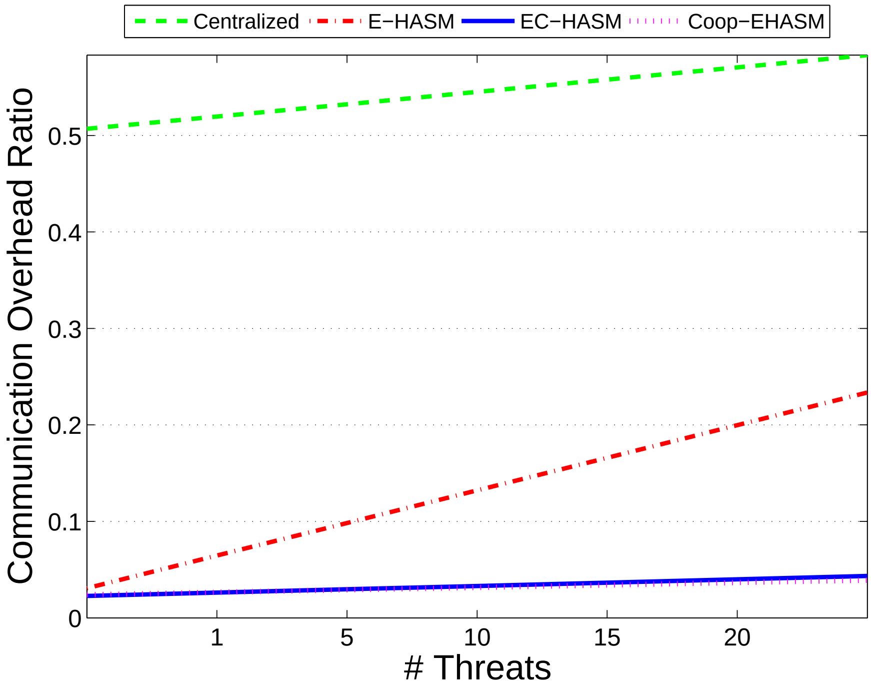


Figure 6.13: The communication overhead versus the increasing number of threats.

6.4.3 Tracking

Figure 6.14 plots the quality of tracking in Coop-EHASM networks versus the number of threats. The tracking quality using the Coop-EHASM, EC-HASM, and E-HASM approaches is consistent with the number of threats, as shown in Figure 6.14 due to the distributed nature of the architecture and the on-board localized processing. On the other hand, the tracking quality of the centralized approach decreases as the number of threats increase. The Coop-EHASM and the EC-HASM provide similar tracking quality with a 4% improvement over that of the centralized approach.

6.4.4 Network Coverage

Figure 6.15 plots the average network coverage throughout the network lifetime versus the number of threats. From Figure 6.15, it can be deduced that the overall network coverage of the EC-HASM tends to decrease as the number of threats increase. This is attributed to the sensor settings, in terms of sensing range, frequency, and sleep durations of the sensor nodes of the EC-HASM, as the energy reserve decreases from monitoring large number

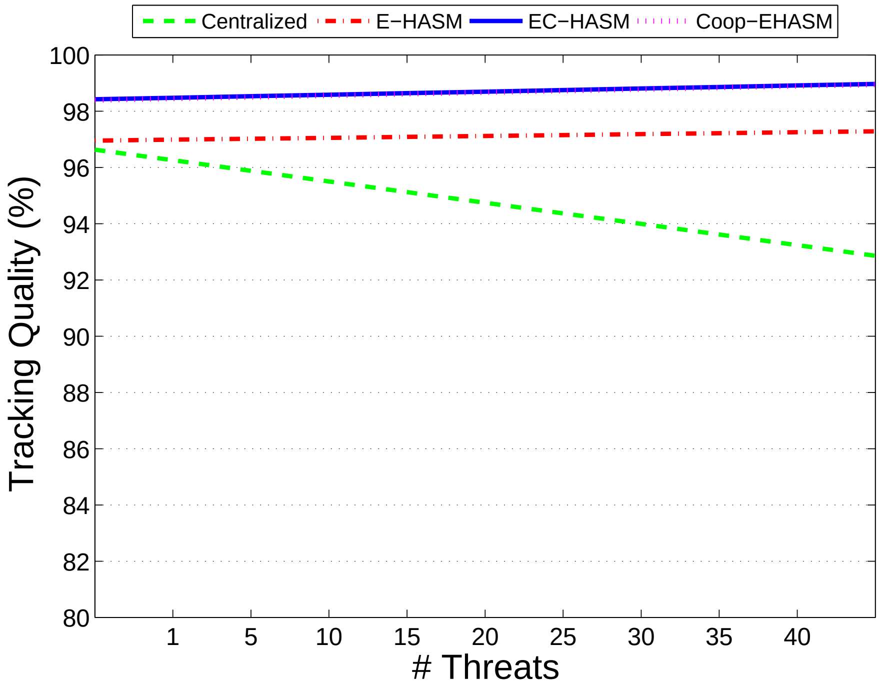


Figure 6.14: The quality of tracking versus the increasing number of threats.

of threats. Moreover, as the number of threats increase and become more distributed throughout the network, the network coverage of the centralized and E-HASM approaches tend to slightly increase because of the reduced variation in the lifetime between various system sensors. However, the Coop-EHASM offers the highest network coverage with 99.8% full coverage on average and this is due to the collaborative nature of the sensor nodes in Coop-EHASM.

6.4.5 Source Information Reliability

The source information reliability refers to the quality and accuracy of observations acquired by a sensor towards a specific phenomenon. Figure 6.16 plots the source reliability versus the increasing number of threats. The E-HASM and the centralized approaches yield the highest source information reliability since sensors in both approaches operate with the highest settings. Nevertheless, both approaches do not maximize the network lifetime and do not adapt the sensor operation according to the sensor and environment characteristics, that is, they operate in a greedy manner in terms of quality of surveillance. On the other hand, the EC-HASM suffers from low source reliability index because of

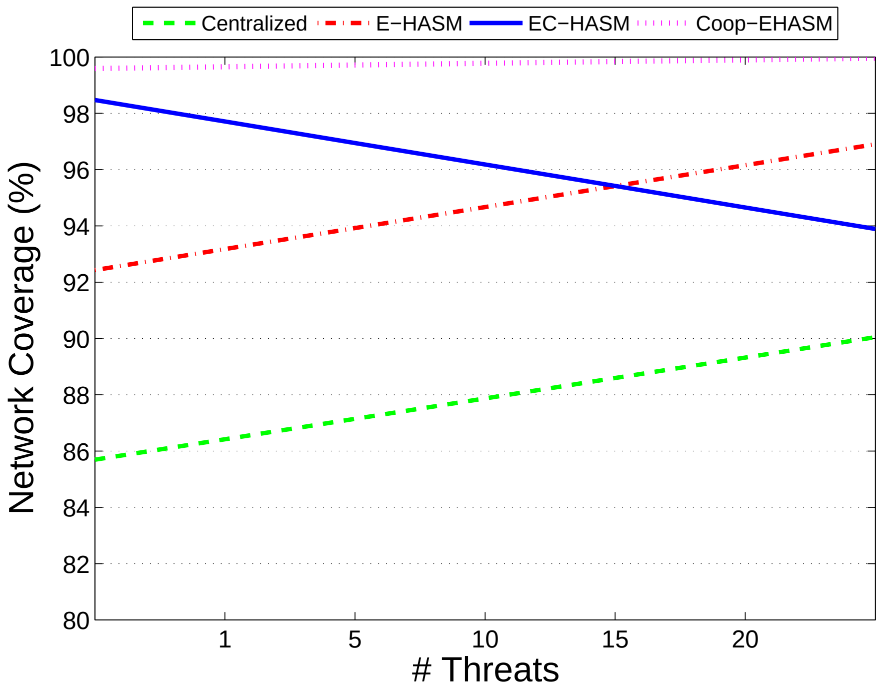


Figure 6.15: The network coverage versus the increasing number of threats..

the autonomous energy conservation strategies that lead to lower resolution sensor measurements. Coop-EHASM offers the best of both worlds, such that it uses smart energy saving strategies to prolongs the network lifetime, while using a reliability-aware scheme to increase the source reliability when monitoring high-threat objects.

6.4.6 Energy Distribution

This section studies the distribution of energy resources of sensor nodes over time. The main objective is to study the load balancing between the sensor nodes in a delegation. Since sensor tasks and operations results in energy dissipation, the load balancing between sensors can be represented by the energy consumption. Figure 6.17 plots the maximum, minimum, and average energy levels of sensor members of a delegation over time and compares the centralized, E-HASM, EC-HASM, and Coop-HASM approaches in terms of the energy distribution. The overall mean and standard deviation of the energy levels of sensor nodes is reported in Table 6.3.

For this set of experiments, a 9×9 environment monitored by 9 sensors and 1 delegate is modelled. Only one threat resides within the VOI, the threat moves in a progressive

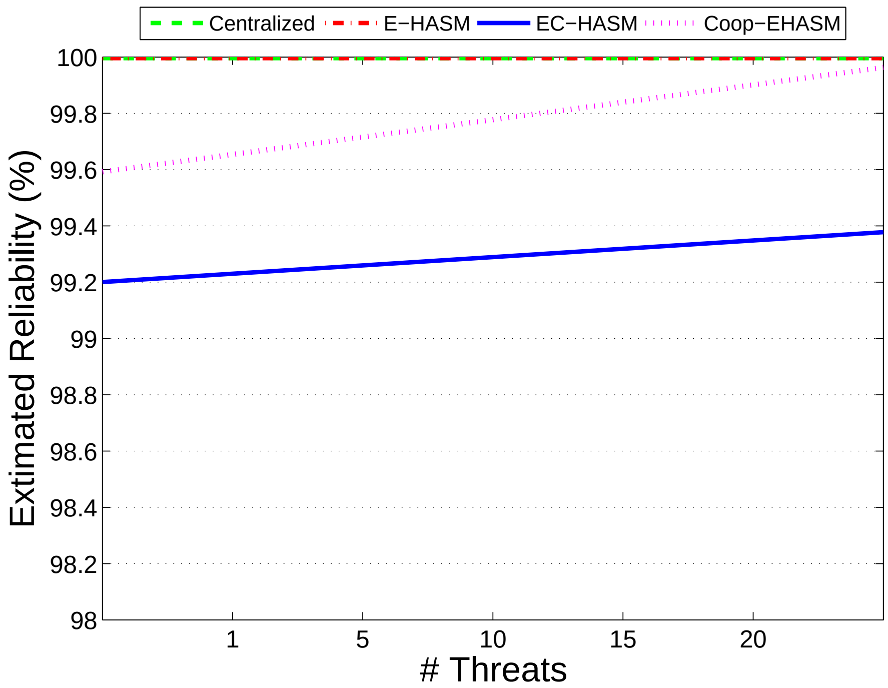
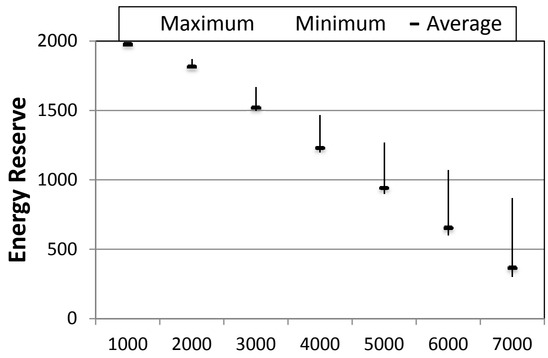
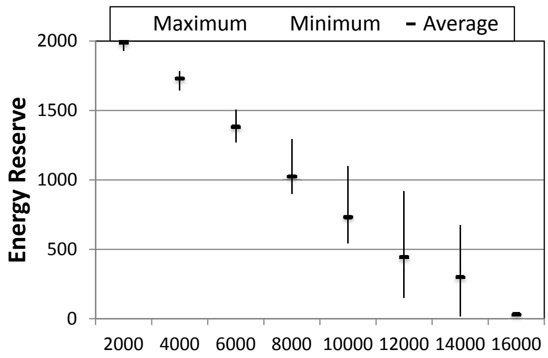


Figure 6.16: The source information reliability versus increasing number of threats.

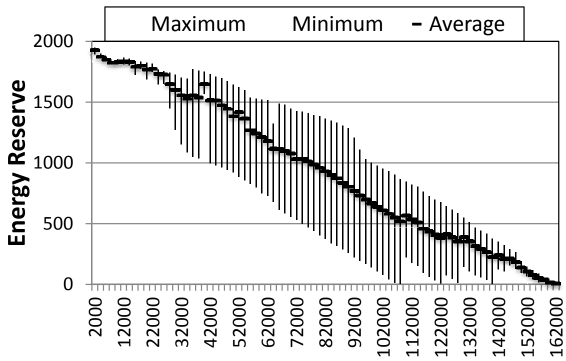
scan manner. From Figure 6.17, it can be noted that the centralized and the E-HASM approaches provide a near-uniform energy distribution among the sensors of a delegation for each time epoch. However, both approaches do not maximize the network lifetime and do not adapt the sensor operation according to the sensor and environment characteristics. Moreover, although EC-HASM deliberates on the use of its sensing strategies in a localized intelligent manner to prolong the network lifetime, the lack of global information results in large variations between the energy levels of sensor nodes within a delegation. Coop-EHASM offers rapid adaptation and collaboration schemes based on sub-global information and statistics about the delegation and the VOI. Figure 6.17(d) shows that Coop-HASM has, on average, smaller variations in the energy levels between different sensors within a delegation. Furthermore, as the energy reserve decreases and the system operation becomes tuned by the delegate node, the variations in the energy levels decrease, and the energy distribution among the member sensors become uniform.



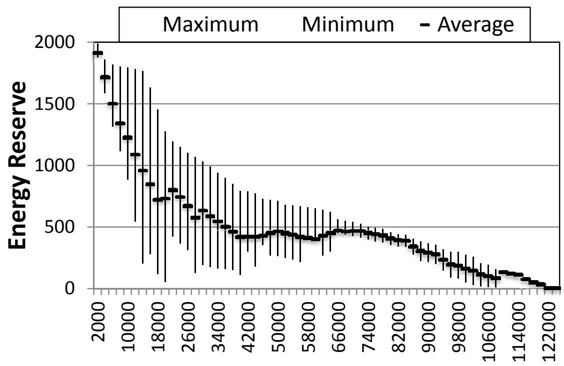
(a) Centralized



(b) E-HASM



(c) EC-HASM



(d) Coop-HASM

Figure 6.17: The maximum, minimum, and average energy distribution for sensors of a delegation versus time.

6.5 Summary

Each sensor node has a partial view of the environment, but collectively the network monitors the entire VOI. Therefore, the collaborative operation of the sensor nodes can significantly increase the quality of the system performance as well as increase the network coverage and information reliability. A stochastic decision-making scheme using Partially Observable Markov Decision Processes (POMDP) formulation that represents the delegation decision-making is proposed in this chapter. The main contribution of this chapter can be summarized as:

- Computation of the delegation statistics based on the individual sensor estimations.
- Methodology for estimation of source information reliability based on the sensor setting and environment dynamics.

Table 6.3: The mean and the standard deviation of the energy distribution over the sensor members of a delegation.

System	Centralized	E-HASM	EC-HASM	Coop-HASM
Mean	1171.944	1162.285	1161.324	975.566
Std Deviation	90.513	145.606	-190.351	168.921

- A low-communication overhead collaborative algorithm,
- Modelling the delegate decision-making as a POMDP using a region-centric and a sensor-centric approaches,
- Formulation of the optimized action policy into a Finite State Controller (FSC) to offer a fast low overhead on-board processing of the delegate node decision-making,
- A closed-loop information reliability-aware sensor management under resource and energy constraints,
- Collaborate operation to maximize the network coverage while minimizing the energy consumption.

In the following chapter, the proposed SMF will be integrated with two external modules for abnormality detection and in-door localization to investigate the performance of the proposed SMF in operation with independent modules.

Chapter 7

IntelliSurv: An Intelligent Pervasive Surveillance System

This chapter introduces a novel intelligent surveillance system (IntelliSurv) that automatically detects and localizes abnormal events in a distributed collaborative manner. IntelliSurv is built incorporating the proposed SMF and manifests its performance with various independent modules. The chapter is organized as follows: After the IntelliSurv system is introduced in Section 7.1, Section 7.2 covers the related literature. In Section 7.3, the design and integration of IntelliSurv various modules are detailed. The simulation setup and the results are provided in Section 7.4. Some concluding remarks comprise Section 7.5.

7.1 Introduction

Smart pervasive surveillance systems employ automatic detection of abnormal events and behaviours, based on information acquired from sensors located in the environment. To achieve such a level of autonomy, the deployment of an intelligent SMF is a necessity to increase the effective utilization of the sensor resources in a manner that achieves the system objectives. This chapter describes a novel intelligent pervasive surveillance system called Intellisurv, such that in the heart of IntelliSurv is the proposed SMF. This chapter is an investigation and a study of the performance of the proposed SMF in an elaborate environment with various independent modules. This chapter is based on the joint work perviously conducted in [197].

IntelliSurv automatically detects and localizes abnormal events in a distributed collaborative manner. The proposed system consists of three primary modules: the intelligent sensor management module, the abnormal event detection module, and the indoor localization module. The sensor management module employs the E-HASM architecture and operates in an energy-aware collaborate manner providing a structured localized control into the surveillance operation. The second module uses acoustic information to reveal abnormalities in the monitored scene. Lastly, the localization module relies on the Received Signal Strength (RSS) information detected by the sensor nodes to direct the law enforcement personnel to the location of the abnormal event.

7.2 Related Work

For the past two decades, surveillance systems have been an active research area [198]. These surveillance systems have been developed in three generations [199]. The First Generation Surveillance Systems (1GSSs) utilized analogue Closed-Circuit Television (CCTV) technologies. 1GSSs consist of a number of cameras located in multiple remote locations and connected to a set of monitors. The disadvantages of these systems include the use of analogue techniques for image distribution and storage, and the requirement of continuous human supervision which becomes ineffective due to the small attention span of human operators. Second Generation Surveillance Systems (2GSSs) required the development of semi-automatic surveillance systems by combining vision technology with digital CCTV systems [200]. Here, the difficulty lies in the development of robust detection and tracking algorithms for behavioural analysis [199]. Third Generation Surveillance Systems (3GSSs) are based on the design of large distributed and heterogeneous surveillance systems for wide area surveillance. The main applications of 3GSSs are in public monitoring [198], whose demands include the efficient integration and communication of information, establishment of design methodologies, and management of multisensory platforms [199].

Building an intelligent surveillance system for event detection and analysis of behaviour patterns in real life scenarios is still a challenge. Recently, the research of acoustic surveillance with the focus of detecting unusual sound events has attracted a lot of attention [201]. In considering the nature of the target event, the content of the information is more than just visual information. Many events are accompanied with useful audio information [202]. Other demands of visual systems include the complexity of higher level processing for the extraction of semantics such as human actions, sensitivity to illumination conditions, occlusions, and the occurrence of events beyond the cameras' field of view. In addition, there are privacy issues. For instance, for events involving humans, the right-to-monitor can conflict with their privacy rights [198].

Audio-based surveillance systems can overcome some of the privacy issues associated with the use of visual sensors. In [203], an audio-based tele-monitoring system is introduced where a multichannel sound acquisition system replaces a video camera. The system analyzes the sound range of the location in real-time and specifies the emergency situations. This system must cover all the area of interest, for example, in an apartment, the system must monitor the bathrooms and the bedrooms. If a video camera is installed in each room, the client might experience the uncomfortable feeling of being spied on. On the other hand, a sound sensor is more discreet and the client's privacy is less disturbed, because there is no continuous recording of the sound in the room. Only a real-time analysis is applied to the last 10 seconds of captured audio. The privacy issues depend heavily on the shared acceptance of the surveillance task as a necessity by the public [204].

7.3 IntelliSurv Architecture

The primary contribution of this chapter is a description of the design and integration of an autonomous surveillance system, called IntelliSurv, for indoor environments. This system comprises an intelligent management module that automatically detects anomaly events within the VOI, and then classifies anomalies by using audio information. The VOI is surveyed by a number of stationary sensor nodes, performing environmental monitoring for potential threatening activities. It is assumed that the VOI is fully monitored by sensors, that is, full coverage of the VOI by the sensor network. It should be noted that the Regions of Responsibility (RoR) of the sensor nodes are non-overlapping such that $RoR_1 \bigcap RoR_2 = \phi$. However, the sensing range can overlap such that $\eta_1 \bigcap \eta_2 \neq \phi$. Figure 7.1 illustrates a high-level design of the components of the proposed IntelliSurv system and their interaction with the environment. IntelliSurv is based on the design principles of the layered organizational design framework discussed in Chapter 3 which is based on the Service-Oriented Architecture (SOA).

As observed in Figure 7.1, the proposed system has two sets of components: sensors and delegates. The design details of the sensor module is denoted in Figure 7.2, and the delegate module in Figure 7.3. In practical surveillance scenarios, the abnormal events must be deduced dynamically, because the operational situation changes with time. Accordingly, the sensor components should be capable of autonomously recognizing the critical

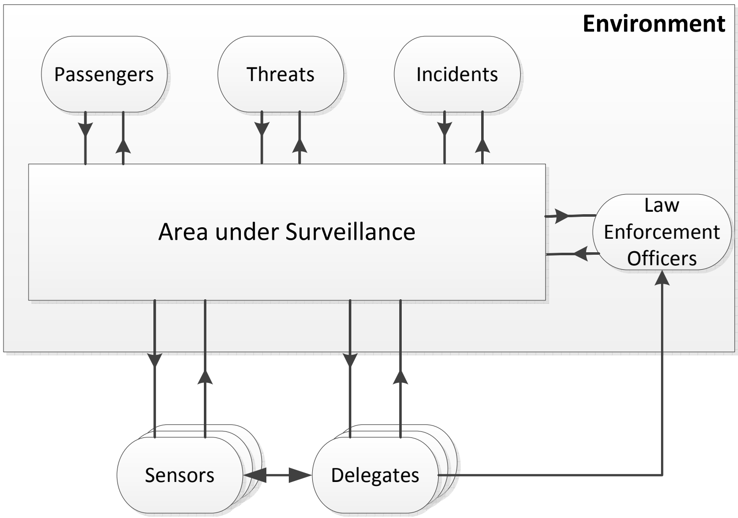


Figure 7.1: The IntelliSurv system overview.

areas/targets within the VOI. Thus, the sensor components are designed to have local anomaly detection and evaluations modules. These modules analyze the data, collected from the ROR, and estimate the level of criticality in the ROR. The level of criticality is used to make a decision on cueing the neighbouring delegate to further investigate the situation in the VOI.

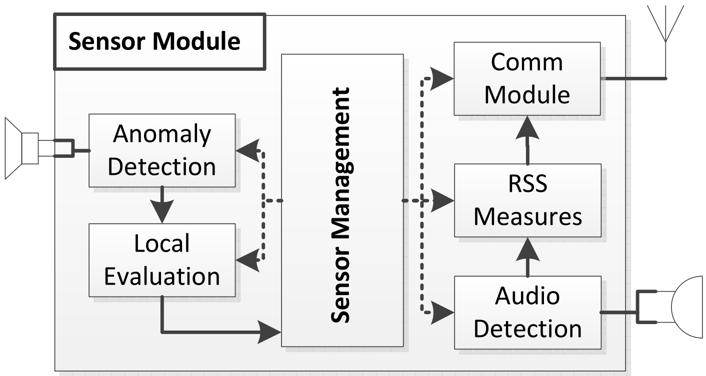


Figure 7.2: The sensor module high-level design.

The anomaly evaluation module integrates audio information in the abnormality detection process by using the signals' features and characteristics. The details on the operation of that module are given in Section 7.3.1. Furthermore, the decision-making process, as well as the sensor components and their interactions, is governed by the sensor management module. The sensor management module employs the E-HASM architecture discussed in

Chapter 4, and operates in a distributed manner with collaboration as discussed earlier in this thesis. The management module is designed to operate under low-energy consumption constraints and to allow the system to scale seamlessly.

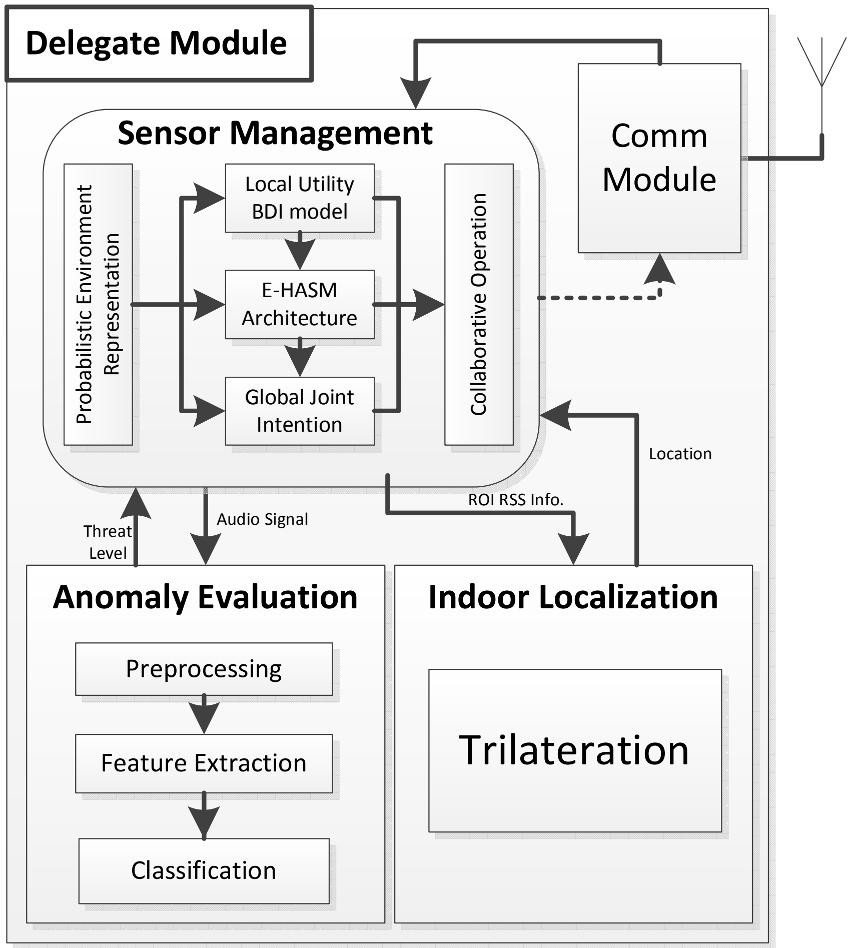


Figure 7.3: The delegate module high-level design.

Communication plays an important role in the operation of the modules and components of IntelliSurv. In case a sensor detects the presence of an anomaly within the ROR, the sensor alerts the delegate within the neighbourhood or cluster of the abnormality via a cue message. Accordingly, the delegate collects the needed sensor measurements and activates the localization module. The localization module adopts the signal strength and attenuation factors to locate the position of the anomaly event to inform the law enforcement personnel. It should be noted that the proposed system is a computer-aided system for the human in the loop. IntelliSurv performs automatic detection, evaluation, classification, and localization of abnormal behaviour within the VOI.

The underlying sensor network of IntelliSurv comprises a number of stationary heterogeneous sensor nodes, equipped with audio and radio detectors. The sensors are assumed to be battery operated. In the following sections, the anomaly detection and localization modules are further explored. These modules are based on the joint work perviously conducted in [197].

7.3.1 Abnormal Event Recognition Module

To date, visual sensors are the most adopted modality in smart pervasive surveillance systems. The use of such a modality adds numerous challenges to pervasive surveillance systems: a higher processing complexity, a sensitivity to illumination conditions, and limitations of the field of view, to name a few. One solution to these problems is to incorporate audio information. Audio cues provide vital information, especially where it is difficult or almost impossible to detect visual signals, for example, an explosion event can be easily captured by microphones compared to video cameras.

Recently, research on acoustic surveillance has attracted a lot of attention, and addresses various applications [201], including: an audio-based surveillance system for identifying abnormal situations, which includes screaming, explosion, and gunshot sound events [205]. Also, an audio based surveillance system for detection and localization of screams and gunshots is presented in [206]. In addition, a system, based on recognizing and classifying a large set of environmental sounds (*i.e.*, human screams, gunshots, breaking glass, door slams, explosions, dog bark, phone rings, children's voices, and machine sounds) for surveillance and security applications, is reported [207].

IntelliSurv detects and recognizes abnormal events that will provide automatic assistance to human operators in order to focus their attention on possible alarming or dangerous situations. Primarily, the system focuses on the detection and recognition of human screams by classifying the incoming audio signal into a normal speech sound versus a scream sound. Figure 7.4 illustrates the outline of the abnormal event detection module which consists of three steps: signal preprocessing, feature extraction, and classification. The following section presents the framework for the abnormal event detection module.

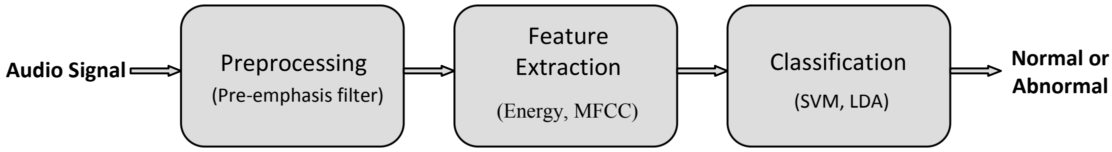


Figure 7.4: A block diagram of the abnormal event detection module.

7.3.1.1 Preprocessing Phase

Due to the differences encountered in the recording environment, the preprocessing step is performed on all input audio signals before extracting the features. The input signal is filtered with a pre-emphasis radiation filter [208] by using

$$H(z) = 1 - 0.97z^{-1}. \tag{7.1}$$

This filter is used to reduce the differences in power of the different components in the signal. In other words, it is used to equalize the effect of the propagation of an audio signal in air [208].

7.3.1.2 Feature Extraction Phase

After the signal is filtered, it is divided into equal overlapping frames with a 25 ms duration and a 10 ms shift. Each frame is multiplied by a hamming window to avoid problems due to discontinuities in the signal and to reduce the ripple in the spectrum. After dividing the signal into frames, short-time energy and Mel-Frequency Cepstral Coefficients (MFCCs) are extracted for each frame. The short time energy is obtained by computing

$$E = \sum_{i=1}^{n} (X_i)^2, \tag{7.2}$$

where E is the short time energy calculated per frame, and X is amplitude of the audio signal of the corresponding frame. The signal energy contains information that is helpful in discriminating between normal sounds with low energy amplitudes and scream sounds which usually have higher energy amplitudes. In addition, MFCCs present a description of the spectral shape of the sound, widely used in the field of speech recognition and proven to model the human perception to speech quite well [209]. The MFCC features are obtained by first calculating the amplitude spectrum by using the short-term Fast Fourier Transform (FFT) from each frame. Then, the frequency bands are positioned logarithmically (on the Mel scale) which approximates the human auditory system response more closely than the linearly-spaced frequency bands. Finally, the Discrete Cosine Transforms (DCTs) are calculated. Since the DCTs have a strong compaction property, the signal information tends to be concentrated in a few low-frequency DCT components. As a result, 13 MFCCs are kept as the final feature vectors from each frame. Subsequently, statistical measures (min, max, range, median, mean, and variance) are calculated along all the frames of the speech signal to produce the final feature vector. Finally, feature normalization is applied as a post processing step to avoid the differences in scaling among the different features.

7.3.1.3 Classification Phase

Various types of classifiers have been used in audio-based recognition systems. Among them are Support Vector Machines (SVM). SVM classifiers have been widely used in the field of pattern recognition in general and extensively used in speech emotion recognition, and yeild better results than other well-known classifiers [210]. The advantages of SVM classifiers include the global optimality of the training algorithms and the existence of data dependent generalization bounds [208]. In this work, an SVM classifier with a Radial Basis Function (RBF) is chosen to classify the audio signal into two categories: an abnormal or a normal event. In addition, a Linear Discriminant Analysis (LDA) classifier is also used as a simple classifier in this work for the purpose of comparison.

7.3.1.4 Abnormal Event Recognition Module Details

In this research, the abnormal event is defined as human screaming, captured by the audio sensor in the network. The main task of the abnormality detection module is to classify the incoming audio signal into either a scream or a normal voice signal.

One of the key issues for designing the system is the availability of publicly available benchmark databases for surveillance application. As a result, the speech under simulated and actual stress database [211] is selected for this study. It is a spontaneous database of noisy speech recordings, characteristics of any surveillance environment. The database consists of recordings from 7 speakers in roller coaster and free fall situations of medium stress, high stress, and screaming, as well as neutral speech samples. A subset of the database, which consists of a total of 1115 samples of scream and neural signals (414 scream, 701 neutral), is used to train the classifier. The data is split randomly into two disjoint sets: 90% for training, parameter optimization for the SVM classifier, and validation, and the remaining 10% are used in the testing of the system. Five-fold cross validation is performed to obtain the optimized RBF kernel parameter, the sigma value, by using the training partition. The average accuracy of the 5-fold runs is calculated at different values of sigma (sigma: 0.1-100) to choose the best sigma value, and the model is retrained by using the entire training subset with the optimized parameter.

Table 7.1 exhibits the mean accuracy results from the 5-fold cross validation runs at different values of sigma for the SVM classifier. The table conveys that the performance increases as the sigma value increases until a certain point, where the performance deterioration begins as sigma becomes larger than 10. As a result, the model is retrained by the optimized sigma value equals to 10 by using the whole training set.

sigma	0.1	2	10	20	50	100
Mean accuracy%	62.8	94.7	99.4	99.3	97.7	91.9

Table 7.1: The mean-accuracy of the SVM abnormality detection model at different sigma values.

7.3.2 Event Localization Module

The accurate localization of objects and people in an indoor environment has long been considered as one of the important building blocks in surveillance systems. Indoor environments are challenging, because the radio propagation in such environments is much more chaotic than in outdoor settings, where the signals travel with little obstruction. IntelliSurv is designed to address the event location estimation problem. The system depends on inconsistent signal measurements, in the form of Received Signal Strength (RSS) or time-of-arrival from anchor sensors with known locations, to estimate the location of the target.

The most common localization sensor for outdoors is the GPS receiver that allows highly accurate localization. Such accuracy is impacted by a number of factors, including satellite positions, noise in the radio signal, atmospheric conditions, and natural barriers in the signal path. Unfortunately, in dense urban areas or indoors, buildings can mask the received signals and prevent accurate localization significantly. It is necessary to use different data modalities, for example, audio, radio, and video, to solve localization problems, especially where the odometry is difficult.

There are several types of measurements such as signal-strength, time-of-arrival, and angle-of-arrival for source localization. Among those measurements, signal-strength is the most accessible and affordable measurement for estimating the node-to-node distance; however, it is prone to noisy and inaccurate measurements or delays due to fading channels.

Most of the current range-based localization methods consist of estimating the distance, based on the empirical channel models, and then inferring the location. Most of practical source localization methods are based on the time delay of the arrival estimation, because they are conceptually simple and reasonably effective. Moreover, the low computational complexity of these methods suits real-time implementation within a sensor network [212].

In addition to measurements, a proper localization method is required to process audio or radio measurements. Trilateration is the most basic and intuitive way for positioning. This method computes a node position via the intersection of three circles. In real-world applications, the distance estimation inaccuracies, as well as the erroneous position information of the reference nodes, result in an infinite set of possible positions [213].

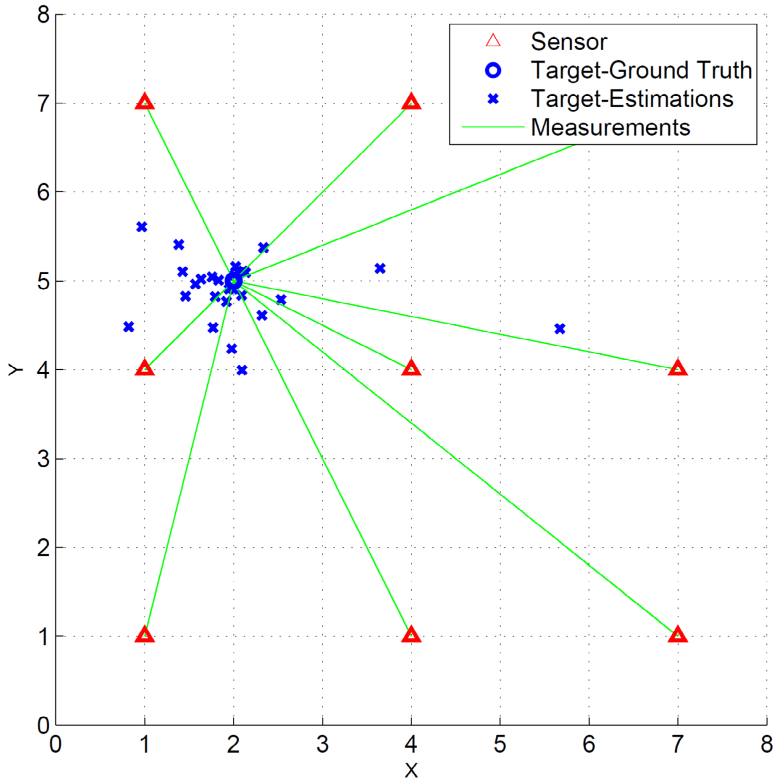


Figure 7.5: The localization in an indoor wireless sensor network. The available measurements from five sensors are processed to estimate the target location.

Furthermore, when a larger number of reference points are available, multilateration is employed to determine the event position, and an over determined system of equations must be solved, as shown in Figure 7.5. Usually, over-determined systems do not have a unique solution ($Ax = b$), but can be easily solved with traditional methods (*e.g.*, the least squares method) [214, 215].

To infer the event location from the signal strength measurements, a propagation channel model can be utilized. In IntelliSurv, to infer the event location from the delegate by extracting the radii of the circles, where the event resides with the highest probability [214], compute

$$(x - \frac{k^2 x_2 - x_1}{k^2 - 1})^2 + (y - \frac{k^2 y_2 - y_1}{k^2 - 1})^2 \tag{7.3}$$
$$= (\frac{kD}{k^2 - 1})^2 * \log_{10}(k) = \frac{A_1 - A_2}{10n} + N(0, \frac{2\sigma^2(1-\rho)}{100n^2})$$

where signal attenuation (A_i), path loss exponent ($n = 4to6$) for lossy indoor environments, distance ratio ($k = \frac{d_1}{d_2}$), distance between two base stations (D), standard deviation ($\sigma^2 = 2.2 - 8.3$), and a correlation coefficient of shadow components ($\rho = 0.3 - 0.8$) are the input parameters [216, 217].

A simple audio-based localization is to estimate the time delay-of-arrival of a sound signal between the two sensors. This time delay-of-arrival estimate is then used to calculate the direction-of-arrival for the triangulation. The direction-of-arrival is calculated by

$$\theta = \arcsin{(t \times v/d)}, \tag{7.4}$$

where t is the time delay-of-arrival estimate, v is the speed of sound in air, and d is the inter-sensor spacing [212].

7.4 Simulation Setup and Results Discussion

The simulations in this section indicate the performance of the proposed IntelliSurv for the surveillance of an airport. This scenario is implemented on the Jadex platform. The rest of this section explains the simulation setup and results.

7.4.1 Simulation Setup

The simulation scenario adopted in this work is the surveillance of the Waterloo International Airport. The layout of the airport is reflected in Figure 7.6. The airport halls are virtually divided into a mesh grid cells by the sensors during the initialization phase. Each sensor has a sensing range of 3×3 grid units. The sensors are stationary with heterogenous modalities and are represented in the graphical user interface by a gray round object and the delegates by the black ones, as shown in Figure 7.7. Each sensor is equipped with a battery of 100 power units. The passengers enter and leave the airport randomly. Impulsive bursts of passengers' arrivals and departures are also randomly generated to simulate the real world. Moreover, the injected targets depart the environment at random times. These benign targets are represented in the simulation by white and black human-like images.

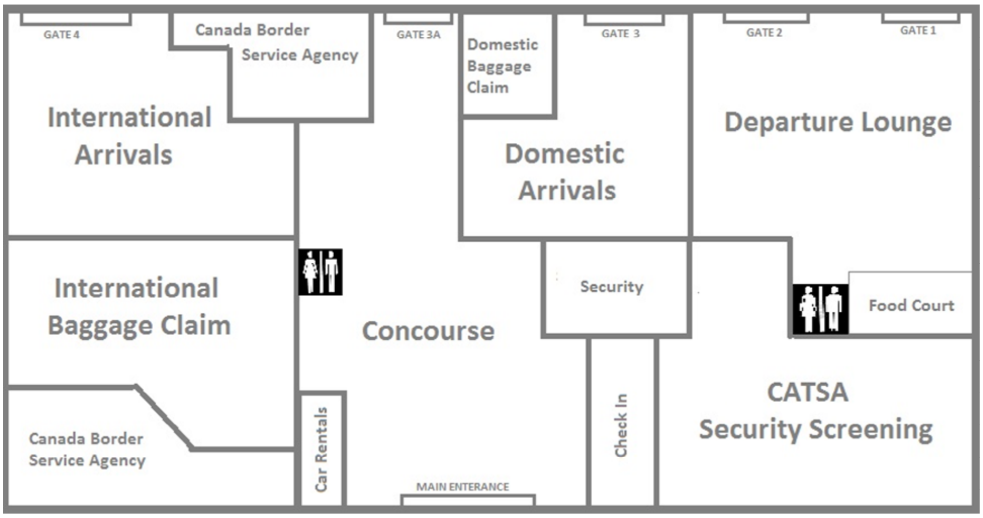


Figure 7.6: The Waterloo Region International Airport layout.

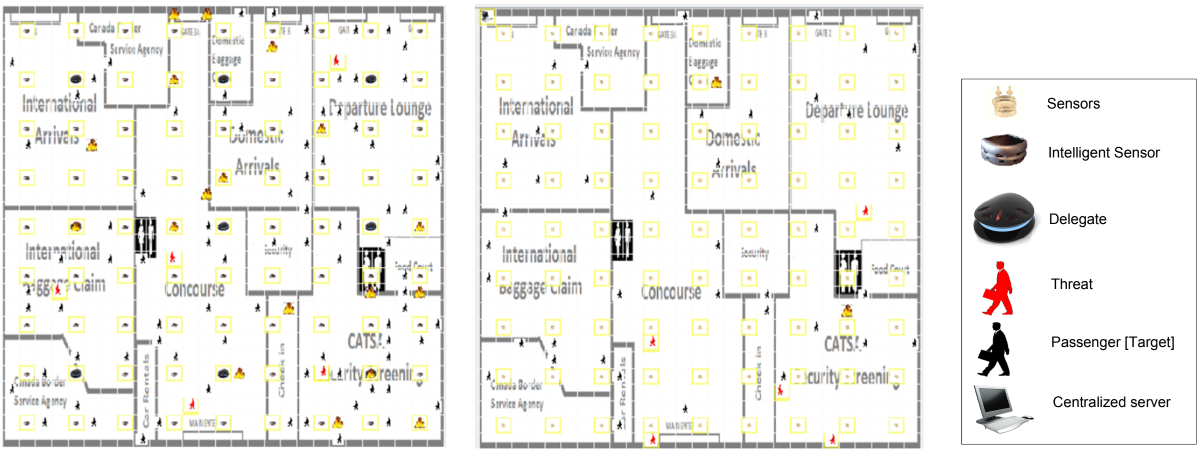
There are two types of threats monitored by IntelliSurv: incidents and human threats. The human threats are represented as intelligent mobile agents with sets of beliefs, desires, and intentions. The number of threats vary between 1-20. The threats do not depart the scene for the duration of the simulation and move all around the airport. Although the motion of the threat is set to a pre-specified pattern, a random motion pattern is invoked arbitrarily. The incidents refer to the abnormal events that impose or imply danger to the passengers in the airport. These incidents can be, for example, a fire, a loud scream, a gunshot. These incidents occur within the VOI for a small duration of time or until the law enforcement personnel intervene. The simulation is carried out until all the sensors run out of energy and the surveillance system fails. Table 7.2 lists the simulation configuration parameters.

Two different approaches: IntelliSurv and centralized, are implemented for comparison. Figure 7.7 is a snapshot of the implemented graphical user interface for the two approaches. The IntelliSurv is composed of a group of smart sensor nodes and a group of delegate nodes. The centralized system, in Figure 7.7(b), is composed of a group of sensors and a centralized processing unit, represented on the top left side of the simulation environment.

Table 7.2: Simulation environment setting.

Parameter	Value
Area	9×9 to 27×27 grid
# Sensors	6 to 81
Battery power	100 power units
Danger levels	3 levels (Passengers, Incidents and Threats)
# Threats	1 to 20
Target motion	preset pattern (progressive scan) random change in direction
Direction	4 direction

The processing power of the centralized unit is ten times faster than that of the delegate nodes in the proposed IntelliSurv.



(a) The IntelliSurv GUI (b) The Centralized GUI (c) Key

Figure 7.7: The airport concourse surveillance scenario implemented using the Jadex Standalone Platform.

A global surveillance mission of all the threats and incidents, occurring within the VOI, is the key mission of the IntelliSurv system. It is assumed that the sensor needs to know only the cell on the grid in which the threat resides to determine the exact location of the threat.

7.4.2 Simulation Results

In the following sections, the results for each module are represented after its integration within the entire system. Various experiments are carried out to evaluate the performance of IntelliSurv and its modules.

7.4.2.1 Sensor Management Module Results

Five different sets of experiments are conducted to evaluate the performance of the sensor management module. The experiments to investigate the effects of the network size, number of threats, signal-to-noise ratio, detection success ratio, and energy consumption on the performance of IntelliSurv SM module will be discussed in the following sections.

7.4.2.1.1 Effects of Signal-to-Noise Ratio: The Signal-to-Noise Ratio (SNR) is a indicator of the level of a desired signal in comparison to the level of the background noise within the environment. This section discusses the results of a set of experiments on the performance of the IntelliSurv SM module over varying SNRs. The experiments are conducted on a 9×9 grid cells, monitored by 9 sensors and 1 delegate. The SNR is assumed to vary between 0 and 100 db. Moreover, it is assumed that only one threat exists within the VOI for the duration of the simulation, although, incidents are randomly generated in the environment in a uniform distribution.

From Figure 7.8, it is evident that as the level of the desired signal increases over that of the noise, the overall network lifetime increases. Moreover, the results indicate that the overall network lifetime increases significantly for the IntelliSurv compared to that of the centralized. In addition, the overall network lifetime for IntelliSurv, in the worst case, is more than three times that of the centralized. Furthermore, it should be noted that for higher SNR values, for example, SNR = 100, the network lifetime for IntelliSurv is almost triple that where SNR = 0. This is due to the decreased false alarm rate and more accurate measurements which result in better on-board event classification leading to less communication overhead.

Figure 7.9 signifies the lifetime of the first sensor to die in the network. Similar to the overall network lifetime, the sensor node lifetime exhibits the same trends over the increasing SNRs. Furthermore, the sensor lifetime of the IntelliSurv outperforms that of the centralized system with a ratio of 3:1.

Figure 7.10 displays the ratio of communication messages exchanged per unit time in relation to the varying SNRs. It is noteworthy that the number of exchanged communication messages decreases, as the SNR increases for both the IntelliSurv SM and the centralized SM approaches. This is the result of reducing the communication overhead, as the quality and accuracy of the sensed information increases. Moreover, the IntelliSurv SM has a lower

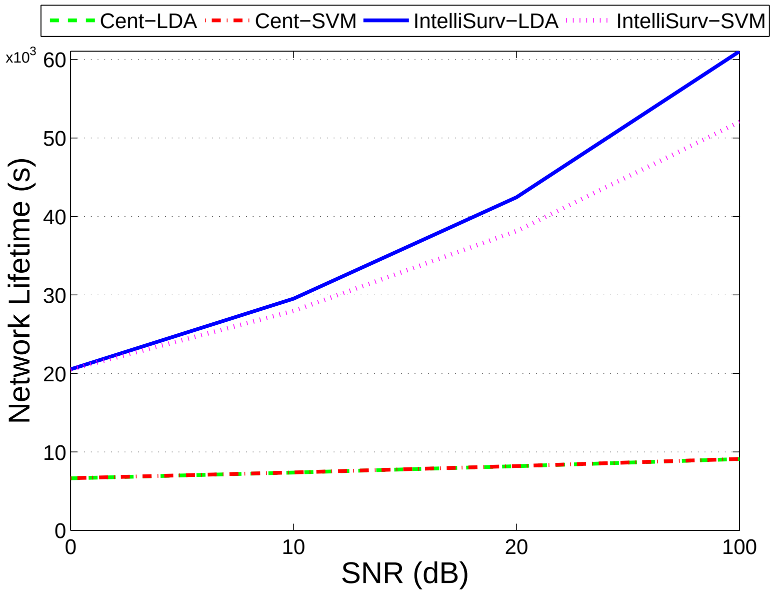


Figure 7.8: The network lifetime over varying SNRs.

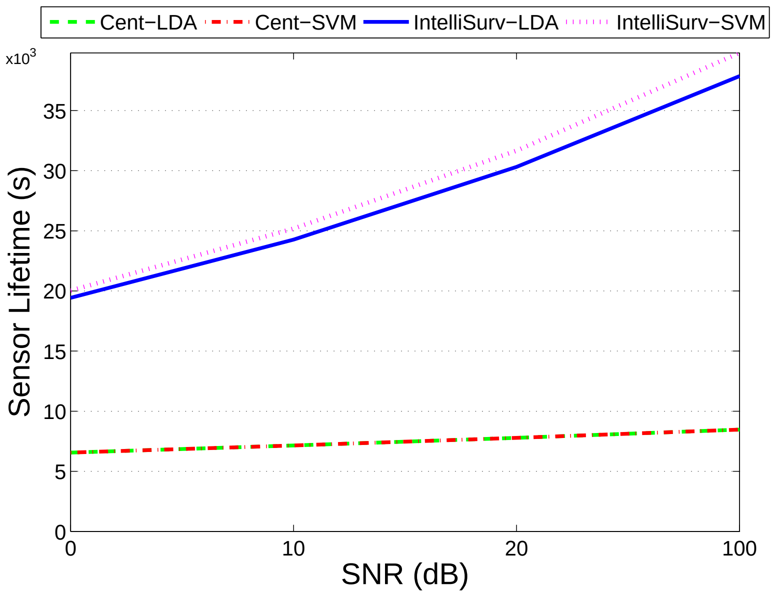


Figure 7.9: The sensor lifetime over varying SNRs.

communication overhead, compared to that of the centralized SM. This is attributed to the reduced communication overhead of the IntelliSurv, compared to that of the centralized approach; and the sensor nodes' on-board preliminary abnormality detection of IntelliSurv.

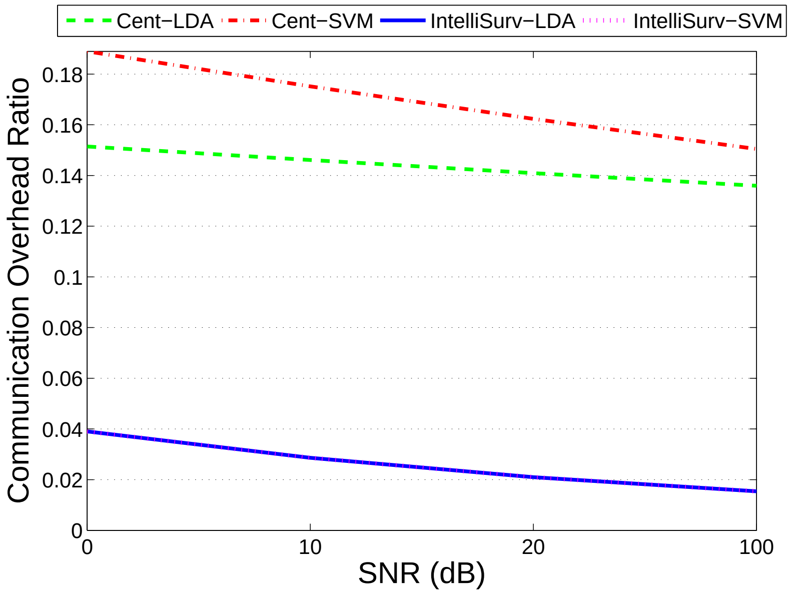


Figure 7.10: The communication overhead over varying SNRs.

7.4.2.1.2 Effects of Network Size: This set of experiments is carried out on varying network sizes from 9×9 grid cells, monitored by 9 sensors and 1 delegate, to 27×27 grid cells, monitored by 81 sensors and 9 delegates. The SNR is assumed to be 20 db and the threats within the VOI is set to 5 threats. It should be noted that incidents are randomly generated in the environment during the simulation time by using a uniform distribution.

Figure 7.11 demonstrates the overall network lifetime in relation to the varying grid sizes. The results show that the overall network lifetime increases as the network size increases in the IntelliSurv SM approach, whereas the overall network lifetime remains almost constant for the centralized SM approach. This is attributed to the cooperative nature of the IntelliSurv SM design, as well as the reduced communication overhead of the IntelliSurv, compared to that of the centralized approach.

Figure 7.12 shows the sensor lifetime in relation to the varying grid sizes. Similar to the network lifetime, the results indicate that the sensor lifetime increases as the network size increases in the IntelliSurv SM approach, whereas the overall sensor lifetime remains almost constant for the centralized SM approach. This is attributed to the cooperative nature of the IntelliSurv SM design, as well as the reduced communication overhead of the IntelliSurv compared to that of the centralized approach. Also, the one-hop communication to the delegate consumes less power than that to a centralized server, which depends on the distance between the sensor and the server.

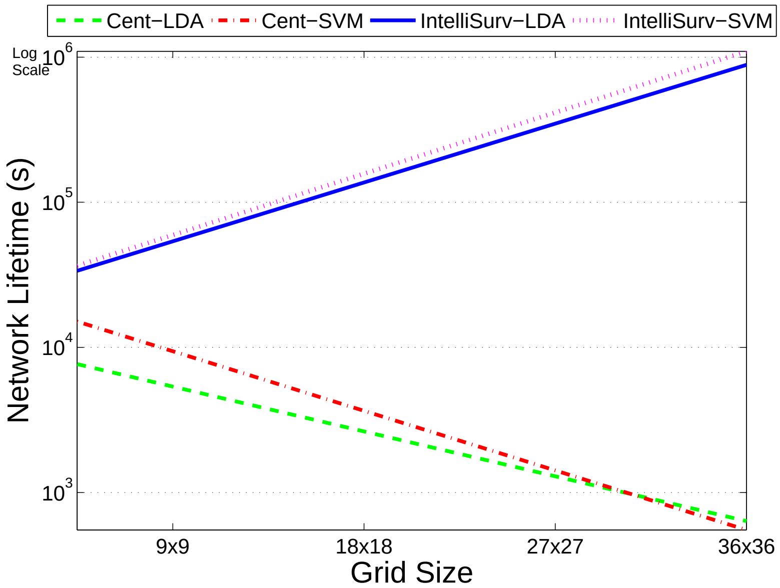


Figure 7.11: The network lifetime over varying network sizes.

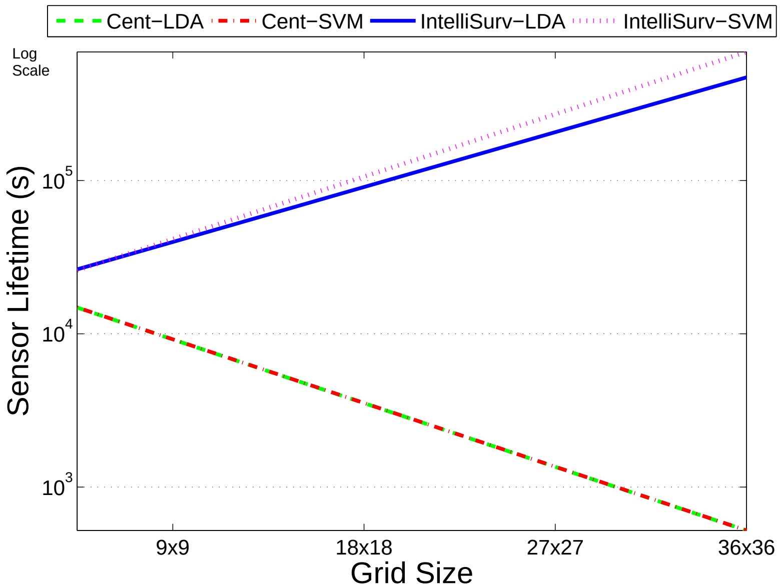


Figure 7.12: The sensor lifetime over varying network sizes.

Figure 7.13 reveals the number of the communication messages that are exchanged per unit time in regards to the varying grid size. Although the number of exchanged communication messages increases as the network size increases for both the IntelliSurv

SM and the centralized SM approaches, the IntelliSurv SM has a lower communication overhead than that of the centralized SM. The difference in the number of messages between the IntelliSurv SM and the centralized SM increases as the network size increases. This is attributed to the reduced communication overhead of the IntelliSurv compared to that of the centralized approach. It is also attributed to the on-board preliminary abnormality detection of the IntelliSurv.

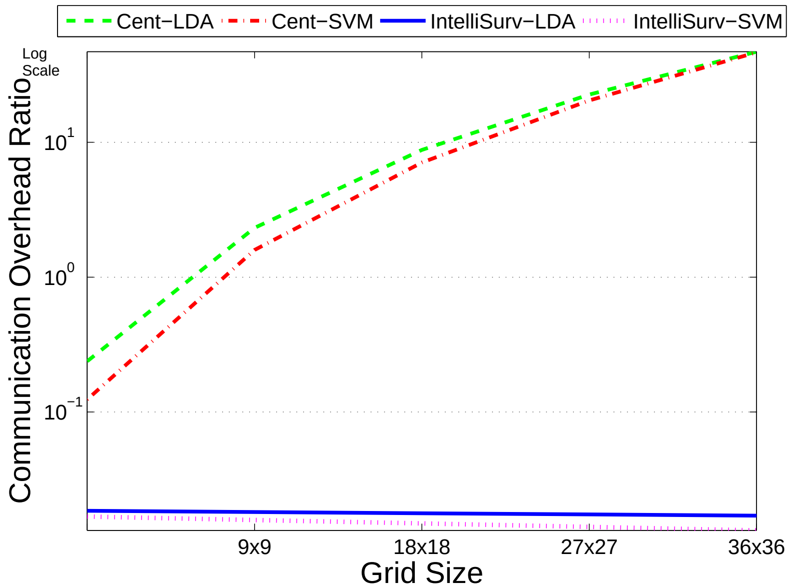


Figure 7.13: The communication overhead over varying network sizes.

7.4.2.1.3 Effects of the Number of Threats: This set of experiments is conducted to investigate the effects of increasing the number of threats on the performance of the surveillance systems. The setup is composed o 9×9 grid cells, monitored by 9 sensors and 1 delegate, the number of threats within the VOI vary between 1 to 20. The SNR is assumed to be 20 db, and incidents are randomly generated in the environment during the simulation time in a uniform distribution.

Figure 7.14 plots the overall network lifetime in relation to the increasing number of threats. The results show that the overall network lifetime remains almost constant as the number of threats increases in the IntelliSurv approach, whereas the overall network lifetime slightly decreases for the centralized SM approach. This is due to the distributed nature of the IntelliSurv SM design and the reduced communication overhead of the IntelliSurv, compared to that of the centralized approach.

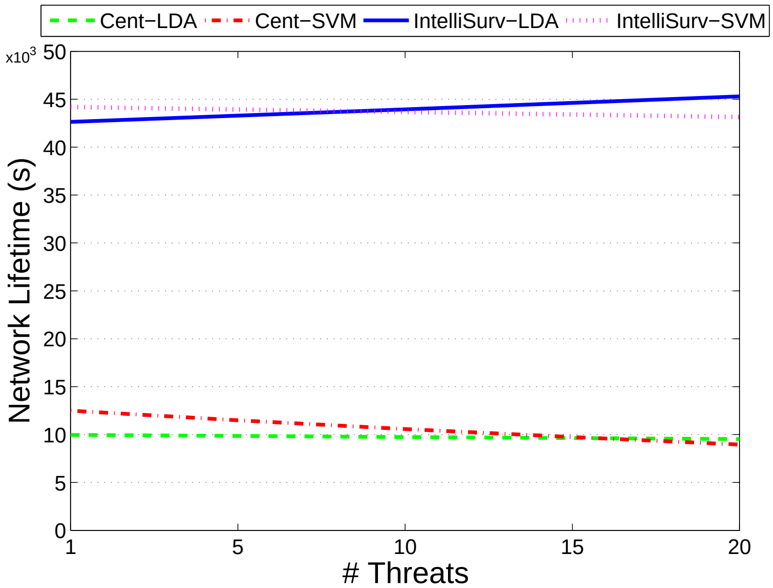


Figure 7.14: The network lifetime versus the increasing number of threats.

In Figure 7.15, the sensor lifetime is plotted in terms of the increasing number of threats. The results indicate that both the IntelliSurv SM and the centralized SM approaches exhibit the same trends such that the sensor lifetime decreases as the number of threats increase. However, the sensor lifetime for the IntelliSurv is more than three times greater than that of the centralized SM approach. Similar to the previous analysis, this is attributed to the cooperative nature of the IntelliSurv SM design and the reduced communication.

In Figure 7.16, the number of communication messages, exchanged in the centralized SM approach, increases linearly as the number of threats increases. On the other hand, the IntelliSurv SM remains constant as the number of threats increases. In addition, the IntelliSurv SM has a lower communication overhead than that of the centralized SM. This is attributed to the distributed nature of the IntelliSurv SM which utilizes the fact that the phenomena are localized.

7.4.2.1.4 Detection Success Ratio: Figure 7.17 plots the detection success ratio for the IntelliSurv and the centralized SM approaches combined with the LDA and the SVM abnormality recognition algorithms. The results are extracted from a 9×9 grid setup with a 20 db SNR. From Figure 7.17, it is clear that the IntelliSurv approach outperforms the centralized one. The IntelliSurv, combined with the SVM approach, provides a consistent performance as the number of threats increases, whereas the centralized approach tends to

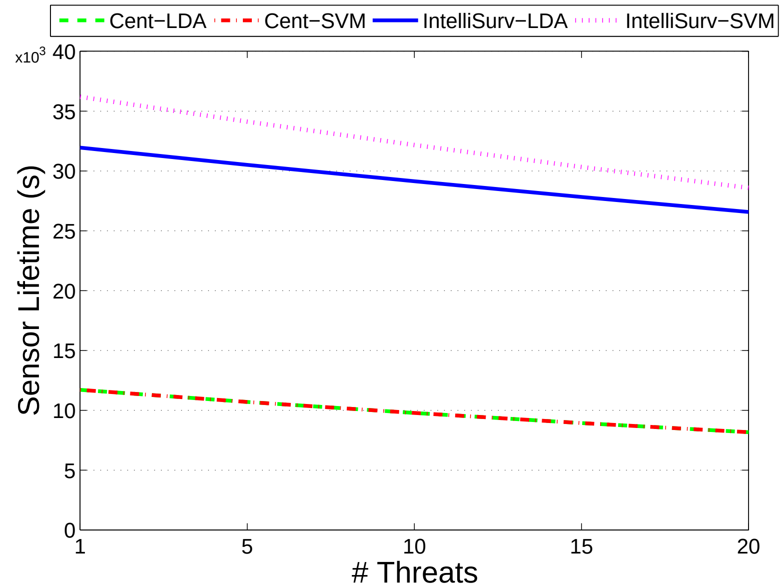


Figure 7.15: The sensor lifetime versus the increasing number of threats.

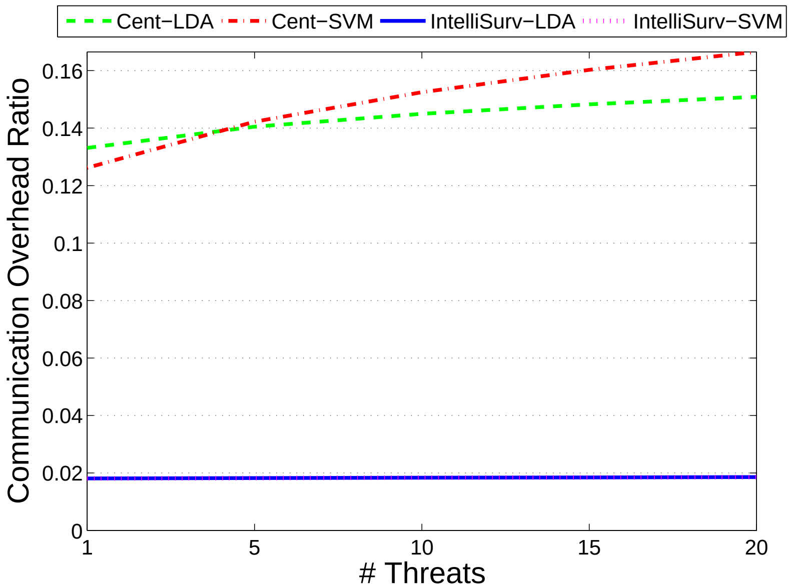


Figure 7.16: The communication overhead versus the increasing number of threats.

slightly decrease.

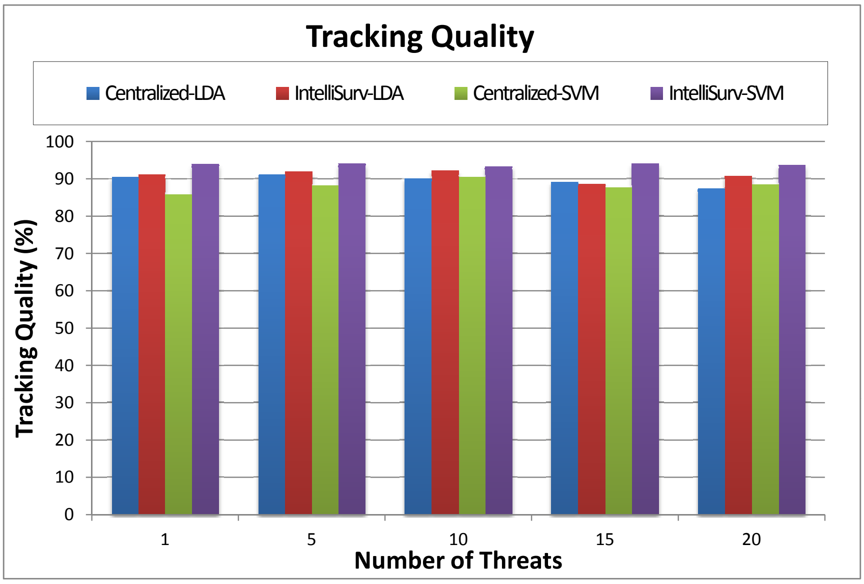


Figure 7.17: The detection success ratio versus increasing number of threats.

7.4.2.1.5 Energy Consumption: The limited sensor resources dictate that the nodes are required to operate under the efficient energy consumption performance. Figure 7.18 illustrates the energy dissipation of both the IntelliSurv and the centralized approaches. From Figure 7.18, it is noted that the centralized approach dissipates energy in a linear, steep manner, whereas the IntelliSurv approach dissipates energy in a much slower manner. This is due to the fact that enengy-aware operation of Intellisurv which reduces the communication overhead and better utilizes the energy reserve.

7.4.2.2 Abnormality Detection Module Results

This section presents the experimental results of the abnormal event recognition module. Two sets of experiments are performed to study the effect of varying the SNR and grid size on the performance of the module. The abnormality detection rate, that is, the accuracy of the system, and the false alarm rate are two of the performance measures used in this simulation. Figure 7.19 presents the accuracy of the abnormal event recognition module for both the centralized and the IntelliSurv systems by using SVM and LDA classifiers. In comparing the accuracies at different SNRs, a considerable degradation occurs in the performance at lower SNR values, where the signal is heavily corrupted. This is due to the fact that the models are trained on the original data for the training partition, whereas

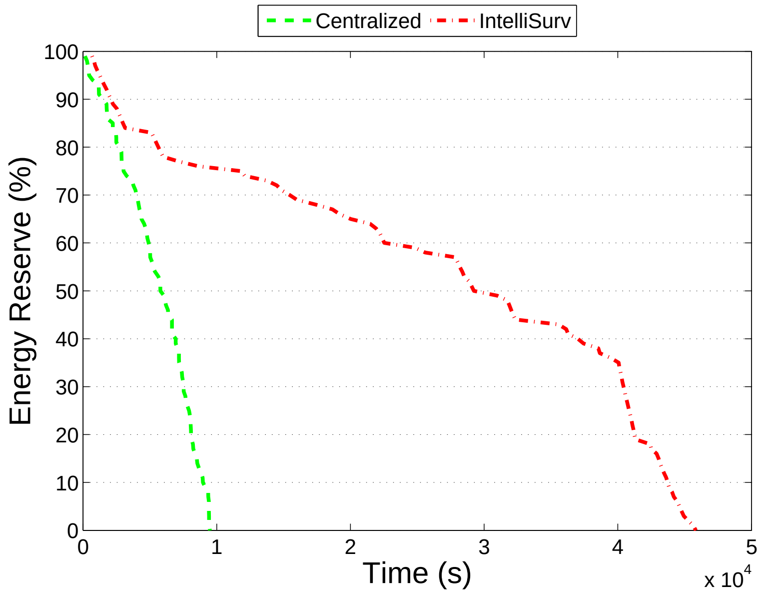


Figure 7.18: The energy consumption of the IntelliSurv SM and centralized SM.

the remaining samples are corrupted with white Gaussian noise and used for testing. In addition, it is shown that, usually, the performance of the SVM classifier is better than the LDA for both architectures.

Also, the SVM classifier yields a much lower false alarm rate, compared to the LDA classifier, as denoted in Figure 7.19. For example, when the SNR equals 20 db and the network size is 9×9, the SVM classifier achieves a false alarm rate of 6.33%, compared to 21.33% for the LDA with the IntelliSurv, and 7.98% compared to 22.64% with the centralized architecture.

The second set of experiments is performed to investigate the effect of varying the network sizes on the performance of the abnormality detection module. Figure 7.20 shows the accuracy results for both the centralized and IntelliSurv systems by varying the network sizes from 9×9 to 27×27 grid cells. It is evident that the SVM classifiers outperforms the LDA classifiers for both IntelliSurv and centralized systems. Also, the IntelliSurv system yields higher accuracy than that of the centralized system for both classifiers used.

Figure 7.21 signifies the false alarm rate of the abnormality detection module at different network sizes. From Figure 7.21, it is obvious that the SVM classifier still yields a lower false alarm rate, than that of the LDA for different network sizes.

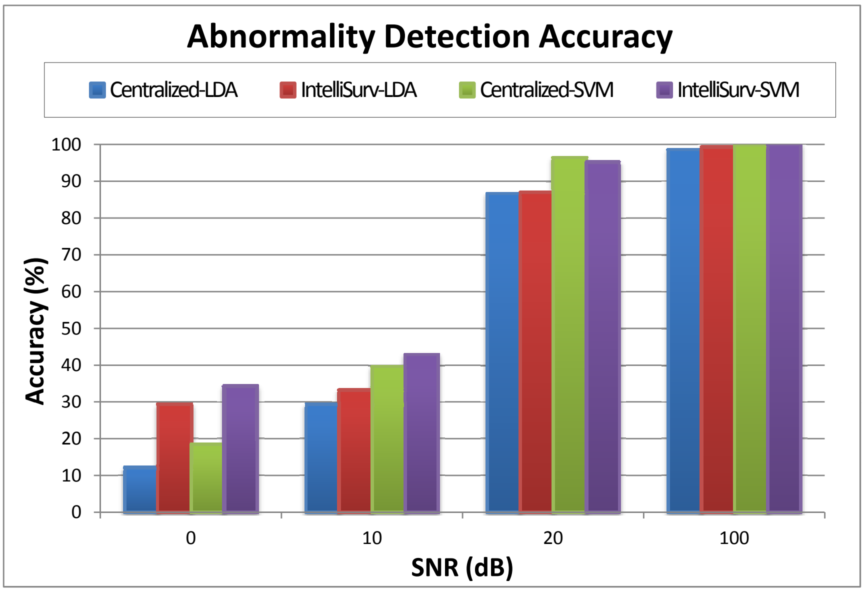


Figure 7.19: The accuracy of the abnormal recognition module using SVM and LDA classifiers versus varying the SNRs.

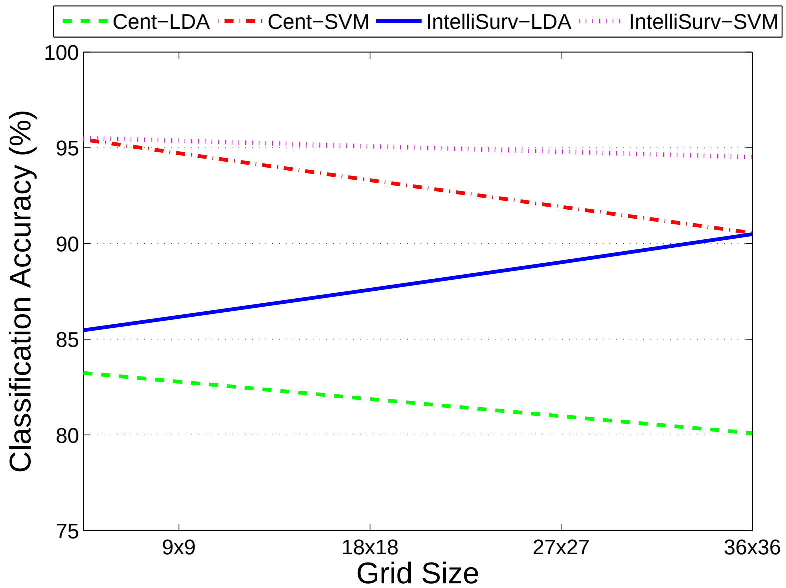


Figure 7.20: Accuracy of the abnormal recognition module using SVM and LDA classifiers versus varying grid sizes.

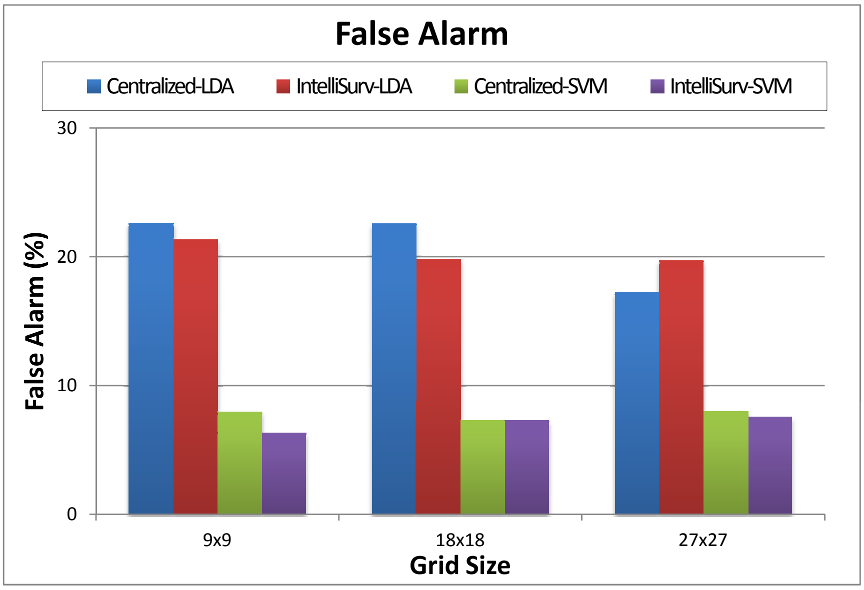


Figure 7.21: The false alarms of the abnormal recognition module using SVM and LDA classifiers versus varying grid sizes.

7.4.2.3 Localization Module Results

This section provides details on the experimental evaluation of the localization module by using the measurements provided from the IntelliSurv SM module. The error estimates are normalized with the maximum error estimation, that is, the longest path in the grid, to provide an accurate result. The estimated sensor location is mapped to one of the grid points in the discrete spatial, *i.e.*, no refinement process. To find the normalized distance estimation error of the target in the performance evaluation, the metric is

$$err = \frac{\| x_i - \hat{x}_i \|_2}{\max(\| x_i - x_j \|_2)}, \; \forall \; j \in [1 \cdot \cdot N], \tag{7.5}$$

Otherwise, Euclidean distance $\| x_i - \hat{x}_i \|_2$ is a proper metric. Figure 7.22 demotes the location estimation error and different SNRs for all the measurements in the system trajectories. The plots are provided for both the actual and snap-to-grid estimates. As expected, in high-SNR regimes, the sensor location can be fully recovered from the available measurements. In the snap-to-grid estimates, an error floor occurs due to a residual estimation error. The system performance depends on different parameters such as the mobile agent trajectory, quality of measurement, environmental noise, and measuring device precision.

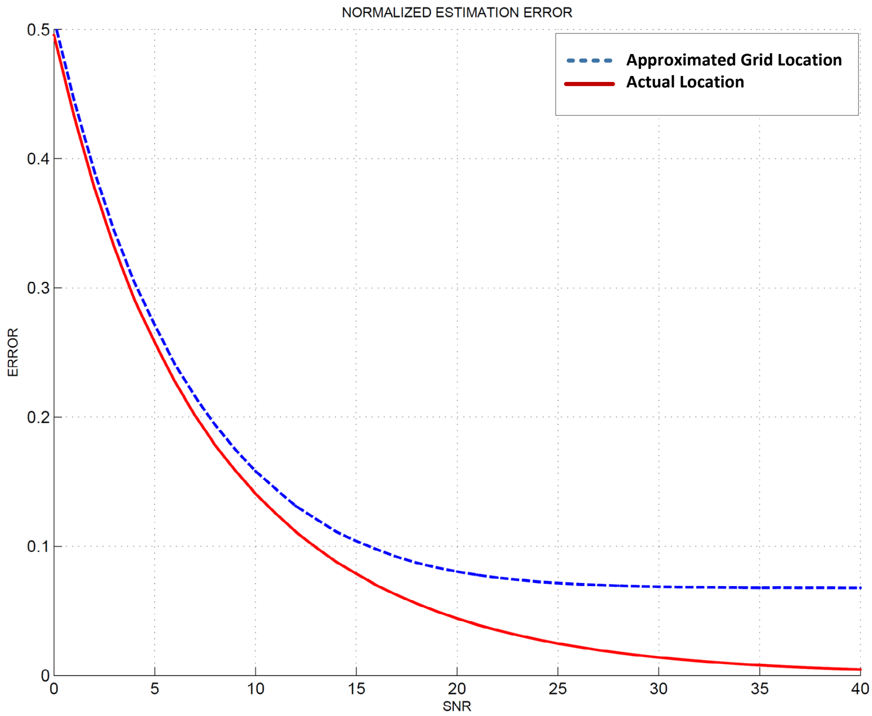


Figure 7.22: The normalized estimated error of the localization module.

7.5 Summary

Smart surveillance systems employ automatic detection of abnormal events and behaviours, based on information acquired from sensors located in the environment. This chapter proposes an intelligent surveillance system, called IntelliSurv, that automatically detects and localizes abnormal events in a distributed collaborative manner. The design of an autonomous surveillance system is specified for indoor environments with the proposed SMF at its heart. The proposed SMF, operating in a distributed manner with collaborative localized decision-making, is the brain of IntelliSurv. IntelliSurv provides a lower energy consumption operation than that of the most widely used centralized systems.

One of the main contributions of this chapter is the integration of audio information in the abnormality detection process by using the audio signal features and characteristics. Furthermore, a novel method for automatic anomaly event classification, based on audio information within the ROI, is introduced. Also, an indoor localization algorithm for the signal strength is proposed to localize the anomalies and alert the human in the loop. The results demonstrates that IntelliSurv outperforms the most widely used centralized system in terms of energy and communication overhead. The contributions of this chapter are summarized as follows.

- The design and integration of an autonomous surveillance system, IntelliSurv, for indoor environments,
- The investigation of the operation of the proposed SMF in an elaborate simulation environment.
- The use of the proposed intelligent SMF, operating in a distributed manner, with collaboration localized decision-making,
- Seamless interfacing between the sensor management module and the other two elaborate modules,
- A lower-energy consumption system, IntelliSurv, than the most widely used centralized systems,
- An increased system scalability, as well as increased overall system lifetime,
- The integration of audio information in the abnormality detection process by using audio signal features and characteristics,
- An automatic anomaly event classification, based on audio information, happening within the ROI,
- The use of the signal strength to localize the anomalies by using trilateration algorithms.
- A decision-support system and the human-in-the-loop is the final decision-maker.

Chapter 8

Conclusion and Future Work

This chapter provides a brief summary of the contributions of this thesis and some suggestions for future work. Section 8.1 concludes this thesis, highlighting the main contributions. Section 8.2 summarizes the research opportunities to extend this work.

8.1 Conclusion

The nature and complexity of emerging security threats have stimulated intense interest in smart pervasive surveillance systems. Such systems need intelligent management systems to control the large number of sensor nodes and the large amount of data. This thesis describes the development of an intelligent Sensor Management Framework (SMF) for use in pervasive surveillance applications. Four primary challenges have been addressed in this work:

- **Lack of SM standardization:** conceptual analysis of the SM problem is needed to avoid test-bed specific solutions that are hard to extend or reuse.
- **Surveillance over a large area:** The need for large area sensor networks has been recognized in numerous applications. These applications are characterized by large and remote geographic areas, which need large numbers of sensor nodes to cover the VOI.
- **Energy-aware Operation:** Sensor nodes are usually battery-operated and the replenishment of their energy reserve is usually not feasible. Therefore, the lifetime of sensors must be prolonged as much as possible without degrading the system performance.

- **Cooperative multi-sensor management:** The world model of a multi-sensor system can be significantly enhanced with cooperative sensing in applications where the environment dynamics rapidly changes.

To address these challenges, the research work in this thesis offers solutions in eight aspects, as discussed next. Figure 8.1 provides an overview of the proposed system in the structure of the high-level components that comprise a SMF and its interaction with the environment.

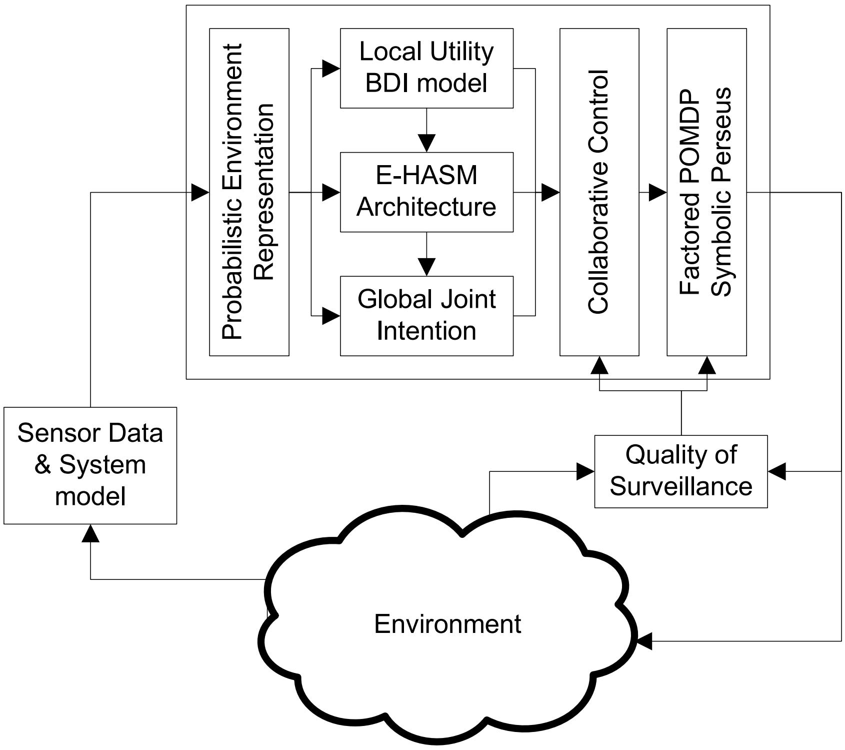


Figure 8.1: An overview of the proposed SMF.

- **Organizational Development Design Framework:** provides a conceptual analysis of the sensor management problem in a layered structure and introduces an organizational development design framework, based on the Service-Oriented Architecture (SOA) to address the requirements of the SMF from a stacked layer perspective. The proposed design framework addresses the large number of non-functional merits, that is, modularity, extendibility, and the reusability, to name a few, that can characterize SMFs.

- **Coordination Architecture:** The proposed architecture, called Extended Hybrid Architecture for Sensor Management (E-HASM), combines the operation of holonic, federated, and market-based architectures in a complementary manner. The proposed E-HASM guarantees that the proposed SMF is scalable, extendible, and reliable.

- **Energy-aware Operation:** Unattended networks suffer from the limited battery resources of sensor nodes. This work propose an efficient approach to minimize energy dissipation while maximizing the quality of surveillance.

- **Sensor Utility Modelling:** Each sensor is responsible for independent reasoning and decision-making that affects its and the overall systems' state. This work proposes a team-theoretic formulation by adopting the Belief-Desire-Intention model and the joint intention theory to represent the E-HASM architecture components.

- **Adaptive Sensor Behaviour:** This thesis proposes intelligent schemes to change the sensor setting in response to the environment dynamics and sensor energy levels. Such schemes include adaptive sleep, active sensing, dynamic sensing range, adaptive multimodality, and constrained communication, and are designed to operate under limited resource constraints.

- **Collaborative Decision-Theoretic Modelling:** Sensor management can be viewed as a decision-making process that determines the most appropriate sensor action to perform to achieve maximum system utility. The decision-making entities are required to operate under uncertainty in stochastic changing environments. Therefore, this research leads to formulating the decision-making entities as Partially Observable Markov Decision Processes (POMDPs).

- **Source Reliability Considerations:** The quality and accuracy of sensor measurements may vary between different sensors, due to several factors that include: relative sensor location, noise, transducers type, partial or full occlusion, *etc.* The information fusion research field has studied the source reliability as a strategy to represent the credibility of the information acquired from different sensors. The proposed SM aims to maximize the reliability of the obtained sensor measurements under resource and energy constraints.

- **Integrated System:** In this thesis, an intelligent surveillance system, IntelliSurv, is proposed that automatically detects and localizes abnormal events in a distributed collaborative manner. IntelliSurv is built by using the proposed SMF and helps illustrate the performance of the SMF in operation with different independent modules.

8.2 Future Work

Intelligent sensor management systems is an active area of research. New SM issues arise as sensory networks develop and new applications emerge. There are a number of issues that should be investigated in the future.

- **Sensor Mobility:** The ability of the sensor nodes to move adds a new dimension to the SM problem such mobility empowers the sensors to make better decisions regarding their positions, such that strategic tasks, such as target tracking, can benefit from node movement. However, the node mobility actuators can be one of the most energy consuming modules of a sensor node. Therefore, mobility management is a major challenge that needs to be addressed in the SMF due, in part, to the dynamically changing network topologies.

- **Network Coverage and Sensor Redundancy:** The proper density to achieve region coverage for random sensors deployment is a fundamentally important problem in the area of Wireless Sensor Networks (WSNs). So far, it has been assumed that after the initialization phase, the network assumes full coverage, and the coverage areas of different sensors do not overlap. In future work, this assumption can be relaxed and partial network coverage, as well as sensor redundancy, should be investigated.

- **System Security:** Due to the distributed nature of WSNs and their deployment in remote areas, these networks are vulnerable to numerous security threats that can adversely affect their proper functioning. This problem is more critical in mission-critical applications such as in a tactical battlefield. Due to resource constraints in WSNs, traditional security mechanisms with high computation and communication overheads are infeasible to run on-board of resource-bounded sensor nodes. Therefore, the SMF must take into consideration the required security measures and deal with infected node or region of a network.

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List of Publications Resulting from this Work

Referred Book Chapters:

- **Allaa R. Hilal** and Otman Basir, “Pervasive Surveillance System Management,” accepted for Effective Surveillance For Homeland Security, CRC Press, Taylor & Francis Group, 2012.

Referred Conference Papers:

- **Allaa R. Hilal**, Alaa Khamis, and Otman Basir, ”Hybrid Holonic Sensor Management Architecture for Pervasive Surveillance System”, in Proc. Multi-Sensor Systems For Surveillance Applications Workshop, 2009, pp. 6-7.

- **Allaa R. Hilal**, Alaa Khamis, and Otman Basir, ”A Multi-Layered Organizational Suite for Sensor Management in Pervasive Surveillance Systems”, Proc. CAMAN, 2011, pp. 1-6.

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- **Allaa R. Hilal**, Alaa Khamis, and Otman Basir, ”HASM: A Hybrid Architecture For Sensor Management in Distributed Surveillance Context,” Proc. IEEE ICNSC, 2011, pp. 492-497.

Refereed Journals Papers:

- **Allaa R. Hilal** and Otman Basir, ”Multi-Sensor Management: Antecedents and Directions,” submitted to IEEE Systems Journal, 2012.

- **Allaa R. Hilal** and Otman Basir, ”A Scalable Sensor Management Architecture for Pervasive Surveillance,” submitted to IEEE Systems Journal, 2012.

- **Allaa R. Hilal**, Aya Sayedelahl, Arash Tabibiazar, Mohamed S. Kamel, and Otman Basir, "IntelliSurv: An Intelligent Pervasive Surveillance System for Abnormal Event Localization in Indoor Environment," submitted to IEEE transc. on SMC, Part C: App. & Reviews, 2013.

- **Allaa R. Hilal** and Otman Basir, "An Energy-Efficient Sensor Management Approach using Team Theory," submitted to IEEE Transactions on Network and Service Management, 2013.

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