(VANET IR-CAS): Utilizing IR Techniques in Building Context Aware Systems for VANET

by

Lobna Nassar

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Author's Declaration

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

Most of the available context aware dissemination systems for the Vehicular Ad hoc Network (VANET) are centralized systems with low level of user privacy and preciseness. In addition, the absence of common assessment models deprives researchers from having fair evaluation of their proposed systems and unbiased comparison with other systems. Due to the importance of the commercial, safety and convenience services, three IR-CAS systems are developed to improve three applications of these services: the safety Automatic Crash Notification (ACN), the convenience Congested Road Notification (CRN) and the commercial Service Announcement (SA). The proposed systems are context aware systems that utilize the information retrieval (IR) techniques in the context aware information dissemination. The dispatched information is improved by deploying the vector space model for estimating the relevance or severity by calculating the Manhattan distance between the current situation context and the severest context vectors.

The IR-CAS systems outperform current systems that use machine learning, fuzzy logic and binary models in decentralization, effectiveness by binary and non-binary measures, exploitation of vehicle processing power, dissemination of informative notifications with certainty degrees and partial rather than binary or graded notifications that are insensitive to differences in severity within grades, and protection of privacy which achieves user satisfaction. In addition, the visual-manual and speech-visual dual-mode user interface is designed to improve user safety by minimizing distraction. An evaluation model containing ACN and CRN test collections, with around 500,000 North American test cases each, is created to enable fair effectiveness comparisons among VANET context aware systems. Hence, the novelty of VANET IR-CAS systems is: First, providing scalable abstract context model with IR based processing that raises the notification relevance and precision. Second, increasing decentralization, user privacy, and safety with the least distracting user interface. Third, designing unbiased performance evaluation as a ground for distinguishing significantly effective VANET context aware systems.

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List of Abbreviations

AACN	Advanced Automatic Crash Notification
ACN	Automatic Crash Notification
AIS	Abbreviated Injury Severity
API	Application Programming Interface
BC	Basic Context
CAS	Context Aware System
CDS	Crashworthiness Data System
CoTEC	Cooperative Traffic congestion deTEction
CRN	Congested Road Notification
df	document frequency
DHLC	Detailed High Level Context
DL	Description Logic
DLLC	Detailed Low Level Context
DOB	Date Of Birth
DOM	Document Object Model Application programming interface
FARS	Fatality Analysis Reporting System
GM	General Motors
HCM	Highway Capacity Manual
HVC	Hybrid Vehicular Communication
iConAwa	An intelligent Context-Aware system
In-V	Inside Vehicle

IR	Information Retrieval
KABCO	Injury Scale**:** K-Fatal A-Incapacitating B-Non Incapacitating C-Possible O-No
LOS	Level Of Service
MAIS	Maximum Abbreviated Injury Scale
MANET	Mobile Ad hoc Network
NASS	National Automotive Sampling System
OWL	Web Ontology Language
P	Precision
PCN	Post Crash Notification
POI	Points Of Interest
PSAPs	Public Safety Answering Points
Qrels	Query relevance sets of manual judgments
R	Recall
RDF	Resource Description Framework
RSU	Road Side Unit
SA	Service Announcement
tf	term frequency
TREC	Text Retrieval Conference
V	Vehicle
V2I	Vehicle to Infrastructure
V2V	Vehicle to Vehicle
VANET	Vehicular Ad-hoc Network
VN	VANET Name space

Chapter 1

Introduction

There are challenges currently being experienced in knowledge querying and message dissemination in VANETs. Firstly, important messages are not delivered on time to interested nodes due to network overload. Secondly, the network addressing schemes currently used in defining groups for message dissemination, like multicasting and broadcasting, do not consider the contextual characteristics of the nodes for optimizing the network traffic [1]. To handle these challenges ***context modeling and processing*** accompanied by smart ***dissemination mechanisms*** should assure efficient use of network resources and on time delivery of relevant services to interested nodes. Consequently, context aware systems in Ad-hoc Networks like VANET should have a middleware responsible for modeling the context, processing it and disseminating information using routing protocols that dynamically adapt to the current context. The main goal behind this work is to achieve on time dissemination of highly accurate information only to highly interested recipients; on time delivery means the notification reaches the recipient before its temporal range, the period over which the event is expected to remain valid, is over. This is necessary to avoid network overload and increase user satisfaction by disseminating precise information, of interest, on time and with minimal distraction.

The proposed research direction is to utilize the findings of the IR field for improving context awareness in VANET since both fields share the same intention; leading the user to documents that will best satisfy his/her information need [2]. Therefore, the uniqueness of VANET IR-CAS comes from: first, utilizing the well established IR techniques in its context processing which significantly enhances the relevance and preciseness of service notifications. Second, its abstract hybrid context model that improves reasoning about context. Third, increasing the decentralized processing achieved by delegating computation tasks to vehicle nodes to reduce the load on the RSU. This minimizes the overall connection time to the RSU, reduces the cost of communication to infrastructure and increases privacy. Fifth: creating an unbiased test model with test collections that serve as fair bench marks among estimation models.

From [3, 4, 5, 6], we deduce that the main three categories of services provided in VANET are commercial, convenience and safety services. In this work, we focus on three services that demonstrate two different VANET communication scenarios. The hybrid vehicular communication (HVC) is selected for commercial services. Using HVC, (V2I followed by V2V), is beneficial since it extends the range of V2I by using other vehicles as mobile routers through V2V, which enables the same applications as V2I systems with a larger transmission range [7, 8]. HVC helps to achieve the decentralization objective and increases user satisfaction. We also formalize the semantics of VANET context domain by creating the VANET ontology to allow for knowledge sharing and scalability. In addition, we improve the relevance of dispatched information to prospective recipients by utilizing IR techniques and partial relevance. On the other hand, the V2V communication is preferred for safety and convenience services.

From [3], we have selected three applications: Service Announcement (SA) for commercial services, Congested Road Notification (CRN) for convenience services and Post-Crash Notification (PCN) for Safety services or Advanced Automatic Crash Notification (AACN) as named in [9, 10, 11]. Three IR-CAS systems have been developed for these applications: the safety Automatic Crash Notification (ACN), the convenience Congested Road Notification (CRN) and the commercial Service Announcement (SA) systems. Then a user friendly interface to utilize these applications is designed with easy to use in-vehicle software for guiding drivers to available amenities relevant to their context, informing them of congested roads, congestion center and severity as well as surrounding crashes associated with their severities while maintaining a high level of comfort and safety with minimal distraction. More attention is given to the CRN and ACN systems since nowadays safety and convenience services are considered as top priority in intelligent transportation systems (ITS) and the optimum goal of most ITS systems is to enhance the safety and convenience of road users. Congested traffic worsens the economic situation by wasting time and fuel as well as the environment due to increasing pollution levels therefore early congestion detection may lessen these drawbacks and lead to efficient use of resources. Besides that the efficient notifications of congested roads with precise severities help drivers take more informative decisions with regard to route selection which adds to their convenience.

Moreover, informing drivers of surrounding crashes and their severities plays an important role in saving the lives of crash candidates therefore ACN can prevent injuries and reduce traffic death rate. Collision notification dissemination delays or mistakes in the disseminated information to emergency responders can highly increase the mortality rate.

With regard to these two applications, we are able to increase the abstraction level by using high level attributes and enhance the preciseness of application notifications by improving reasoning about situation certainty and severity. The standard evaluation of VANET context aware IR systems is crucial for fair comparisons between proposed models, therefore two test collections with half million records each are developed for these two applications. The established test collections can also be reused by researchers for testing their models and fine tuning the studied IR function.

A number of challenges are faced in this work. One of these challenges faced in developing the IR-CAS systems (SA, ACN, CRN) is choosing the files to be sent to the vehicle such that the inter-vehicle and RSU connection time, the size of sent files and the in-vehicle processing are minimized while staying fully informative. The second challenge is faced while creating the ACN test collection and that is finding test data with actual crashes to act as a bench mark for testing the considered models. Third challenge is faced during the CRN test collection creation and that is finding a way to cover all possible freeways in North America with their estimated congestion levels as reusable judgments. Forth challenge is faced with the ACN and CRN systems in finding the distance measures that are based on differences in the absolute value of each relevance/rank rather than rank order. Fifth challenge is faced with the IR-CAS interface which is how to have the least distracting interface that allows for blind selection needed in emergencies where eyes should constantly be kept on the road.

In section 1.1, the research objectives are discussed, these objectives are presented into a set of specific research questions in section 1.2, the work scope is then defined in section 1.3. Finally, the overall organization is summarized in section 1.4.

1.1 Objectives

This work intends to achieve five main objectives: First, increase the decentralized processing by reducing the reliance on the central RSU processing and increase the In-vehicle processing and privacy. Second, provide high abstract scalable context aware system that supports context aware dissemination of service notifications that are precise, relevant and informative. Third, provide reliable evaluation model with real life test collections for fair evaluation of proposed models that can be used for evaluating the effectiveness of the context aware dissemination systems. Fourth, design use interface that achieves the minimal distraction for users.

1.2 Addressed Issues

The dissertation is addressing the following issues:

- How to disseminate the right information to the right destination on time while avoiding ***network overload?***
- How to increase ***user satisfaction*** by disseminating information ***of interest, on time and with minimal distraction*** while maintaining ***high degree of privacy*****?**
- How to form ***more informative, accurate and precise notification*** messages for safety and convenience services?
- How to ***increase the abstraction and scalability*** of the VANET context aware system?
- How to ***evaluate and compare the effectiveness*** of the resulting context aware information dissemination systems in an unbiased way?

1.3 Scope

In this section the proposed solution scope that achieves the intended objectives is presented. The main solution theme is utilizing appropriate information retrieval techniques to enhance the effectiveness of context awareness in information dissemination. Services representing the three main VANET application areas are studied; including the commercial, convenience and safety applications. For solutions effectiveness evaluation, a standard evaluation for context aware systems is not readily available which necessitates a design of a proper reusable evaluation model and test collections for this type of systems.

First, the proposed solution for the ***commercial services*** with the service announcement (SA) as an application representative for this class of services can be summarized as follows:

- Introduction of the HVC communication to achieve the ***decentralization objective and increase user satisfaction and privacy***.
- Formalizing the semantics of VANET context domain to allow for knowledge sharing and ***scalability***
- ***Enhancing the relevance of dispatched information*** to prospective recipients by utilizing IR techniques to calculate the partial relevance ***based on the context similarity*** between the considered user and the provided services.

The post crash notification (PCN) or the automated crash notification (ACN) is the application chosen to represent the safety services while the congested road notification (CRN) represents the convenience services.

Second, the proposed solution for the ***safety and convenience services*** includes:

- Increasing the ***abstraction*** by reasoning about high level attributes instead of raw sensor data.
- Increasing the ***decentralization*** by relying on the vehicle's internal processing and In-V and V2V communication rather than heavily centralizing the processing at the RSU side and relying on the V2I communication.
- Improving the ***reliability of application notifications*** by improving reasoning about situation certainty and severity.
- Allowing for a fair comparison between the possible VANET context aware IR models. This can be achieved by building an evaluation model that assesses the IR model effectiveness against a proper test collection based on real records of safety threatening situations and congestion cases.
- Designing visual-manual and speech-visual dual-mode interface that requires minimal eye-off road time to use. This reduces drivers' distraction, improves their safety, increases convenience and speed up option selection. Using large image icons aligned to screen borders or pinned to corners facilitates options blind selection useful in emergencies.

1.4 Organization

The rest of the dissertation is organized as follows: In chapter 2 background knowledge is given about the main information retrieval concepts, models and evaluation methods. It also elaborates on context awareness especially in VANET and explains the rationale behind using IR techniques for context processing. Chapter 3 outlines details of the proposed solution describing the IR-CAS system architecture, the proposed context modeling, processing for the three considered applications (the commercial, convenience and safety applications), context aware dissemination scenarios and system interface. In Chapter 4, experiments that test and assess the system performance are presented along with their results and corresponding evaluation. The IR-CAS systems are evaluated against related work in Chapter 5. Chapter 6 draws the conclusion and gives an overview of future work.

Chapter 2

Literature Review

2.1 Information Retrieval

The academic definition for information retrieval is:

> "Information retrieval (IR) is finding material (usually documents) of an unstructured nature (usually text) that satisfies an information need from within large collections (usually stored on computers)" [12].

In information retrieval each document is perceived as a set of words and the documents collection over which we perform the retrieval is called the corpus. The main task of any IR system is to provide a list of documents relevant to the user information need that is conveyed to the computer through the query. The user usually needs relevant documents even if the exact terms he/she used in the provided query are not present in these documents. The uncertainty nature of IR differentiates the IR systems from other information systems.

According to [13], there are four main types of ***search tasks*** that usually take place in the IR process. The first is the ***ad-hoc search*** where the retrieval process result is a list of documents relevant to an arbitrary text *query*. The second is the ***filtering*** which is basically selecting documents relevant to user *profiles* without having an explicit user text query. The third is the ***classification*** which involves labeling documents as relevant or not. Finally, the ***question answering*** which lets the user write a question and instead of finding a whole relevant document a specific text answer is found for the question. The view of relevance is represented in more than one IR model. Most IR models are statistical which indicates that they rely on statistical counts for document features, e.g. term count, rather than analysis of linguistic features, e.g. parsing sentences. The IR models are evaluated using IR evaluation measures to estimate retrieved documents closeness to user information needs. The *input* to the evaluation process is the documents test collection, queries and associated relevance judgments. The *processing* is the execution of effectiveness measures as those in Table A.3 and the *output* is the degree of effectiveness of the IR model; e.g. precision and recall. Achieving a high level of user satisfaction is essential for the success of the IR models since used query terms do not reflect the exact information need of the user. Therefore, it is advisable to use some contextual aspects to guide the search process.

2.1.1 Indexing

To simplify and speed up the process of information retrieval a preprocessing stage that includes indexing available documents should be completed before starting the retrieval process. The input is all corpus documents and the output is an index that has all the main terms available across these documents, along with its associated list of documents where the term occurred at least once; a term here is any non-trivial word reduced to its word stem. The indexing process includes four main sub-processes which are document tokenization, stop words removal, tokens normalization, and stemming; see Figure 2.1. The *preprocessing* algorithm shown in Figure 2.1, a sub-module of the indexing process, is applied to the corpus and queries. The *indexing* module calls the *preprocessing* to prepare the documents for indexing then creates the index using the main terms in all the corpus documents. These terms form the content of the *IR dictionary*. Tokenization means turning each document or query into a list of tokens; i.e. the text is split at spaces and any punctuation characters are removed. The second step is dropping stop words or frequent terms which occur with high frequency across the corpus to the extent that they lose their significance; e.g. words like “the”, “and”, or “what” are irrelevant to documents or query content. These words should be deleted to reduce the amount of processing and speed up the retrieval. The most commonly used stop words are: a, an, and, are, as, at, be, by, for, from, has, he, in, is, it, its, of, on, that, the, to, was, were, will, or with [14]. The third step is the normalization of tokens so term matching can be achieved regardless of differences in the token character sequence [12]. The term is a normalized token which is a class of all tokens containing the same character sequence. The characters have to be changed to lower case, “Hard” is the same as “hard”, then characters like hyphens should be removed to allow two tokens like “pre-process” and “preprocess” to be mapped into the same term “preprocess”. The fourth and last step is stemming which brings the words to their root to help find the word regardless of its format; term groups like (direct, directive, directed, directing, direction, directions), are mapped into a single term like _direct by removing the suffixes -ED, -ING, -ION, IONS. So the process refers to getting rid of the ends of the words and the removal of derivational affixes like chopping the “ness” from the end of the word so that words like clever and cleverness are mapped to _clever[12]. This reduces the total number of terms in the IR system, and hence reduces the size and complexity of the data in the system, which is always advantageous. Finally, the index should be created, see Figure 2.2. The index has the term and the list of documents where it occurred as described in the indexing algorithm in Figure 2.3.

Preprocessing(x)

{ for each document (d) in **x{**

1. d_T = Tokenize(d)
2. d_{SW} = Stop-word-removal(d_T)
3. d_N = Normalization(d_{SW})
4. d_S = Stemming(d_N)
5. add d_S to the **preprocessed-x**}

Return (**preprocessed-x) }**

Figure 2.1: Module for preprocessing docs before indexing

Document index	
brutus	d1,d3,d6,d7
Caesar	d1,d2,d4,d8,d9
Julius	d10
Killed	d8
Noble	d5
With	d1,d2,d3,d5

Figure 2.2: Example for document index [12]

Indexing (corpus)

{**preprocessed-corpus** = Preprocessing(corpus)

index = an empty file

for each document(**d**) in the **preprocessed-corpus**

for each term (**t**) in **d**

{ if (**t** in **index**) then append **d** to the document list of **t**

else add a new index entry to **index** that has **t** and **d** **}**

return(**index**)}}

Figure 2.3 : Module for preprocessing and indexing

An index can have the list of terms in the IR dictionary associated with, not only the list of document ids where the term is found, but also the frequency of its occurrence in each document that can be utilized in the ranking later; see Table 2.1. So instead of keeping (termID, docIDs) pairs in the index the 3-tuples (termID, docIDs, termfrequency) are kept.

Table 2.1: The index has the term document frequency & term frequency per document [12]

Doc 1: I did enact Julius Caesar. I was Killed i' the Capitol; Brutus Killed me			**Doc 2:** So let it be with Caesar. The noble Brutus hath told you Caesar was ambitious		
term	**Doc. Freq.**	**(doc-ID, frequency)**	**term**	**Doc. Freq.**	**(doc-ID, frequency)**
ambitious	1	(2,1)	Julius	1	(1,1)
be	1	(2,1)	killed	1	(1,1)
Brutus	2	(1,1),(2,1)	let	1	(2,1)
capitol	1	(1,1)	me	1	(1,1)
Caesar	2	(1,1),(2,1)	noble	1	(2,1)
did	1	(1,1)	so	1	(2,1)
enact	1	(1,1)	the	2	(1,1),(2,1)
hath	1	(2,1)	told	1	(2,1)
I	1	(1,1)	you	1	(2,1)
i'	1	(1,1)	was	2	(1,1),(2,1)
it	1	(2,1)	with	1	(2,1)

2.1.2 Scoring Models

To be able to give a score to each document according to its relevance to the query there should be a method by which documents can get a weight representing their degree of relevance which is the scoring model or the IR model. There are various models for scoring and they differ in their ranking process. One model may base the document weight on the query term frequency of occurrence in the document regardless of where it appears while others can give different weights according to the position of the term in the document or the importance of the term in the query. For example, the vector space scoring model uses the free text queries which consider the query and the document as a set of terms with no specific order or difference in importance resulting from the order of term appearance in the query or in the document. Ranked Boolean retrieval, on the other hand, is another way of scoring that relies on zone scoring which means different weights are given to the terms according to the place or the zone where they appear within the document. So the weight given to the terms occurring in the title is different from that given to the terms occurring in the body [12].

These models of information retrieval differ in their document as well as query representation in addition to their methods of matching both and ranking the results [15]. Several models of information retrieval are used like the vector space, the binary and the fuzzy logic model. The results of using each of these models should be evaluated using a standard IR evaluation system to be able to compare their performance. The coming sections give a brief description of the most commonly used retrieval models as well as a description of the common IR system evaluation techniques.

2.1.2.1 Vector Space

Vector space retrieval model can be used to find documents with high term frequency. The idea behind the vector space is that each document is represented by the weights of its terms (t_1 to t_n) as a vector of weights as in formula 2.1. Therefore an n-dimensional vector space has n unique terms in the data set and each unique term in the document or the query corresponds to a dimension in the space.

$$V(d) = (w(t_1, d), w(t_2, d), \ldots , w(t_n, d)) \qquad \text{as in [16]} \qquad (2.1)$$

These weights are usually calculated by the *tf–idf* measures. The use of term-weighting based on the distribution of a term within a collection, like using the *tf* measure, has always improved the performance or at least does not have a negative effect on performance. The vector space also gives a higher weight to infrequent terms across the documents even if they appear frequently in the document itself by using the Inverse Document Frequency (IDF) [17]. Each query is represented as a vector too which is V(q) and similarity cosines or the cosine of the angle between the query vector and the document vector can then be used to measure the relevance of the document to the query as discussed later in this chapter [12]. This similarity score is the inner product of the query vector and the document vector, (score (q, d) = v (q).v (d)), which can then be normalized by dividing the score by the document length, score [d] ← score [d] / length[d]. Then ranking according to this score should take place to limit the results to the top K scores [16].

Table 2.2: Weights calculation using the vector space model [18]

TERM VECTOR MODEL BASED ON w_i=tf_i*IDF_i											
Q: ***"Best coffee and burger"*** **D_1:** "Soups, Turkish Coffee and American coffee." **D_2:** "sandwiches, coffee and Cheese burger." **D_3:** "jeans and shoes " **N=3: I**nverse **D**ocument **F**requency **IDF= log(N/df_f)**											
	Count tf_f						**Weights, w_i=tf_i*IDF_i**				
Terms	**Q**	**D_1**	**D_2**	**D_3**	**df_i**	**N/df_i**	**IDFi**	**Q**	**D_1**	**D_2**	**D_3**
Soups	0	1	0	0	1	3	0.47712125	0	0.477121	0	0
Coffee	1	2	1	0	2	1.5	0.17609126	0.477121	0.954243	0.477121	0
sandwich	0	0	1	0	1	3	0.47712125	0	0	0.477121	0
burger	1	0	1	0	1	3	0.47712125	0.477121	0	0.477121	0
Cheese	0	0	1	0	1	3	0.47712125	0	0	0.477121	0
jeans	0	0	0	1	1	3	0.47712125	0	0	0	0.477121
shoes	0	0	0	1	1	3	0.47712125	0	0	0	0.477121
Turkish	0	1	0	0	1	3	0.47712125	0	0.477121	0	0
American	0	1	0	0	1	3	0.47712125	0	0.477121	0	0

Like any IR model, the vector space model has advantages as well as draw backs. The first benefit of using vector space is having ranked retrieval. The second is the fact that weighing the terms is done according to their importance. The third is being able to achieve partial matching [19]. On the other hand, the model has its disadvantages as well. One of the vector space weaknesses is that the weights are calculated intuitively since they are not based on a formal theory [19].

2.1.2.2 Distance Measures and Similarity Metrics

This section gives an overview of the distance measures used to estimate vectors similarity.

- **The Weighted Average:** In [20], the weighted average is defined in the vector space context over real numbers R: $(v_1,v_2,...,v_n) \in V$, $(\alpha_1,\ldots,\alpha_n) \in R$, $\alpha_i \geq 0$ and $\alpha = \sum_{i=1}^{n} \alpha_i$. If we write βi for αi/α then 0≤ βi≤1 and $\sum_{i=1}^{n} \beta_i = 1$ and the weighted average is $\sum_{i=1}^{n} \beta_i v_i$.

- **Manhattan distance:** for two vectors $X=(x_1, x_2,\ldots, x_n)$ and $Y=(y_1, y_2,\ldots,y_n)$ with the same dimensions or number of attributes/features n, the Manhattan distance is:

$$d(X,Y) = \sum_{i=1}^{n} |x_i - y_i| \qquad (2.2)$$

- **Weighted Manhattan distance:** Weighted Manhattan distance is defined in [21] as:

$$d(X,Y) = \sum_{i=1}^{n} w_i |x_i - y_i| \qquad (2.3)$$

  It measures the distance between continuous variables with complexity O(n).

- **Cosine similarity:** It is used in IR to measure the distance between user queries and searched documents [21] and to measure document similarity where documents are represented by vectors and each attribute represents the weight of each document term.

$$\text{Cosine}(x, y) = (x \cdot y) / (\| x \| \| y \|) = \frac{\sum_{i=1}^{n} x_i \cdot y_i}{\sqrt{\sum_{i=1}^{n} {x_i}^2} \sqrt{\sum_{i=1}^{n} {y_i}^2}} \qquad (2.4)$$

- **Euclidean Distance Metric:** Distance between X $(x_1, x_2, \ldots, x_n)$ and Y $(y_1, y_2, \ldots, y_n)$ is

$$d = \sqrt{\sum_{i=1}^{n} (x_i - y_i)^{\,2}} \qquad (2.5)$$

- **Euclidean Squared Distance:** Omits Equation 2.5 square root to speed up calculations.
- **The weighted Euclidean distance:** The attribute importance is represented by a weight in the range [0,1]. Each attribute is normalized by its range. The distance as in [22] is:

$$d = \sqrt{[\sum_{i=1}^{n} w_i^2 (x_i - y_i)^{\,2}]} \qquad (2.6)$$

  Then the similarity score is calculated as follows:

$$s = 1 - \frac{d}{\sqrt{\sum_{i=1}^{n} w_i^2}} \qquad (2.7)$$

- **Chebyshev distance:** finds the maximum difference between vector features rather than averaging over all differences [23]. The equation used is as follows:

$$d_{Chebyshev}\ (X,Y) = \max_{i=1\ to\ n}(\ |x_i - y_i\ |\ ) \qquad (2.8)$$

- **Hamming Distance:** counts mismatching values of categorical variables in data sets; e.g. image retrieval [24]. In *Weighted Hamming distance* weights are added as follows:

$$d(\mathrm{V1},\mathrm{V2}) = \frac{1}{\mathrm{W}} \sum_{i=1}^{n} (w_i|\mathrm{a}_i - \mathrm{b}_i|\,) \qquad w_i \in [0,1] \tag{2.9}$$

  No need to divide by W if a normalized weight vector is used as follows:

$$d_{WH}(\mathrm{V1},\mathrm{V2}) = \sum_{i=1}^{n} (w_i|\mathrm{a}_i - \mathrm{b}_i|\,) \qquad w_i \in [0,1], \qquad \sum_{i=1}^{n} w_i = 1 \tag{2.10}$$

- **Pearson's Correlation Coefficient:** As described in [25], the correlation is the measure of the linear relationship between the features of two vectors and used in classification. Normalizing the vectors help avoid having an input overpower other attributes by its large range. The coefficient is used in Pearson and Pearson squared for vectors X and Y:

  1. Pearson's distance:

$$d_{\mathrm{x,y}} = 1 - \rho_{\mathrm{x,y}} \tag{2.11}$$

  The Pearson correlation coefficient is calculated as follows:

$$\rho_{\mathrm{x,y}} = \frac{1}{n-1} \sum_{i=1}^{n} \left(\frac{\mathrm{X_i} - \bar{\mathrm{X}}}{\mathrm{S_X}}\right)\left(\frac{\mathrm{Y_i} - \bar{\mathrm{Y}}}{\mathrm{S_Y}}\right) \tag{2.12}$$

  S_X and S_Y are the standard deviations while $\bar{X}$ and $\bar{Y}$ are the means for vectors X and Y values respectively. The coefficient range is [-1, 1] while the distance range is [0, 2].

  2. Pearson Squared:

$$d = 1 - \rho^{2} \tag{2.13}$$

  where ρ is defined as in Equation 2.12.

  It detects positively or negatively correlated vectors. For example, consider the attributes for the two cases presented in Figure 2.4: the left side vectors are the blue vector (6, 2, 9) and the red vector (7, 5, 11). The right vectors are the red vector (2, 9, 6) and the same blue vector as the left side (6, 2, 9). The Pearson Correlation would classify the two vectors in the same cluster in the first case and in different clusters in the second. Conversely, the Pearson Squared classifies them in the same cluster in both cases.

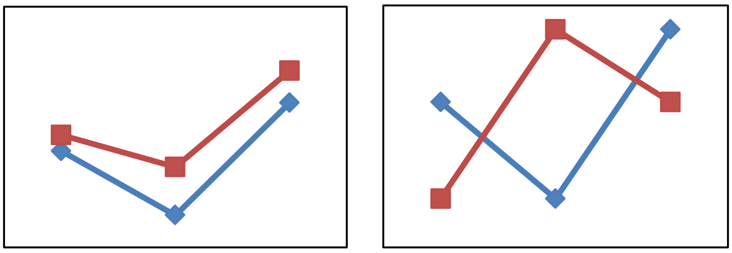


Figure 2.4: Correlated and inversely correlated vectors

- **Spearman Rank Correlation:** finds the similarity between vectors based on their general trends with time; i.e. their attributes or rank pattern rather than their exact magnitude, content similarity or the mean and variance as aspects of similarity. It measures the correlation between two sequences of values separately ranked. The difference in rank is calculated at each position i. The range of Spearman Correlation is [-1, 1]. The distance between $\boldsymbol{X} = (x_1, x_2, \ldots, x_n)$ and $\boldsymbol{Y} = (y_1, y_2, \ldots, y_n)$ sequences where $\boldsymbol{x}_i$ and $\boldsymbol{y}_i$ are the sequences $_ith$ values is:

$$\rho = 1 - \frac{6\sum_{i=1}^{n}(rank(x_i)-rank(y_i))^2}{n(n^2-1)} \tag{2.14}$$

- **The Average Distance Measure (ADM):** The most commonly used effectiveness measures for evaluating the information retrieval systems are binary such as the precision and recall assessment measures that are based on the concept of binary retrieval and binary relevance. Because of using arbitrary thresholds with precision and recall to decide the relevance, the two methods are found to be hyper-sensitive to small variations and to lack sensitivity to big variations [26]. In [26], it is proved that the non-binary ADM (Average Distance Measure) that is based on the continuous relevance and retrieval concepts is adequate for measuring the effectiveness of the information retrieval systems and overcomes the drawbacks of the binary measures. The ADM is calculated by finding the absolute differences between the IR system relevance estimations and the actual document relevance as in Equation 2.15 [26, 27]:

$$ADM = 1 - \frac{\sum_{d_i \in D} |s_i - u_i|}{|D|} \tag{2.15}$$

  Where D is the whole document collection, for any document $d \in D$ let s_i denote the relevant score estimated by the IR system of the ith document, and let u_i denote the actual relevance score of the ith document. The ADM value is in the range [0-1], with 0 representing the worst performance. The advantage of using the ADM non-binary measure instead of the precision and recall binary measures can be summarized in reducing the number of queries needed in assessing the information retrieval systems and measuring the effectiveness of queries that have very few relevant documents in a more reliable way [26].

2.1.2.3 Fuzzy Model

The Fuzzy logic flexibility, high performance, simplicity and formality make it a good candidate model for IR [28]. In 1965, Lotfi Zadeh introduced the theory of fuzzy logic in a paper. He introduced the idea of fuzzy sets where the membership of domain values in any of these sets is represented by a membership function that maps the values of the domain to a normalized value that ranges from 0, which means the value is not a member in the set, and 1, which means the value is a full member of the set [15]. The range of membership values is [0, 1] decided by a membership function like the L-shape, triangular, trapezoidal, and the S-shape function or a combination [29]; the choice of one is application dependent. This stage of deciding the fuzzy variables, fuzzy values, the fuzzy membership functions and getting the membership values is called ***fuzzification***. Each term or fuzzy variable can have multiple fuzzy values associated with it. These fuzzy values should then be related to relevance using fuzzy rules which can be designed intuitively or based on experience. We can then replace the rule parameters by the corresponding fuzzy value and apply the Zadeh operators. The Zadeh operators used in fuzzy logic can either be taken from Boolean logic operators or they can be more linguistic operators. When using the Boolean logic operators AND, OR, and NOT in fuzzy logic they are redefined as the minimum, maximum, and complement respectively. The interpretation of these operators goes as follows for the fuzzy variables a and b: [**NOT** a = (1 - truth(a)) , a **AND** b = minimum (truth(a), truth(b)) , a **OR** b = maximum (truth(a), truth(b))]. The more linguistic operators are called hedges. These are generally adverbs such as "very", “extremely” or "indeed", which are sometimes called modifiers since they change the meaning of a set by using a mathematical formula [30, 31]. Atomic terms like weak, expensive, etc. are known as linguistic variables in fuzzy logic. The last stage is ***defuzzification***, which is transferring the calculated fuzzy values into one value that can be used for example to rank service documents or decide a situation severity. Figure 2.5 shows the information flow through the fuzzy logic modules as discussed.

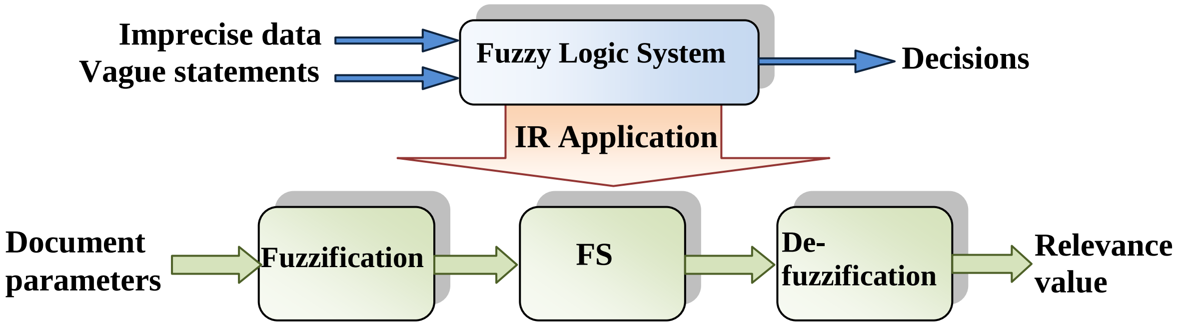


Figure 2.5: Fuzzy system FS information flow as [32] & its application in IR field

2.1.3 Information Retrieval System Evaluation

For one application there exist many possible information retrieval systems. The question is how to evaluate these IR algorithms and choose the most effective one. The evaluation should be reliable, not biased, so that decisions based on it be as authentic as possible.

- **Ranking algorithms have the following features:**
  1. Scoring functions that assign scores to each query result reflecting its relevance.
  2. *Test collections* consisting of a set of queries, document collections and query relevance sets of manual judgments (qrels) [33]; for each query a set of relevant documents is retrieved and prearranged into a partial/total order by human assessors.

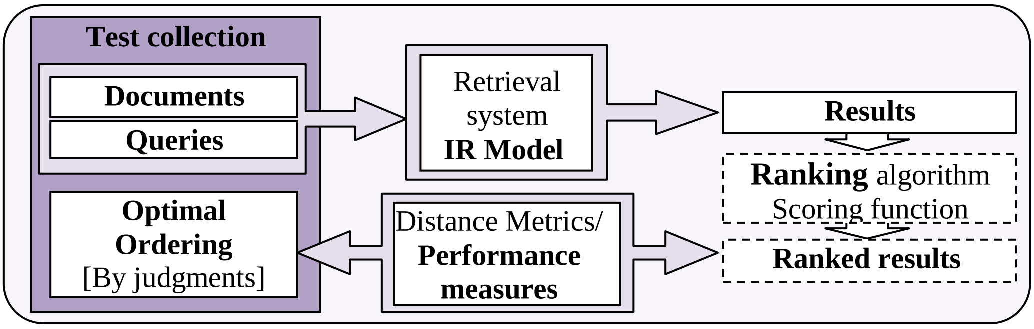


Figure 2.6: Information retrieval evaluation

- **IR Evaluation:** distance between algorithm ranking and “optimal” judges ordering is measured and averaged over the entire collection; see Table A.3 for distance metrics.
- **Text Retrieval Conference (TREC):** IR researchers test their IR systems using a common base consisting of a broad range of problems. Currently, the common reusable test collections are created in various topics as part of the Text Retrieval Conference (TREC). As described in [34], TREC has two advantages to the IR community:
  1. Facilitates fair comparisons of researchers’ results; proposed techniques or ranking formulas are compared to standard methods using well established test collections.
  2. Reusable standard test collections tune retrieval formulas and assess IR effectiveness.
- **TREC judged test collection creation:**
  1. Develop topics and distribute with target document collection.
  2. *Queries* created automatically from the topics; usually the title field.
  3. A pool of the top 100 documents in each participant’s rank/run created and judged on a binary scale. Judgments/qrels are used for calculating optimal precision or recall.

Collections can have 100,000 or more documents, fifty or more topics and a clear statement per topic describing relevant items to the topic based on a human judgment [12]. The TREC experiments are structured into various tracks with each track specialized in an area of IR.

Significant improvement is noticed in IR areas immediately after their track introduction into TREC. A new contextual suggestion track is initiated in TREC 2012 which is a sign of rapid development in the context awareness area in the IR field. This track is specialized in evaluating IR models that serve information needs stemmed from the user context and profile. The recent launch of this track confirms the high need for research efforts in the area of context awareness in the IR field. Therefore, the creation of test collections that include user profiles and context information is the new trend that is followed in TREC for the coming years; Figure A.8 shows a sample of the contextual suggestion test collection.

2.1.3.1 Effectiveness Measures

The ranking algorithm effectiveness is needed to compare alternatives and improve the search by selecting parameter values that are appropriate for the application. There are different types of effectiveness metrics as in [13, 27]: binary, non-binary, multi-grade or partial relevance for a single or a collection of queries Q; see Table A.3 for details. Metrics should be chosen to measure outcomes that make sense for the application.

2.1.3.2 Efficiency Measures

Efficiency means that if two algorithms are similar in their effectiveness then the algorithm that takes less time should be preferred. As described in [20]: If T (A_1, D) less than or equal T (A_2, D) then A_1 is at least as efficient as A_2. A_1 and A_2 are possible algorithms, D is a common test data set and T is the processing time; more than one data set should be tested. The algorithm choice may depend on the application objectives; minimizing the worst case, maximizing the best case or average task completion as in [35]. For distributed search applications, the network usage should be monitored and reflected in the efficiency measure.

2.1.3.3 Statistical Significance

The statistical test compares two retrieval algorithms A and B in an unbiased way. Biased comparisons may show difference between the solutions due to “sampling errors” like uncontrolled factors or random variations. If the magnitude of the difference is high enough then it is statistically significant and proves that a solution B is better than a base solution A [36]. Increasing the sample size increases the test power; e.g. increasing the number of queries; a small sample size may lead to a large sampling error [36]. As summarized in [13], to compare ranking algorithms and decide difference significance you should decide the effectiveness measure, the test statistic reflecting the difference in effectiveness, and compute a P-value based on the test statistic level. Choosing significance tests is application dependent; three tests are found in [13]: the t-test, Wilcoxon signed-rank test, and sign test.

2.2 VANET

This section starts by giving some background about context awareness in VANET with all its necessary modules. Reasons why the solutions for the IR problem may be of benefit to VANET context awareness problem are then discussed. Finally, the services available in VANET are demonstrated with more focus on the ones considered in this work.

2.2.1 Context Awareness in VANET

Context can be defined as any information that can be used to characterize the situation of an entity [37]. According to [37], context may have four categories: *computing* context, which refers to the system capabilities such as communication bandwidth and available resources, *physical* context accessible to the nodes using sensors such as location or time and *user* context such as user profiles and preferences. Context can also be classified according to its continuous change overtime into static and dynamic context [38]. Static context is acquired directly from users or services and stored in a central repository, while dynamic context can be accessed by sensors and it is processed right away [38]. A third classification is the low level context representing context data gathered from Hardware/Software (HW/SW) sensors, and high level context which is usually deduced from reasoning over the low level context [38]. A context should be accompanied by a context management system capable of gathering, managing, evaluating, and disseminating context information [39].

In order to process all mentioned types, a ***context model*** is needed. The model should define and store context data in a machine processable form [40]. As explained in [39], a good context model should be simple, maintainable, and evolvable. It should provide a high-level context abstraction and expressive power to support reasoning while maintaining good computational performance. The model should represent data relationships plus handling the heterogeneity, mobility, and imperfection of data sources. There are various types of context models including key value markup-based models which are good for domain specific modeling, object-role based, spatial and ontology-based models of context information, see [39].

After model creation the appropriate ***context processing*** should be chosen such as rule based reasoning over the ontology model to infer high level implicit context from low level explicit context [38]. Relevance calculation can be viewed as another crucial context processing stage. In Ad-hoc Networks both the service provider context as well as that of the candidate nodes should be considered for matching the nodes with their relevant services. For example, provided VANET services are generally classified as safety services (e.g. post crash notification-PCN), convenience/efficiency services (e.g. congested road notification-CRN) or commercial services (e.g. SA) [3, 4, 5, 6]. The nodes interested in these services can either be vehicles or roadside unites (RSU). To achieve efficient use of available resources, services should only be delivered to nodes if they are highly relevant to the nodes' context. This relevance can be divided into two types, binary relevance as in [1] or partial relevance as in [41]. In case of binary relevance the service context can either be relevant or irrelevant to the node context. If the context has more than one attribute and the relevance is calculated by finding the ratio of the number of matched attributes to the total number of attributes then this can be called discrete relevance. On the other hand, the partial relevance discussed in [41] is based on the vector space model and each context parameter is represented as a vector. The partial relevance provides a degree of relevance calculated by the weighted distance between the optimal service vector and the recipient's context vector.

Finally, the communication/ ***dissemination*** mechanisms used to deliver the relevant services to interested nodes should maximize network utilization. This can be achieved by dynamically adapting these mechanisms to the type of supported services, the services' relevance to the nodes' context and the available network resources at runtime. An important issue that helps in choosing an appropriate communication as well as routing mechanism for the current situation is the type of provided services. Despite the fact that VANET can be seen as a special case of MANET especially when it utilizes V2I communication, VANET is differentiated by its higher processing power and its high dynamic nature [42]. These special features of VANET necessitate that the V2I communication be complemented by the decentralized V2V communication [43]. However, a criterion is still needed to choose when it is best to use each of these communication methods. The type of services provided can be seen as one important factor in deciding whether V2V or V2I communication is more suitable. Examples found in [44] for how the provided services decide the type of communication; V2I is chosen for locating attraction points for tourists and V2V for vehicle breakdown warning.

2.2.2 VANET Services and Scope

In [45], four forms of VANET communication methods are defined; Vehicle to Infrastructure (V2I), HVC, V2V and In-V (inside Vehicle). The type of communication is decided based on the provided service type as can be seen in Figure 2.7. In [3, 4, 5, 6] they agreed that the main three categories of services provided in VANET are commercial, convenience and safety services. For each type one application is chosen in this study. Restaurants discovery, or more broadly service announcement (SA) as named in [3], is chosen for the commercial services, congested road notification (CRN) for the convenience services and post crash notification (PCN) or automatic crash notification (ACN) for the Safety services.

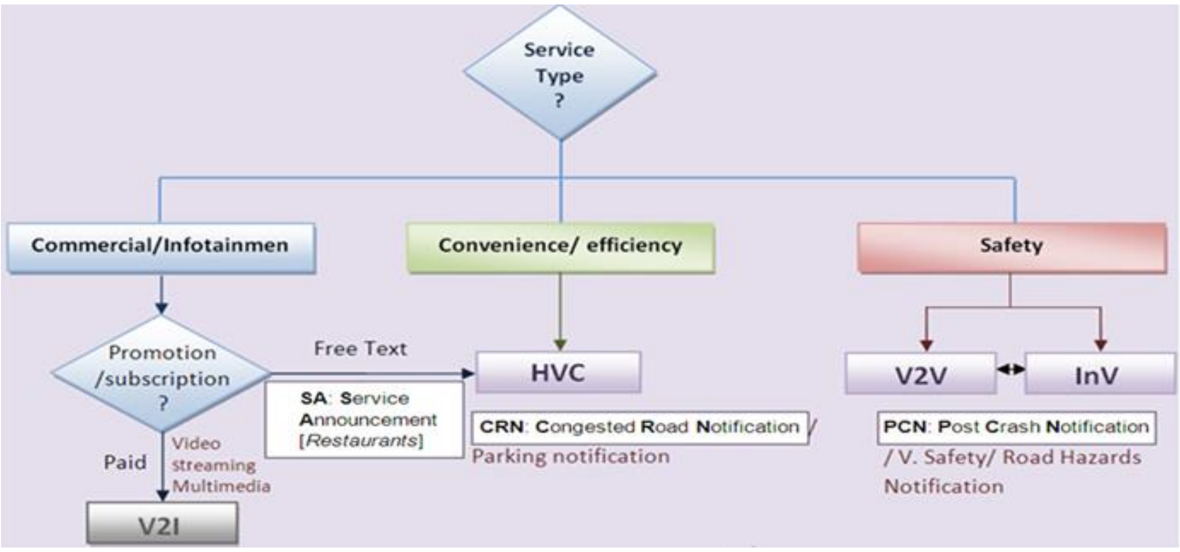


Figure 2.7: Studied VANET services with their proposed communication types

- ***Service Announcement (SA)***: Road commercial services use the SA application to promote their services to the vehicles driving through their areas. The notifications are considered as announcement for the existence of the service in the area and include basic service information; the name of the service, address, the highest and lowest price.
- ***Congested Road Notification (CRN):*** Vehicles in one road zone share congestion information as detected by each vehicle in the zone. Aggregation of such information is necessary to increase the certainty of the detected situation. After zone vehicles reach a conclusion regarding the congestion level in their zone using V2V, V2I can be used to report the resulting congestion level to the RSU so that far away zones get congestion information and have a better chance to avoid the congestion by taking alternative roads ahead of time. Current notifications are binary; flag congestion when it occurs with no indication of its severity level.

- ***Post Crash Notification (PCN) or Automatic Crash Notification** (**ACN**)**:* This automatic crash notification (ACN) /post crash notification (PCN) application detects an accident situation and notifies the nearby vehicles of that accident. The current implementation of this application uses binary notifications, an accident or not an accident, as in General Motors (GM) Figure 2.8. This implementation may help redirect zone vehicles to lanes other than the accident lane to avoid further accidents and limit congestion rate. On the other hand, it doesn't contribute much to saving lives of crashed vehicles occupants. Recently GM started to deploy the AACN in most of its vehicles but the solution still has drawbacks discussed in Section 2.3.1, see also [46, 47]. Therefore, the ACN has been succeeded by the advanced automatic crash notification (AACN) which helps decide whether the accident is life threatening or not. When accidents occur the crash sensor data recorded by the on-board crash recorders, such as the rollover or impact points, see Figure 2.10, is sent to a server. The server runs the URGENY algorithm for deciding the urgency or possible injury level of the occupants based on the received data in order to identify critical cases. This server is usually located at the automaker call center which after calculating the severity degree and confirming it with a possible call to the vehicle driver, sends the public safety answering points (PSAPs) the results. Based on reported severity, the PSAPs should manage to communicate the message to emergency responders to make the proper emergency and medical services available at the crash site as immediate as possible. According to a report issued by the *Centers for Disease Control and Prevention* (*CDC*) in [48], the trauma care services lower the risk of death by 25% for severely injured patients, compared to what happens in hospitals without trauma care services. Therefore, choosing the proper hospital and transportation of injured candidates based on the urgency level can be a life saving step.

"*Providing emergency responders with vehicle crash information may help them make the appropriate field triage decisions, so crash victims can get to the right type of health-care facility at the right time*," Dr. Richard Hunt, director of the CDC Injury Center's Division of Injury Response**.**

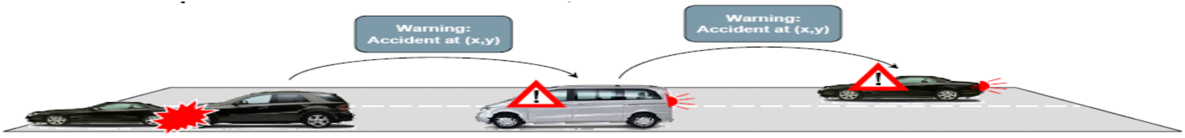


Figure 2.8: GM PCN with the accident location forwarded to vehicles behind [49]

Roads are usually divided into virtual zones based on the possible wireless transmission ranges. Each vehicle in the road has a role relative to its position in these zones. Table 2.3 summarizes the scope of vehicles role in this work.

The idea of a leading vehicle is applied in other fields like the platoon driving where the leading vehicle is a service provider for the platoon vehicles; in [50] it allows autonomous vehicles run on any road. The leading vehicle in their proposed solution possesses the organizational assistant software that is used to send other led vehicles set points describing longitudinal acceleration and the curvature of the driven path, not that of the road. The followers are responsible to keep a minimum gap and a maximum lateral offset with their front vehicle. The leading vehicle keeps track of the platoon separation distances. In case of a joining vehicle, the leading vehicle can command a following vehicle to increase the gap to give space for the joining vehicle.

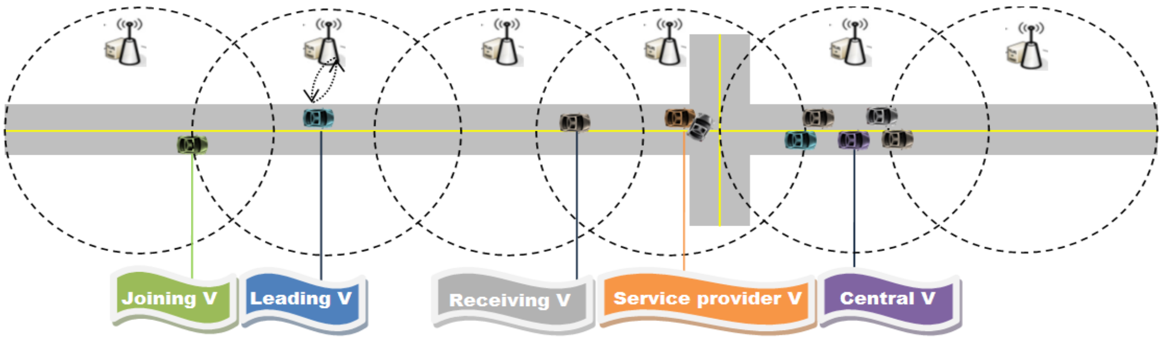


Figure 2.9: Possible road zones and different roles for zone vehicles

Table 2.3: Vehicle role description

Role	Description
Leading V as a service disseminator [Commercial services]	- The leading vehicle is the first vehicle to acquire services from the RSU - The vehicle accesses the basic context of nearby vehicles then compares it to the services available to the leading vehicle. If the available services are relevant to the nearby Vs their XML files and index are disseminated to them.
V as a **service provider** [Safety and Convenience services]	Vehicle context is periodically compared to an optimal context file predefined for each convenience providing or safety threatening situation**.** This optimal file has the maximum values for the situation attributes. Degree of similarity between the current situation and the optimal file reflects the severity degree of the situation. If severity degree passes a predefined threshold the service situation is detected, predefined actions are taken and data is disseminated to intended recipients.
V as a **dissemination recipient** [Safety/Convenience/ commercial services]	**Commercial services:** Vehicle basic context is accessed by the leading vehicles and relevant service files are received according to relevance **Convenience /Safety services:** Get notification files, recalculate relevance according to the spatial and temporal range of the service basic context then decide to re-forward to others or not based on relevance
Joining **V** [Commercial services]	The basic context of the joining vehicle is sent to other vehicles in the new zone The sent context is matched with service contexts available in the zone vehicles If the available vehicles have relevant services to the joining vehicle context, - The services' XML files are disseminated to the vehicle - Degree of services relevance to user profile is calculated - Results presented to user with priority of relevance If no relevant services are readily available within the zone leading vehicles the vehicle context is sent to the RSU and the vehicle becomes a leading vehicle.
Central **V**	Is the vehicle located in the zone center that is able to aggregate information sent from zone vehicles and send the summary to the RSU and zone vehicles.

2.2.3 IR and Context Awareness

The main goal of context awareness in VANET is to disseminate information based on the relevance between the sender context and that of the recipient so that only relevant information is disseminated. This happens to be the same objective behind information retrieval which is retrieving those files that best match the interest of the user. As described in [2], IR and filtering are considered to be two sides of the same coin. Both of them help us to obtain the information needed to perform their tasks. If we closely study the information retrieval problem we realize that: First, a structured representation is required for both information items and information needs. Second, relevance is modeled by the similarity between both representations. Third, ranked results are presented to the user to assist his/her quick retrieval of the most relevant documents. Conversely, if we consider the problem of improving *context awareness* in VANET we find that: First, context modeling, or acquisition and representation of the obtained context information, should take place in the best way for processing. Second, context processing should involve context reasoning and calculation of its relevance to applications. Third, results ranking or filtering based on context is needed so that only the most relevant information is disseminated. From the mentioned analysis, the problem of context awareness as means of filtering the disseminated information in VANET can be considered as a special case of the IR problem. Realizing such synonymy between the two problems justifies importing the research findings of the well established field of IR into the developing field of context awareness in VANET. This requires customization of adopted solutions to match VANET requirements as an application field; the context representation should be adjusted to enhance the IR, likewise, the IR process should be customized to match the dissemination requirements in VANET.

2.3 Related Work

2.3.1 Centralized Systems

- **The iConAwa system**

The iConAwa system described in [38] is a context aware system for MANET where mobile users get information about nearby POI relevant to their context and also communicate with each other by exchanging messages. iConAwa is a context-aware multi-agent system with two OWL Ontologies at the server; a user *Context* ontology and a POI/attraction points ontology.

By using rule-based context reasoning similar to that described in [51], the system is able to derive high level implicit context from low level explicit context. As in [51], the centralized system for mobile applications allows the user situation semantic attributes as well as their profiles to be fed into an inference engine that deduces the appropriate set of web-based information and services matching the user demand and situation. In [38], Jena semantic web framework is used to manipulate the Ontologies and also for rule based reasoning. The client agent sends its Id and location to the context agent at the server side. The server has all users' profiles and preferences saved in the context ontology. The user profile is retrieved using his Id and POIs nearest to his location are presented to him with their matching degrees to his preferences calculated by counting the common keywords between the POI and the user profile.

- **BMW Advanced Automatic Crash Notification (AACN)**

The BMW Advanced Automatic Crash Notification (AACN) is discussed in [52], crash data collected by BMW car sensors is analyzed to deduce severity based on which recommendations are sent to public safety answering points (PSAPs, or 911 call centers), automaker call centers, or hospitals/trauma centers. In [11], the ACN is defined as a standalone system that doesn't require mobile phones and triggered by automatic emergency call or manually by pushing the SOS or Save Our Souls button if assistance is needed. The AACN came out later as an enhanced version of the ACN where the recorded crash sensor data are sent to a central server usually located at the automaker call center that runs a severity predictive algorithm called URGENCY. The algorithm processes crash information to improve rescue care by predicting the accident severity. It identifies crashes with critical injuries and is trained using data from 2000-2006 NASS CDS (National Automotive Sampling System / Crashworthiness Data System) for model year 1998 and later. Each model is evaluated using the 2007 population of NASS CDS cases meeting the same criteria used for training.

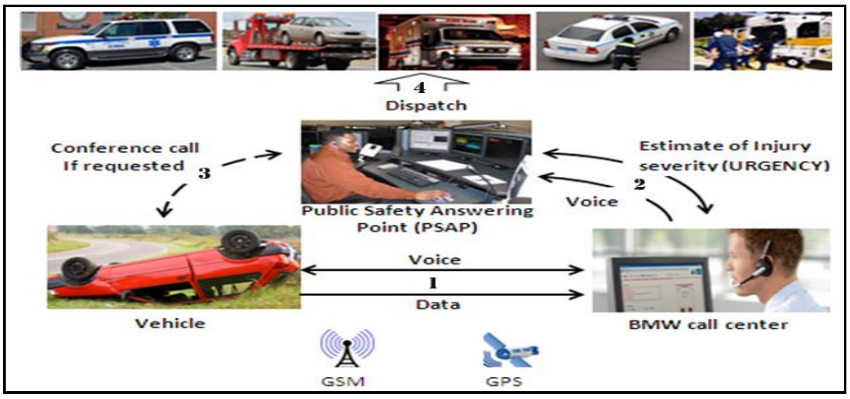


Figure 2.10: BMW AACN dataflow

Figure 2.10 presents the four steps of the BMW AACN functionality chart. When a crash occurs, the sensor data recorded by the on-board crash recorders, such as the delta velocity, the rollover or impact points, are sent and processed centrally by the automaker call center which decides the urgency or possible injury levels of the occupants based on received data to recognize critical cases. After calculating the severity and confirming it with a possible call to the vehicle occupants as in step 1 in Figure 2.10, results are sent from the call center to the public safety answering points (PSAPs) as in step 2. PSAPs might communicate directly with the crashed vehicles in step 3 before informing authorities in step 4.

The Urgency algorithm is trained using the NASS CDS data set. The learned coefficients are utilized for predicting the injury severity for unseen cases. George Bahouth paper published in 2012 [53], came up with the following coefficients and equations.

- **Urgency algorithm equations**

$$w = (Intercept) + \beta_1 \ * deltaV + \beta_2 \ * factor_2 \tag{2.16}$$

$$P(MAIS\ 3+) = \frac{1}{(1+\exp(-w))} \tag{2.17}$$

- **Algorithm performance measure**

$$Positive\ Predictive\ Value\ (PPV) = \frac{correctly\ identified}{false\ positive + \ true\ positives} \tag{2.18}$$

Table 2.4: Coefficients for URGENCY Algorithm trained using NASS/CDS 1998-2007 data evaluated by 2008 and 2009 datasets

Variable	Frontal	Near Side	Far Side
Intercept	-5.2321	-5.9529	-5.0963
Delta_v	0.1335	0.2092	0.1641
Impact	0.2743	1.0401	0.6528
Rollover	1.526	-0.4525	0.8247
Belt_Use	-1.1045	-0.5558	-1.9522

Note: Maximum Abbreviated Injury Scale [MAIS] 3+ group includes those who need immediate medical attention due to one or more potentially life threatening injuries with an Abbreviated Injury Severity (AIS) Score of 3 or higher.

The advantage of having such learned function is that it can be used directly to get binary indication of accident severity. Prediction of severe accidents can happen by substituting the accident attributes and applying a threshold to get a binary flag of whether it is an MAIS 3+ case or not. The disadvantage of the learning algorithms is their significant performance degradation when evaluated using datasets different from those used in the training phase.

- **A publish/subscribe method**

In [54], a publish/subscribe method is deployed where vehicles subscribe to services then receive asynchronous notifications. Contextual information used consists of the drivers' profiles in addition to nearby road points of interest (POI) or situations as congestion.

Contextual information is modeled by OWL-DL Ontologies, the Profile and Environment ontology, with rules that match user preferences with surrounding road POI. The Environment ontology is available for each road zone to represent the POI attributes like petrol stations, or touristic places such as shopping centers or museums and is kept in the Environment server (ES).The context aware processing goes as follows:

1. Users subscribe to services of interest by manually selecting them from a predefined set
2. The vehicle is identified by its ID and location once it enters a service area
3. The driver's information and profile are retrieved using the found ID
4. The available POIs are matched with the user's profile. The relevance rate is calculated by dividing the number of satisfied user preferences by the total number of preferences.
5. POIs are ordered in a descending order of relevance and sent to the vehicle.
6. Other road events can reach the vehicle as messages from nearby vehicles or the RSU

For performance evaluation a test model is developed. The model is composed of 110 POIs for the Environment ontology and 4 different user profiles each representing a different service.

2.3.2 Decentralized Systems

- **Vehicle grouping based on interest using V2V communication**

In [1], peer to peer network is used and the proposed solution relies mainly on V2V communication. Context aware communication is used to enable grouping vehicles based on their common interest. It is claimed that this approach reduces the overall network traffic by avoiding the dissemination of large portion of irrelevant information. The transferred context message used in group formation for group G_D is in the form of $G_D = <C_D, I_D, SI_D>$ Where C is criteria set for group formation (location), I is the main interest, and SI is sub-interest of the vehicle; for example < *[A2], [Traffic Info], [Accident]*>. Feedback is initiated stating whether the message is relevant, irrelevant, duplicate, or too frequent. In case the message is irrelevant it won't be sent again, duplicates are discarded and the original path is recorded, and in case it is too frequent the resend interval is increased. The network is divided into sub-areas based on spatial coverage and the scenario of discovering, joining and updating groups is illustrated in Figure 2.11. When the vehicle is about to go beyond the coverage area of a group and enter another area, it broadcasts its interest in the new area. The request is forwarded and once a vehicle with matching interest is found, it sends to the requesting vehicle a join message.

Only then the joining vehicle sends a leave message to its current group. The network traffic NT is measured using the formula NT $=\sum n\ (M_s + M_f)$; M_s sent messages and M_f forwarded messages.

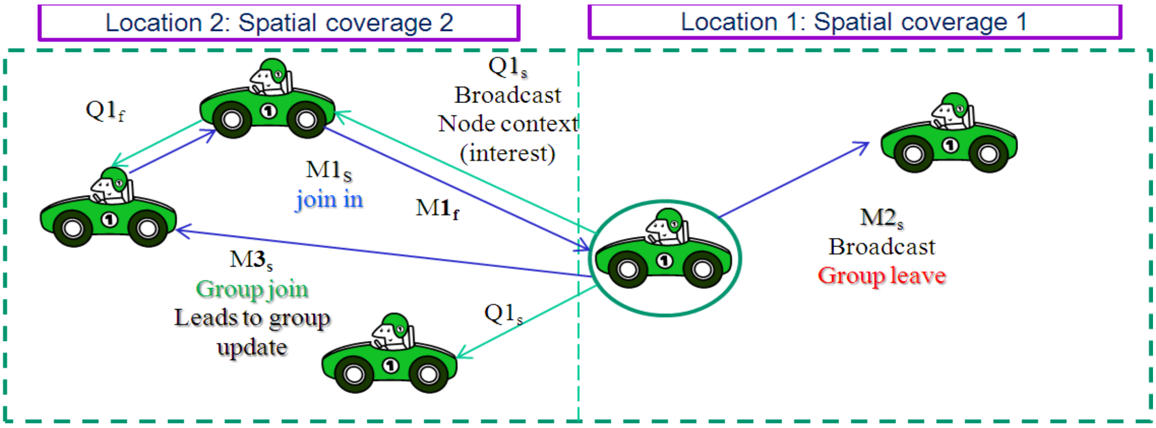


Figure 2.11: Group join and leave scenario and disseminated messages as in [1]

Some of the advantages of the proposed solution are that: First, it eliminates irrelevant information which reduces the overall network traffic in a scalable way. Second, it performs context sensitive tasks and uses information that can't be sensed directly by the vehicle.

- **CoTEC (COperative Traffic congestion detECtion) using Fuzzy logic**

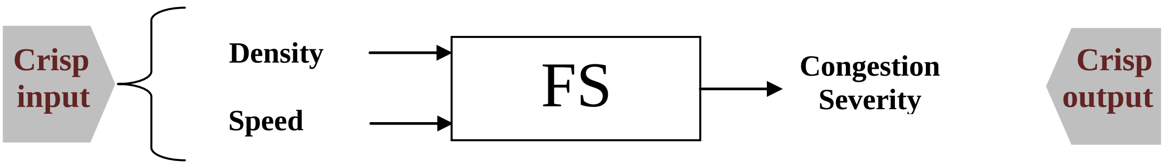


Figure 2.12: Input & output variables to the Fuzzy system (FS) in CRN application

The proposed model is compared to another model which is the fuzzy model that is utilized by the CoTEC system described in [55]. The two main fuzzy variables are the speed and density. Each vehicle implementing CoTEC estimates its local traffic conditions based on its vehicular speed and surrounding traffic density. Therefore, each vehicle can estimate its local traffic conditions and then feeds these values into the congestion detection system. These values are aggregated using the methods discussed in [55] to reach one common congestion severity degree. CoTEC uses the fuzzy logic model based on the Skycomp congestion rating described in [56]. In [55], the triangular membership function is used with four fuzzy sets for each of the two congestion indicators, density and speed, as in Figure 2.13.

The four Skycomp congestion classifications resulting from the fuzzy rule base inference are: Free-flow, Slight, Moderate, and Severe see Table 2.5. It is worth mentioning that CoTEC considers all A to E LOS as free-flow or A level and it further divides the F level into three extra levels Slight, Moderate, and Severe to distinguish between the levels of highly congested flows.

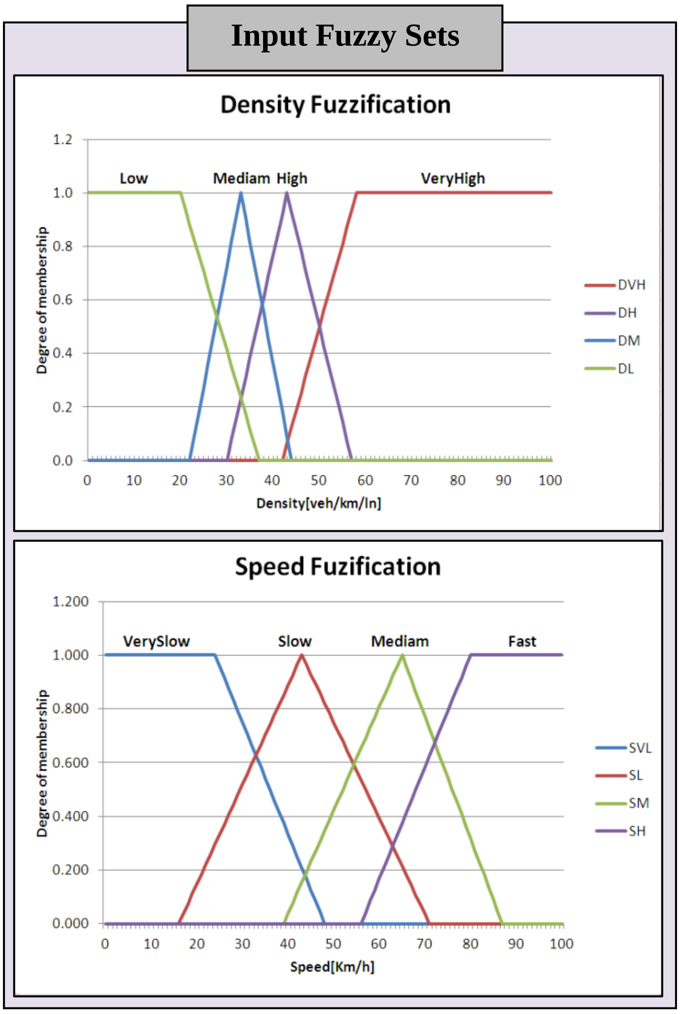


Figure 2.13: Density & Speed Fuzzification as in [55]

Table 2.5: CRN Fuzzy Rule Base Inference as in [55] [R: Rule, D: Density, S: Speed, C: Congestion, V: Very, H: High, M: Medium, L: Low]

R#	D		S		C	C_{VH}= MAX(
1	VH	AND	VL	→	H	Min (VH**D**,VL**S**))
	D		**S**		**C**	C_M = MAX(
2	VH		M		M	Min(VH**D**, M**S**)
3	VH	AND	L	→	M	Min(VH**D**,L**S**)
4	H		L		M	Min(H**D**,L**S**)
5	H		VL		M	Min(H**D**,VL**S**)
6	M		VL		M	Min(M**D**,VL**S**))
	D		**S**		**C**	C_L = MAX(
7	VH		H		L	Min(VH**D**,H**S**)
8	H	AND	M	→	L	Min(H**D**,M**S**)
9	M		M		L	Min(M**D**,M**S**)
10	M		L		L	Min(M**D**,L**S**)
11	L		VL		L	Min(L**D**,VL**S**))
	D		**S**		**C**	C_{VL}= MAX(
12	H		H		VL	Min(H**D**,H**S**)
13	M		H		VL	Min(M**D**,H**S**)
14	L	AND	L	→	VL	Min(L**D**,L**S**)
15	L		M		VL	Min(L**D**,M**S**)
16	L		H		VL	Min(L**D**,H**S**))

The triangle function is chosen for its simplicity and efficiency. This is only one way of applying fuzzy logic and there are many other ways to do the same task. The fuzzy logic is chosen only as an alternative IR model to the vector space model and the preference of a model over the other will only be feasible after creating a strong evaluation system for the effectiveness of context aware systems in VANET.

2.3.3 Hierarchical Context Modeling

In [39] the hierarchical context modeling is proposed in general not in VANET context. So in this work we customize the proposed model to fulfill the VANET requirements. The proposed model is a hybrid hierarchical model. The main role of the multilayered model is:

1. Representing data directly acquired from sensors.
2. Deriving high-level context data (e.g. situation identification) on the basis of raw data (e.g. the represented sensor context data resulting from 1) using efficient reasoning.
3. Reasoning about the identified situations resulting from 2.
4. Generating or triggering system actions based the result of reasoning conducted in 3.

The model has three layers, with layer 3 as the top most layer in the abstraction level and layer 1 as the bottom most layer. The layers functionality can be described as follows:

Layer 1: In this layer sensor data is taken as input from sensors and fused by statistics-based techniques.

Layer 2: This layer is the middle layer with intermediate abstraction level which is higher than the lower sensor fusion layer and lower than the ontology abstraction level.

Layer 3: This layer has the highest abstraction level where the ontology representation and reasoning take place.

Chapter 3

Proposed VANET IR-CAS

In this section an overview of the proposed system is presented. It begins with the introduction of the overall layered architecture followed by the detailed description of the proposed hybrid context model, associated processing, and context dissemination for all types of studied services. Lastly, the multimodal IR-CAS system user interface is presented.

3.1 System Architecture

IR-CAS is designed to provide context aware information processing layer that interacts with the users and service applications from one side and the vehicle sensor fusion layer from the other side as an improvement to the architecture described in [39] and [57]. As can be seen in Figure 3.1, the context aware layer has two major parts: the first one is the hybrid context model and the second one is the context processing associated with each model. A hybrid context model is required since the context layer is expected to serve all types of VANET applications with their dissimilar requirements which are difficult to satisfy with only one model. The following section provides the details of the context modeling which is followed by a section explaining the details of context processing.

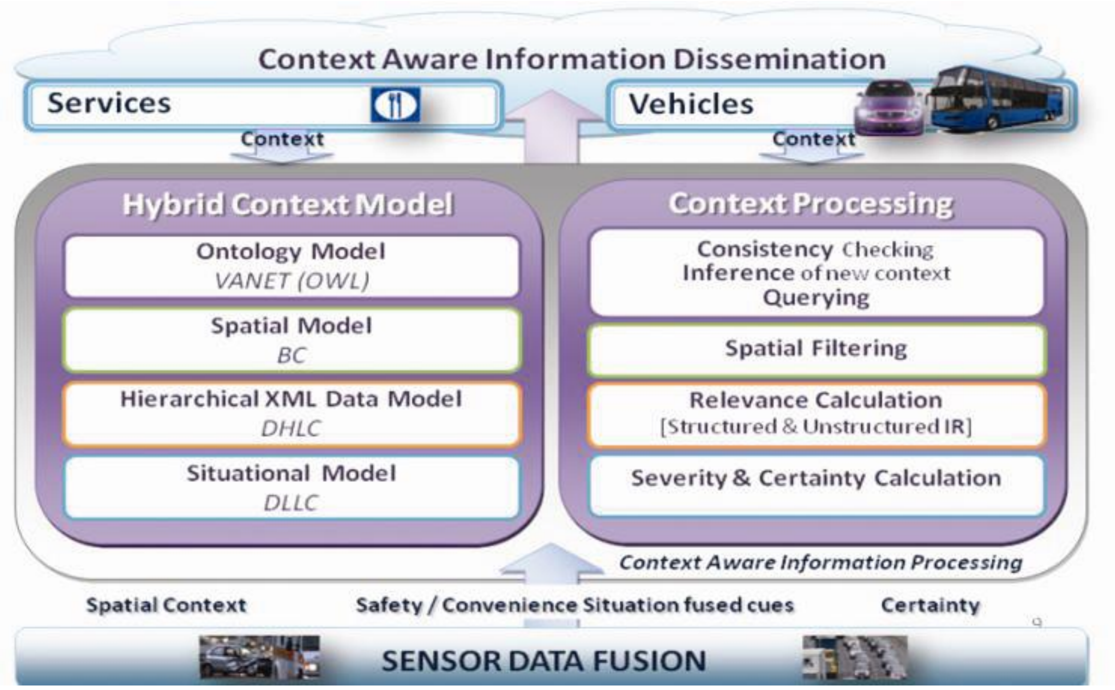


Figure 3.1: IR-CAS layer architecture [the hybrid context model and associated processing

3.2 Context Modeling

Since no single model can achieve all the requirements for a good context model as described in [39], it is decided to have a hybrid context model. Each part of the model fulfills a specific requirement of the supported services.

a. The ***Spatial model*** is needed to filter the disseminated files to the vehicles based on their spatial context. This is necessary to cope with the mobility requirement and to provide efficient access to RSU services. Eventually, this spatial pre-selection of relevant context information helps to speed up the retrieval process that will take place later in the vehicle by reducing the number of dispatched files processed by the vehicle's retrieval algorithm [39].
b. The ***Key value markup model*** is needed for nodes communication; therefore the XML format is chosen to be the transferred files format since it is a universal format for data exchange [58]. The Document Object Model Application programming interface (DOM API) is used to process the XML documents [12]. In addition, XML has the ability to represent the semantics of data in a structured, documented, machine-readable form which enhances the information retrieval especially as many service providers are publishing their information using XML and standard schemas [59].
c. The ***Situational context model*** is utilized to recognize safety and convenience services situations based on low level context attributes. It also helps trigger the emergency predefined actions based on reasoning over situation attributes. As mentioned in [40], adaptations in context-aware applications like safety and convenience services are caused by the change in situations. In addition, further abstraction can be achieved by defining relationships between situations which reduces complexity. High level of abstraction and simpler system design and implementation is achieved since reasoning is based on situations not on all context signs that create the situation [39].
d. ***Ontology based context model*** is used since it allows for knowledge sharing, reuse, validation and aggregation [38]. Ontologies are used to store static contexts with dynamic structure, such as services context, while dynamic context is handled programmatically [38]. Their reasoning capability is used to check the consistency of the context knowledge base as well as deriving new context information based on existing information. The Protégé ontology editor is used to create the VANET context ontology and Jena, a Java API for RDF, is used to interface with and query the ontology.

The ontology is mainly used to save the commercial services context since it is static and for checking its consistency. The *Pellet* Java based OWL-DL, (Web- Ontology Language with description logics), reasoner is used with Jena to check ontology consistency after each update or addition of a new service.

To serve all these models keeping in mind that the vehicle context as well as the service context should be represented in a format suitable for efficient dissemination and retrieval of information, it is decided that the context should be classified into three types:

a. The Basic Context (***BC***) which is a short context list used mainly for spatial filtering like the location, time, spatial range and temporal range attributes plus a short keywords list.
b. The Detailed High Level Context (***DHLC***), which lists the high level attributes describing the context. It represents the user profile and preferences when used in the vehicle and the detailed description of service attributes when used with services. For example, the service *DHLC* is described by the attribute set (*Name, Highest Price, Lowest Price, Contact, Type, Items, and Description).*
c. The Detailed Low Level Context (***DLLC***) for the physical context. It represents the context cues for safety and convenience services situations. It is used mainly to indicate emergency situations or convenience services. For example, the accident detection or PCN service *DLLC* is described by the attribute set (*Pad Pressure*, *Noise*, *Vibration*, *Temperature*, *Speed*, *Belt_Use, Multiple Impact, Rollover, Make, Occupants, and Model*). While the *DLLC* for the congestion detection or the CRN service is described by the attribute set *(Central, Density, and Speed*).

3.2.1 XML Tree

Figure 3.2 shows the tree structure of the XML service files. For each of the commercial services there are two nodes, one for the *BC* and the other for the *DHLC*. The commercial services are not designed to have *DLLC* as the case with the safety and convenience services as well as the vehicle context. The DOM API is used to process the XML documents by starting at the root element and then descending down the tree from parent to child nodes [12].

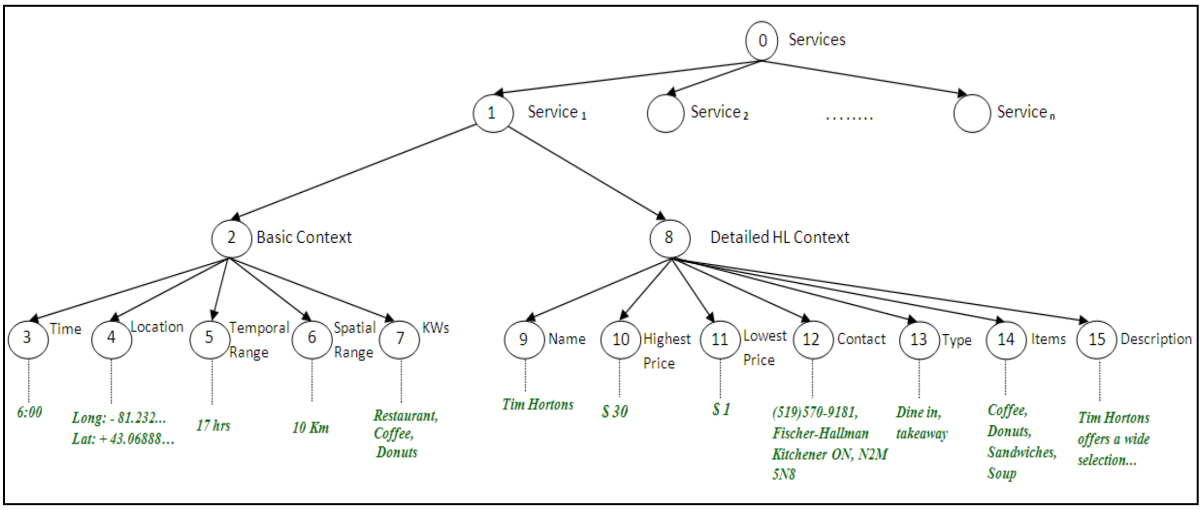


Figure 3.2: Tree representation of commercial services XML documents

Part of the user context file is shown in Figure 3.3. This file includes three types of contexts: the *BC* with a minimum list of attributes describing the high and low level context, the *DLLC* with attributes for sensor readings grouped by the safety and convenience situations they define and the *DHLC* which represents the user profile summarizing the personal information and preferences of vehicle occupants.

```xml
<BasicContext>
      <Time>9:00 am</Time>
      <Location>43.448411,-80.549928</Location>
      <SpatialRange>100 m</SpatialRange>
      <TemporalRange>5 min</TemporalRange>
      <KWs>post crash,ACN,After Accident</KWs>
</BasicContext>
<DetailedHLContext>
 <PersonalInfo>
      <Name>Noha Salim</Name>
      <Address>70 Iron Gate street , Kitchener, Ontario, Canada</Address>
      <Contact>5193456,5193344</Contact>
      <Email>Noha777@gmail.com</Email>
      <DOB>01/10/1993</DOB>
      <Gender>Female</Gender>
      <BloodGroup>o+</BloodGroup>
 </PersonalInfo>
 <PersonalPref>
     <Kw1 kv="Restaurant">
          <Name>Pizza Hut, starbox</Name>
          <HighestPrice>40</HighestPrice>
          <LowestPrice>10</LowestPrice>
          <Contact>N/A</Contact>
          <Type>dine in</Type>
          <Items>coffee,pizza</Items>
     </Kw1>
     <Kw2 kv="Shopping">
          <Name>N/A</Name>
          <HighestPrice>20</HighestPrice>
          <LowestPrice>10</LowestPrice>
          <Contact>N/A</Contact>
          <Type>N/A</Type>
          <Items>clothes</Items>
     </Kw2>
     <Kw3 kv="Hotel">
          <Name>Holiday Inn</Name>
          <HighestPrice>200</HighestPrice>
          <LowestPrice>100</LowestPrice>
          <Contact>N/A</Contact>
          <Type>five stars</Type>
          <Items>single bed room</Items>
     </Kw3>
</PersonalPref>
</DetailedHLContext>
<DetailedLLContext>
   <Situation type="PCN">
      <RegistrationId>Ontario ABZM-167</RegistrationId>
      <Model>2004</Model>
      <Make>Ford</Make>
      <Vibration vcertainty="100%">100</Vibration>
      <ImpactSound ncertainty="100%">100</ImpactSound>
      <PadPressure pcertainty="100%">100</PadPressure>
      <Temperaturelevel tcertainty="100%">80</Temperaturelevel>
      <delta_V dVcertainty="100%">64</delta_V>
      <FrontalImpact>1</FrontalImpact>
      <FarSideImpact>0</FarSideImpact>
      <NearSideImpact>0</NearSideImpact>
      <Belt_Use Bcertainty="100%">1</Belt_Use>
      <multiImpact mIcertainty="100%">0</multiImpact>
      <Rollover Rcertainty="100%">0</Rollover>
      <NumberOfOccupants Ncertainty="100%">1</NumberOfOccupants>
    </Situation>
   </DetailedLLContext>
```


Figure 3.3: Part of user context XML file

3.2.2 Ontology

The Protégé ontology editor is used to create the VANET context ontology. VANET has three subclasses: *Node*, *Context* and *Service.* The main considered class under VANET is the *Service* class which is divided into different types of services and the different applications of each service are grouped under each type of service. Figure 3.4 shows the main class hierarchy of the ontology, the detailed VANET ontology class hierarchy is illustrated in Figure 3.5. The VANET ontology object properties and data properties are shown in Figures 3.6 and 3.7 respectively. Jena, a Java API for RDF, is used to interface with and query the ontology. The *Pellet* Java based OWL-DL reasoner is used with Jena to check the consistency of the ontology after each update or addition of a new service.

3.2.2.1 Class Hierarchy

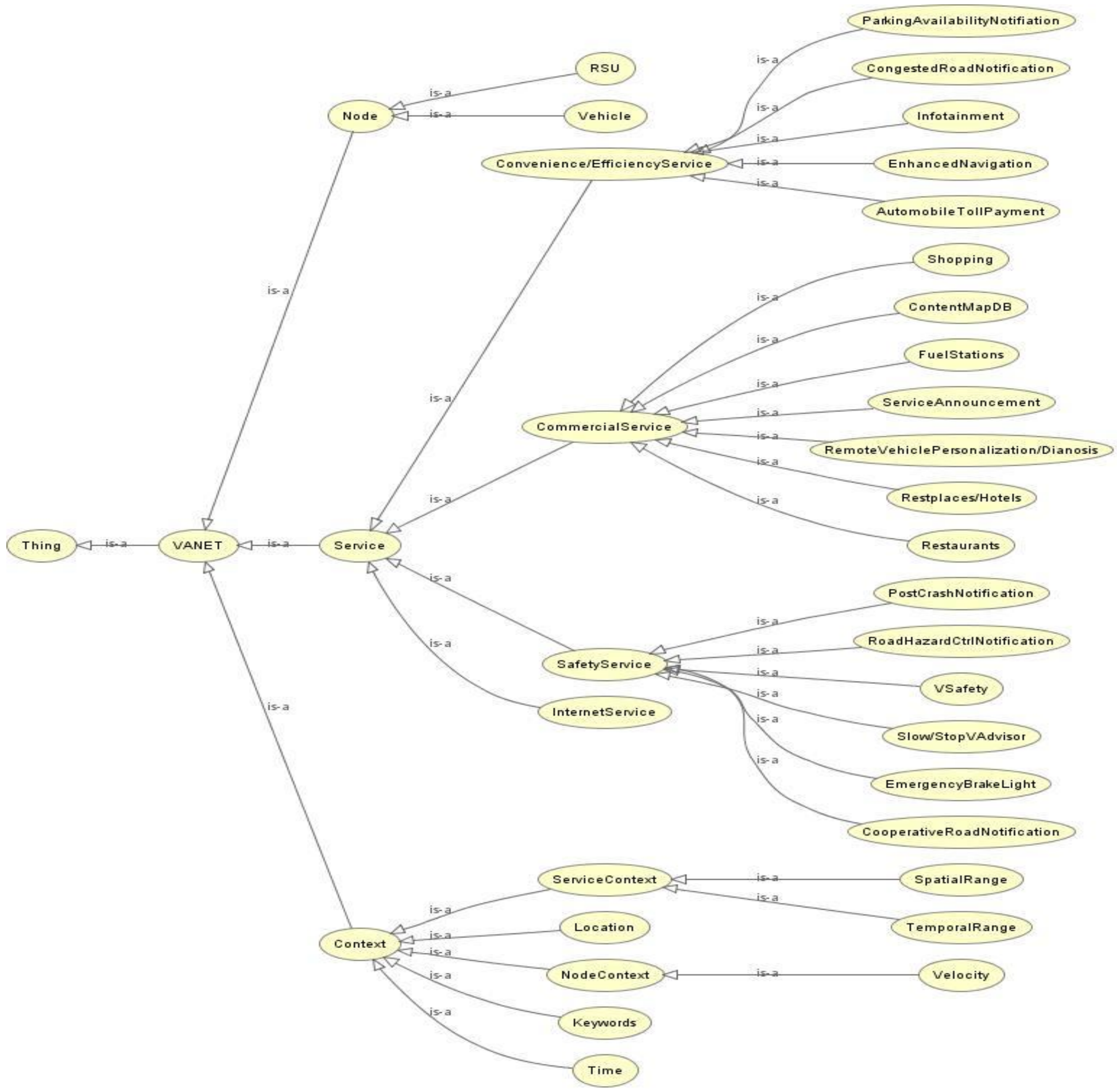
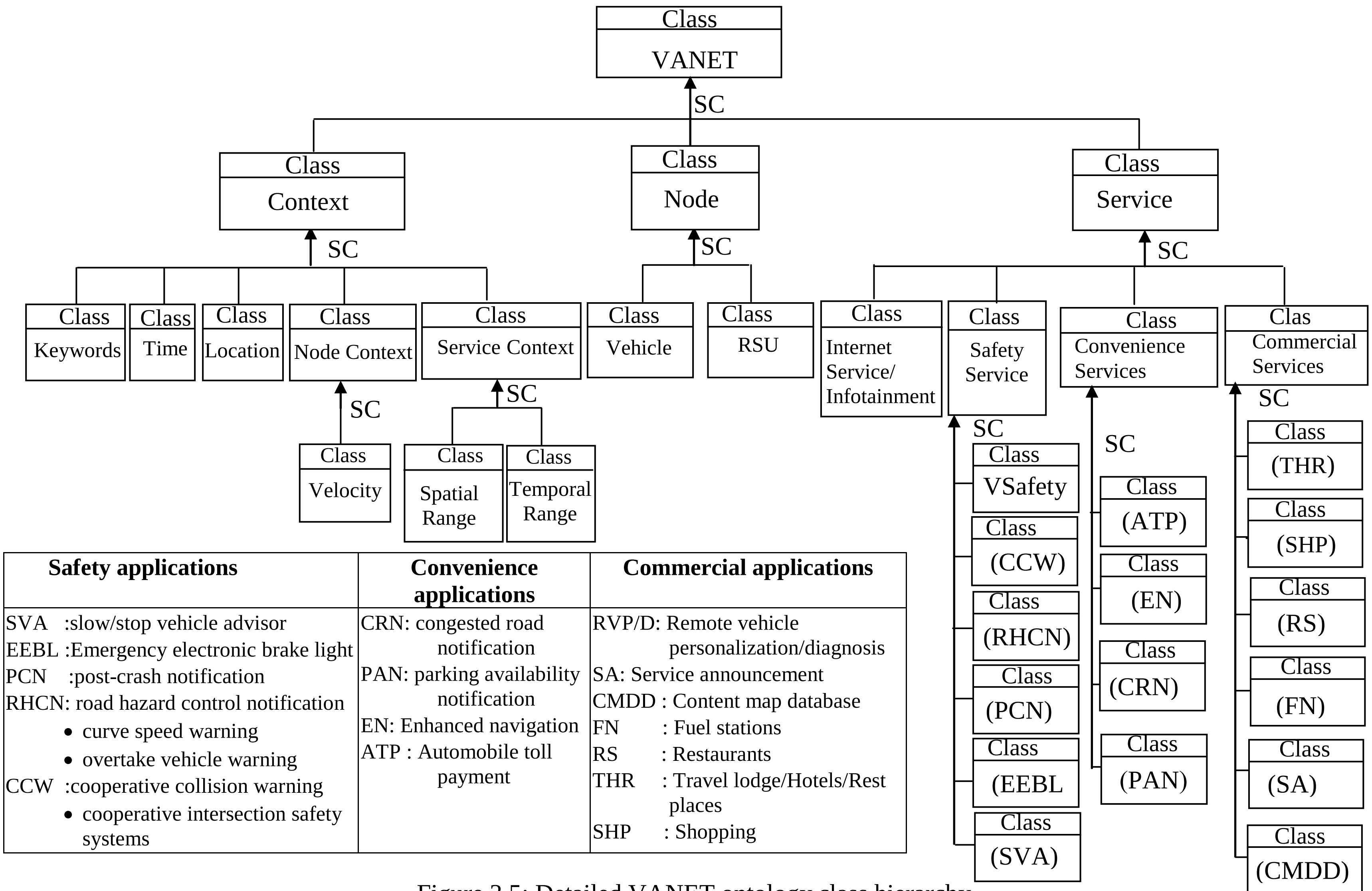


Figure 3.4: VANET ontology main class hierarchy



Safety applications	**Convenience applications**	**Commercial applications**
SVA :slow/stop vehicle advisor EEBL :Emergency electronic brake light PCN :post-crash notification RHCN: road hazard control notification • curve speed warning • overtake vehicle warning CCW :cooperative collision warning • cooperative intersection safety systems	CRN: congested road notification PAN: parking availability notification EN: Enhanced navigation ATP : Automobile toll payment	RVP/D: Remote vehicle personalization/diagnosis SA: Service announcement CMDD : Content map database FN : Fuel stations RS : Restaurants THR : Travel lodge/Hotels/Rest places SHP : Shopping

Figure 3.5: Detailed VANET ontology class hierarchy

3.2.2.2 Properties

- ***Object properties***

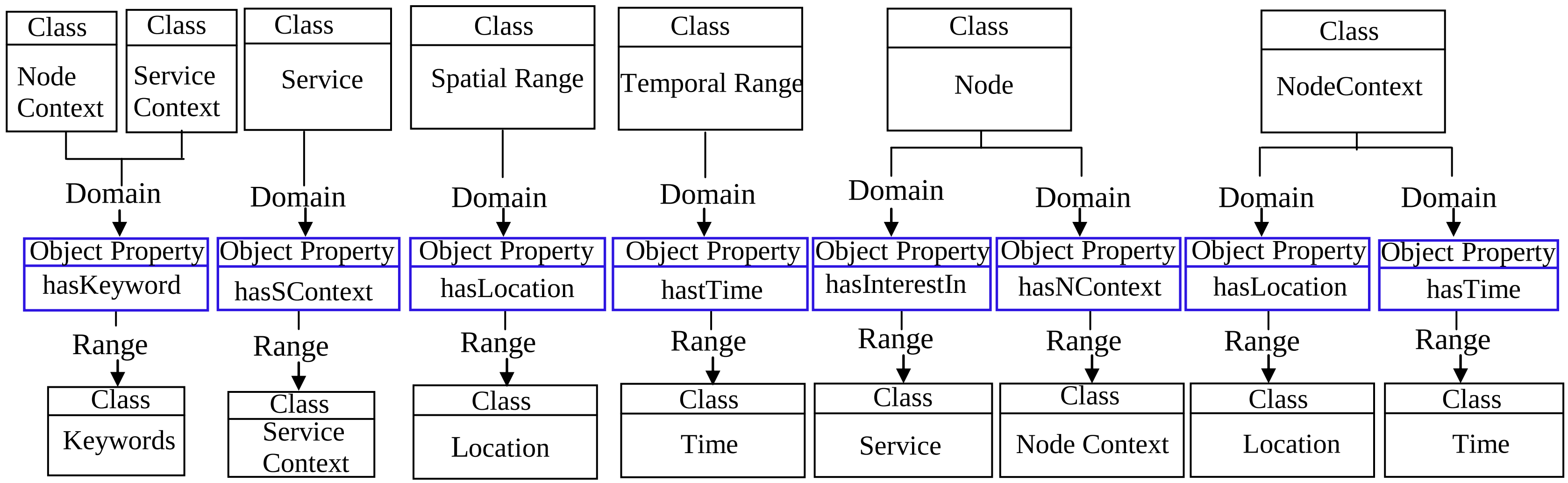


Figure 3.6: VANET ontology object properties

- ***Data properties***

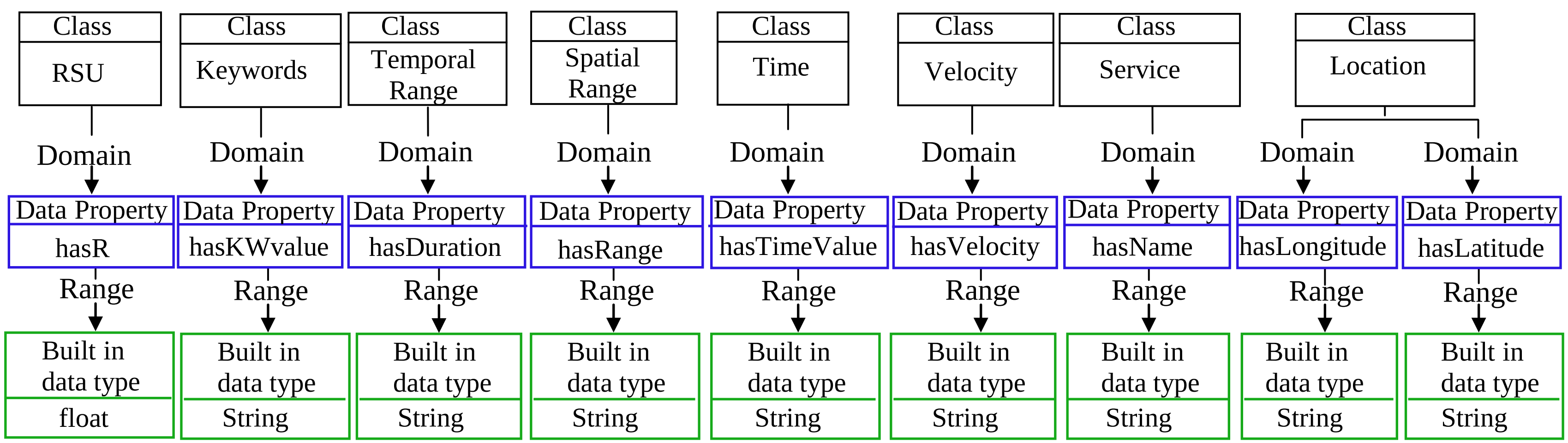


Figure 3.7: VANET ontology data properties

3.2.2.3 Rules

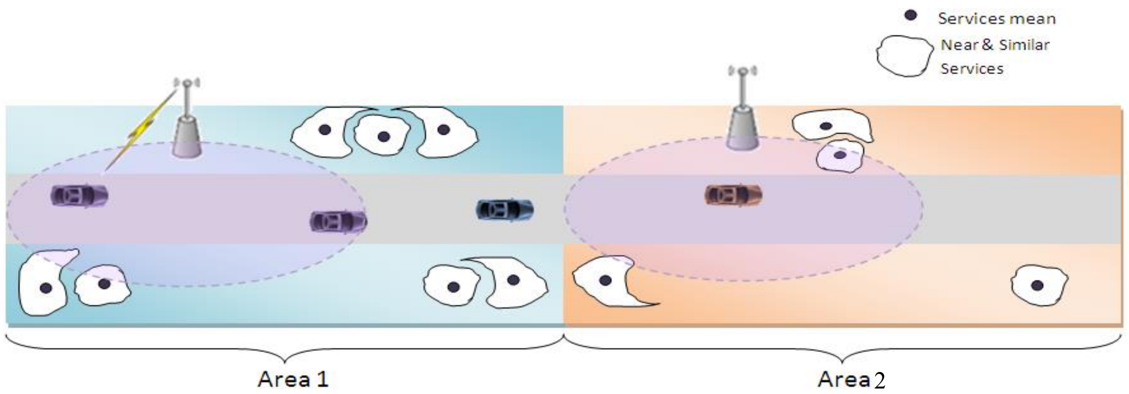


Figure 3.8: RSU coverage areas & the inferred near & similar RSU service groups

In [7] a routing protocols survey is presented but no information is found regarding the usual distance between successive RSUs as assumed in Figure 2.9. In Figure 3.8, the assumption of having an RSU available every fixed distance is ignored. The road is divided into areas that start with the coverage area of the RSU, which is decided based on its transmission range, and ends right before the beginning of the coverage area of the successive RSU. Services locations are used by the rule base to infer their belongingness to an RSU area. For each RSU area, services within the specified nearness range in meters from one another form a *Near* group. The shaded ellipse in Area1 defines the area reachable by the first RSU; the rest of Area1 is not covered by the RSU. Leading vehicles are responsible for dispatching services to requesting vehicles in the uncovered area; e.g. the blue car. Grouping and filtering take place as follows:

a. Services in one area are classified into groups according to their nearness and similarity.
b. Two services within the near group are similar if their Δ time < 1hr, Δ Temporal Range < 1hr and Δ Spatial Range < 1Km; these values can be changed or customized to match the application conditions.
c. To have efficient filtering the services are pre-grouped first according to their RSU groups then by their nearness and similarity. The vehicle *BC* is used to filter the service groups, rather than filtering individual services. If the vehicle is relevant to a service group the whole group of services are dispatched to the vehicle without a need to examine each service in the group.

The advantages of this enhanced design are:

a. Increasing the abstraction level by using inferred high level knowledge from the ontology.
b. Efficient processing due to the size reduction of the knowledge used in filtering.

c. Reduction of the connection time to the RSU and infrastructure.

d. Scalability since the RSU area is inferred from the ontology rather than fixing it in programs.

Since successive RSUs are sharing servers that have information about commercial services available to the whole geographic area, then grouping the services by their closeness and similarity can help reduce the time spent in filtering them according to the vehicle's BC context. New primitives called 'Near', 'Similar', 'HaversineDist' are defined; which are a custom Jena built-in that extends the Java class *com.hp.hpl.jena.reasoner.rulesys.builtins.BaseBuiltin*. The built in primitives are registered as built-in primitives instantiated from *Near, Similar* and *HaversineDist* classes. The *Near* and *Similar* functors return true if the services are near and similar while the *HaversineDist* returns the Haversine distance between two locations. The following rules update the ontology with inferred facts about services based on their features:

- The ***Similar*** Rule:

  Role: Finds whether two service entities are similar in their spatial context; i.e. opening time, duration and range.

  Action: If they are similar a new fact is added to the ontology stating that *service-entity-a* is similar to *service-entity-b*.

  Pseudocode: If (Commercial Service(*SA*, *SB*), Δ time(*SA*, *SB*) ≤ 1 hr, Δ Temporal Range(*SA*, *SB*) ≤ 1 hr, Δ Spatial Range(*SA*, *SB*) ≤ 1Km) then Similar(*SA*, *SB*)

  [Similar:(?Service rdfs:subClassOf VN:CommercialService), (?srva rdf:type ?Service),
  (?srvb rdf:type ?Service), (?srva VN:hasRange ?r1), (?srvb VN:hasRange ?r2),
  (?srva VN:hasDuration ?d1), (?srvb VN:hasDuration ?d2),
  (?srva VN:hasTime ?t1), (?srvb VN:hasTime ?t2), (?t1 VN:hasTimeValue ?tv1),
  (?t2 VN:hasTimeValue ?tv2), Similar(?tv1,?r1,?d1,?tv2,?r2,?d2) ->
  (?srva VN:isSimilarTo ?srvb)]

- The ***FindNear*** Rule:

  Role: The rule finds out if two service entities are physically near; i.e. within 500 meters from each other.

  Action: If they are near a new fact is added to the ontology stating that *service-entity-a* is Near to *service-entity-b*.

  Pseudocode: If (Commercial Service(*SA*, *SB*), Δ Location(*SA*, *SB*) ≤ 0.5 Km)
  then Near(*SA*, *SB*)

  [FindNear:(?Service rdfs:subClassOf VN:CommercialService), (?srva rdf:type ?Service),
  (?srvb rdf:type ?Service), (?srva VN:hasLocation ?loc1),
  (?srvb VN:hasLocation ?loc2), (?loc1 VN:hasLatitude ?l1),
  (?loc2 VN:hasLatitude ?l2), (?loc1 VN:hasLongitude ?lg1),
  (?loc2 VN:hasLongitude ?lg2), Near(?l1,?l2,?lg1,?lg2)
  -> (?srva VN:isNear ?srvb)]

- The ***RSUArea*** Rule:

Role: Finds whether a service entity resides in the area of the RSU or not.

Action: If yes a new fact is added to the ontology stating that *service-entity-a* is in the area of *RSU*-b. The Haversine distance between the RSU and the service entity is calculated, if it turns out to be less than the preset RSU range the service entity is declared to reside in the RSU area and the fact is added to the ontology.

Pseudocode: If (Commercial Service(*SA*), RSU(*RA*), *RG* is range of *RA*, ∆ Location(*SA*, *RA*) ≤*RG*) then *SA* is in area of *RA*

[RSUArea:(?Service rdfs:subClassOf VN:CommercialService), (?srv rdf:type ?Service),
(?srv VN:hasLocation ?srvloc), (?srvloc VN:hasLatitude ?lsrv),
(?srvloc VN:hasLongitude ?lgsrv), (?rsu rdf:type VN:RSU),
(?rsu VN:hasLocation ?rsuloc), (?rsuloc VN:hasLatitude ?lrsu),
(?rsuloc VN:hasLongitude ?lgrsu), (?rsu VN:hasR ?rsuR),
HaversineDist(?lsrv,?lrsu,?lgsrv,?lgrsu,?hDist), lessThan(?hDist,?rsuR)
-> (?srv VN:inAreaOf ?rsu)]

- The ***RSUServicesGrp*** Rule:

*R*ole: Finds the service entities available in the RSU area then includes them in one group.

Action: Adds a class for each RSU and includes in that class the service entities residing in the RSU range.

Pseudocode: If (Commercial Service(*SA*), RSU(*RA*), *RGP* is group of *RA*, *SA* is in the area of *RA*) then *SA* is member of *RGP*

[RSUServicesGrp:(?Service rdfs:subClassOf VN:CommercialService),
(?rsu rdf:type VN:RSU), (?srva rdf:type ?Service), (?srva VN:inAreaOf ?rsu),
Concat(Servises,?rsu,?rsugrp) -> (?srva rdf:type ?rsugrp)]

- The ***RSUNear&SimilarGrps*** Rule:

Role: Finds sub-service groups within the RSU area that are near in location and offer similar services.

Action: Adds a class for each service and includes in it the list of near and similar services to that service.

Pseudocode: If (Commercial Service(*SA*,*SB*), RSU(*RA*), RSU-Near-Similar-Grp(*RGPC*) in *RA* group, Near(*SA*,*SB*), Similar(*SA*,*SB*), *SA* & *SB* are in area of *RA*, not a member *SA* or *SB* in *RGPC* then add *RGPA* as a new RSU Near & Similar Group for *SA* and make *SB* a member of *RGPA*

[RSUNear&SimilarGrps:(?Service rdfs:subClassOf VN:CommercialService),
(?rsu rdf:type VN:RSU),(?srva rdf:type ?Service), (?srvb rdf:type ?Service), (?srva VN:inAreaOf ?rsu), (?srvb VN:inAreaOf ?rsu), (?srva VN:isNear ?srvb),
(?srva VN:isSimilarTo ?srvb), (?srvc rdf:type ?Service),
Concat(?srvc,?rsu,?rsugrpc), noValue(?srva rdf:type ?rsugrpc),
noValue(?srvb rdf:type ?rsugrpc), Concat(?srva,?rsu,?rsugrpa)
-> (?srvb rdf:type ?rsugrpa)]

3.3 Context Processing

This section gives an overview of the context management and processing. It demonstrates how the problem of context awareness is redefined as a retrieval problem. The main objective of context aware systems is to disseminate the information based on the context of the sender as well as the recipient so that only relevant information is disseminated. This happens to be the same objective behind information retrieval which is retrieving those files that best match the interest of the user. Therefore, it is decided that the proposed context processing should include the following *retrieval tasks* categorized by the service type:

a. Commercial services (see Figure 3.9):
   - Deciding the intended candidate vehicles for the provided services based on the *relevance* of the vehicle *BC* to the service *BC*
   - *Ranking* the delivered services to the vehicle according to the *DHLC* as well as the *BC* relevance of the dispatched services to the Vehicle

b. Convenience and safety services (see Figure 3.12):
   - Identifying a service situation based on the vehicle *DLLC* relevance or resemblance to the service optimal vector (e.g. the *DLLC* of the severest congestion or accident situation)
   - Deciding the situation severity based on the *DLLC similarity* between the vehicle and the optimal vector.

In both cases, two types of relevance calculation methods are examined. The binary relevance method is implemented which gives a Boolean response of True/False (i.e. accident/not accident, congestion/ not congestion and relevant service/irrelevant service). In addition, a partial relevance method is implemented using the vector space model as well as other distance measuring methods that deliver a continuous degree of severity or relevance based on the distance between the context vectors as discussed in the following sections.

3.3.1 Commercial Services - SA

The system is developed based on the assumption of having the commercial services available to the RSU and that passing by vehicles submit their *BC* to get the list of XML files of relevant services to their spatial context. A *leading vehicle* of a service group is defined to be the vehicle that connects to the RSU and gets the service XML files and their index from the RSU. It then filters and dispatches these files to other vehicles based on their spatial context plus calculating the dispatched files *BC* relevance to the recipient vehicles.

A further assumption is that vehicles will connect to the RSU only if they fail to find a nearby leading vehicle with relevant services to their context. Based on these assumptions, the commercial services context processing is designed to achieve five tasks; two RSU tasks, *adding* services and *retrieval* based on *BC,* and three tasks carried by the leading vehicles, *showing, querying and disseminating* services retrieved from the RSU; see Figure 3.9.

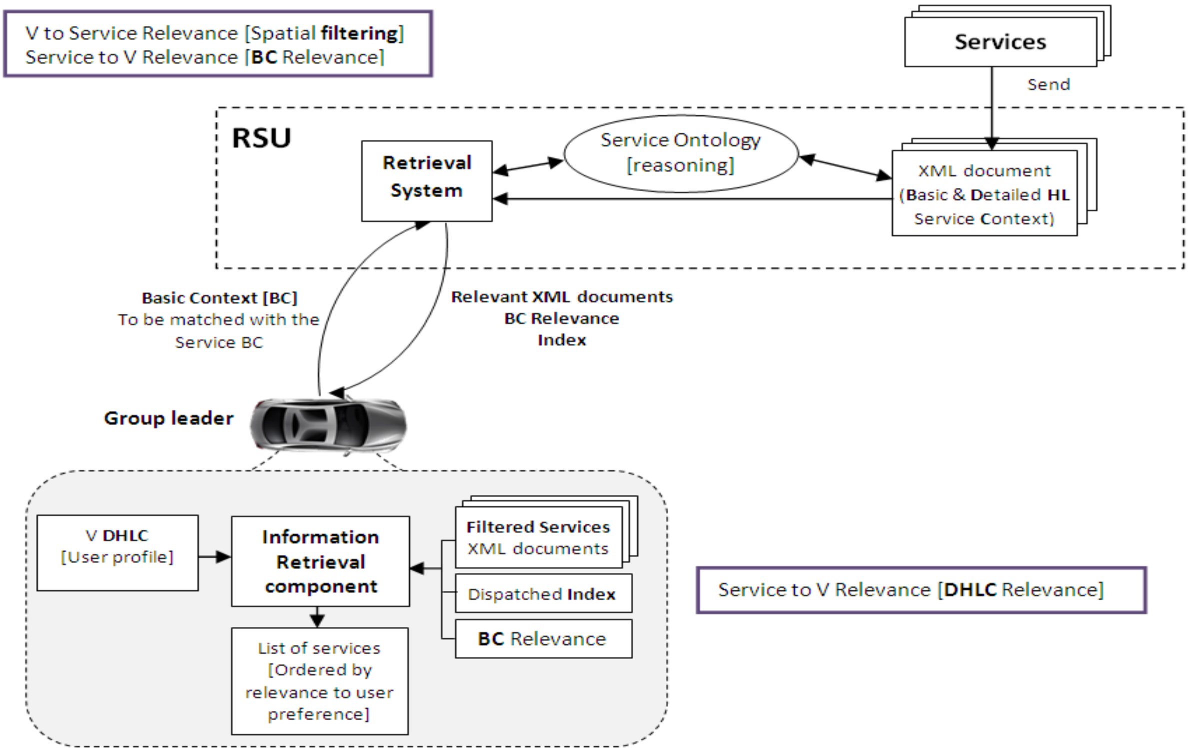


Figure 3.9: Context processing for commercial services

First, the **RSU tasks** can be summarized as follows**:**

***Task1*: *New Service launching*:** the following steps take place when a new service is lunched in the RSU area to register or publish its XML description file through the RSU.

a. Populate the ontology with the instance of service context using the submitted service XML file.

b. Check the consistency of the provided service details using the ontology.

c. Update the services description index file after removing the stop words and stemming the new service description.

***Task2*: *Retrieval based on basic context (BC)*:** This task takes place when a *leading* vehicle requests the list of the most relevant set of services to its context.

a. Get the requesting vehicle's *BC.*
b. Use spatial filtering for services based on the relevance of the vehicle spatial context to the service or service group spatial context.
c. Calculate *BC* relevance which shows how relevant the service *BC* is to the vehicle *BC.*
d. Retrieve relevant XML service files and dispatch them along with their index file and calculated *BC* relevance to the requesting vehicle.

Second, the three **vehicle tasks** are described as follows:

Task1: View Services

a. Calculate the *DHLC* relevance of each of the received services to the vehicle/user profile.
b. Calculate the overall relevance by taking the weighted average of the *BC* relevance received from the RSU and the internally calculated *DHLC* relevance.
c. Sort the received services in descending order of their overall relevance.
d. Show selected service details to the user.

Task2: Query Services [Ad hoc search]

a. Let the user enter his text query.
b. Remove the stop words and stem the query.
c. Match the query with service description index.
d. Calculate the relevance of the retrieved files to the user information need.
e. Display the relevant services in descending order according to their calculated relevance.

Task3: Disseminate Services to relevant vehicles (Vs)

- Do steps ***a to d*** of the previously described ***RSU Task2:Retrieval based on basic context***

Appendix A provides a detailed description of all the tasks' algorithms and flowcharts. After spatial filtering is used for deciding whether the vehicle is considered as an intended service recipient or not, the *BC* relevance of the service to the vehicle is calculated using Equation 3.1. Since the basic context consists mostly of continuous variables, the Euclidian distance is used to measure the distance between the two vectors *(*Vehicle *BC &* Service *BC).*

$$d_{Euc}(BC_V, BC_S) = \sqrt{w_{loc}(loc_V - loc_S)^2 + w_{time}(time_V - time_S)^2 + w_{kw}(KW_V - KW_S)^2} \quad (3.1)$$

Where the *BC* vector is represented by BC_V : (loc_V, $time_V$, KW_V) for the vehicle and by BC_S : (loc_S, $time_S$, KW_S) for the service. The *w* represents the importance of each attribute to the final relevance, while the difference in keywords is represented by the overlap ratio between the two sets of keywords.

3.3.1.1 Structured Retrieval

In order to help the user take a quick decision with minimal distraction it is important to rank the dispatched services with the highly relevant ones at the top. Therefore, the structured retrieval techniques are used to measure how relevant the dispatched services are to the vehicle context. This can be considered as an autonomous querying step where the user predefined *DHLC* representing his/her preferences is used to calculate the relevance of the dispatched set of services to the vehicle context.

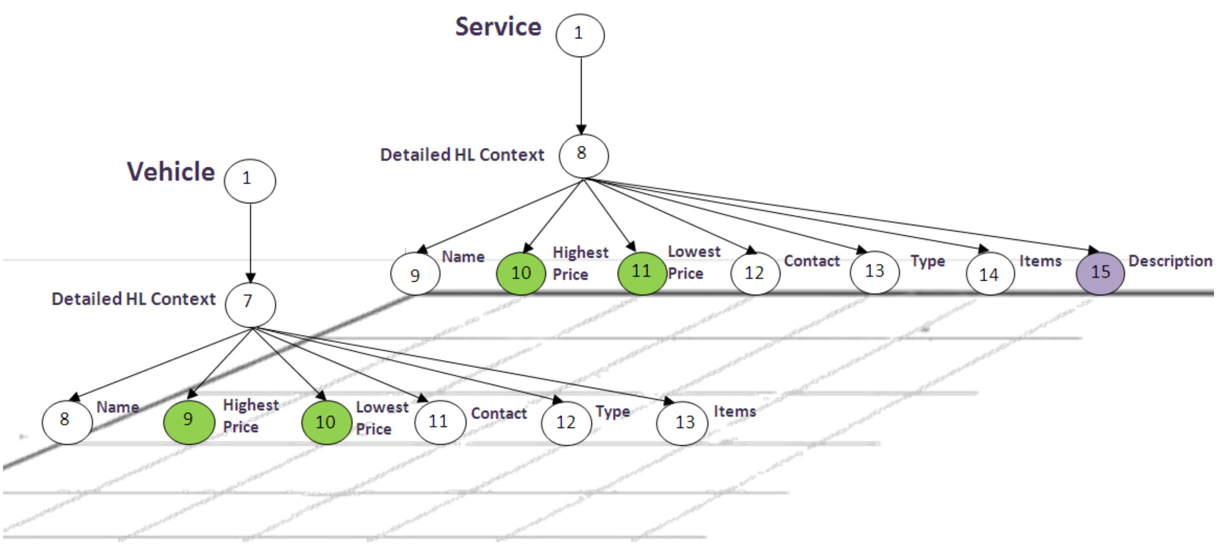


Figure 3.10: The DHLC sub-tree for both the vehicle and the service

As can be seen in Figure 3.10, the *DHLC* node, whether for the vehicles or services, has different types of child nodes. The white nodes are categorical variables that have a possible set of discrete values while the green nodes are continuous variables. On the other hand, the purple node is a free text node that is designed to hold the brief text description of the provided service. The *DHLC* relevance as well as the *BC* relevance are used to rank the dispatched services. The chosen distance measurement method for relevance depends on the considered *DHLC* attribute or the type of the considered child node of the *DHLC*.

Since the majority of the attributes are categorical variables, the *Weighted Hamming distance* with non-normalized weight vector is preferred over the Euclidian distance and used as given by Equation 3.2. It has to be noted that for the continuous variables the absolute difference is used. All attribute distances are normalized by dividing their difference by the maximum possible difference or the worst case.

$$d(DHLC_V, DHLC_S) = \frac{1}{\mathrm{W}} \sum_{i=1}^{n} (w_i |\mathrm{a}_i - \mathrm{b}_i|) \qquad w_i \in [0,1], \quad W = \sum_{i=1}^{n} w_i \neq 1 \quad (3.2)$$

Where the *DHLC* vector is represented by $\boldsymbol{DHLC_V}$: *(Name$_V$, HighestPrice$_V$, LowestPrice$_V$ Contact$_V$, Type$_V$, Items$_V$)* or (a_i, ..., a_n) for the vehicle & $\boldsymbol{DHLC_S}$: *(Name$_S$, HighestPrice$_S$, LowestPrice$_S$ Contact$_S$, Type$_S$, Items$_S$)* or (b_i, ..., b_n) for the service. The *w* represents the importance of each element to the relevance.

As can be seen, the description element is excluded from the ($\boldsymbol{DHLC_S}$) service vector since this node is dedicated for the free text description of the service. This free text description, as illustrated in the coming sections, allows the user to search the dispatched services using unstructured queries.

3.3.1.2 Unstructured Retrieval

The unstructured retrieval techniques are used to achieve the vehicle *TASK2* which is *Query Services* or the *Ad hoc search* as mentioned above. This task enables the user to write a query and get a list of relevant services ranked by their relevance score to the provided query. For this purpose, the index of service descriptions received by vehicles with the commercial service files is used to calculate a relevance score for each relevant service document to the query.

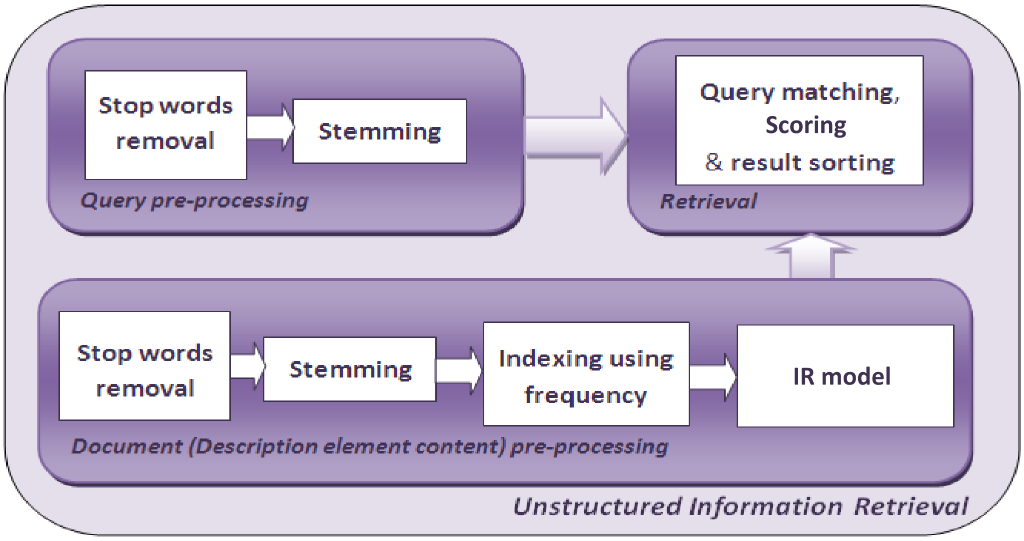


Figure 3.11: The unstructured information retrieval stages

- **Indexing**

Indexing takes place in the RSU using the term frequency–inverse document frequency weighting scheme (*tf-idf*) [12], as can be seen in Table 3.1.

Table 3.1: RSU index for service files

Service ID	Description
S_1	D_1
S_2	D_2
⋮	⋮
S_n	D_n

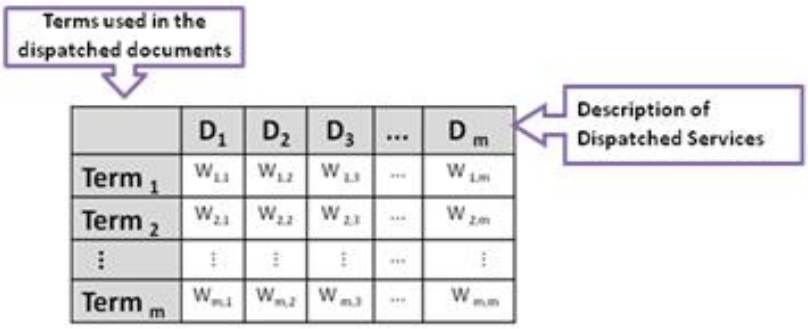
	D_1	D_2	D_3	...	D_n
Term $_1$	$W_{1,1}$	$W_{1,2}$	$W_{1,3}$	...	$W_{1,n}$
Term $_2$	$W_{2,1}$	$W_{2,2}$	$W_{2,3}$	...	$W_{2,n}$
⋮	⋮	⋮	⋮	...	⋮
Term $_n$	$W_{n,1}$	$W_{n,2}$	$W_{n,3}$	...	$W_{n,n}$

The term weight in the service document is calculated using Equation 3.3.

$$w_{t,d} = \frac{tf_{t,d}}{d_{length}} \times idf_t \qquad where\ \ idf_t = \log\frac{N}{df_t} \tag{3.3}$$

Where ***N*** is the total number of service documents available to the RSU, ***tf*** is the number of term ***t*** occurrences in the considered document ***d***, ***df*** is the number of term ***t*** occurrences across all RSU service documents, and $\boldsymbol{d_{length}}$ is the number of all terms in the document. When services are disseminated to a vehicle, a sub-index is created that has only the (***m***) dispatched service description terms out of the total (***n***) terms available in the original index where ($\boldsymbol{m \le n}$), see Table 3.2.

Table 3.2: Sub-index for services dispatched to vehicles



	D_1	D_2	D_3	...	D_m
Term $_1$	$W_{1,1}$	$W_{1,2}$	$W_{1,3}$	...	$W_{1,m}$
Term $_2$	$W_{2,1}$	$W_{2,2}$	$W_{2,3}$	...	$W_{2,m}$
⋮	⋮	⋮	⋮	...	⋮
Term $_m$	$W_{m,1}$	$W_{m,2}$	$W_{m,3}$	...	$W_{m,m}$

- **Ranking Methods for Query Results**

Two methods are used to decide the relevance, the first is binary and the second is partial. For the binary relevance a threshold is assumed to be 50% and Function 3.4 is used to decide whether a document *d* is relevant to a query *q* or not.

$$Relevance(q,d) = \left\{ \begin{array}{ll} TRUE & if\ score \geq th \\ \\ FALSE & if\ score < th \end{array} \right\} where\ (th)\ is\ a\ preset\ threshold \quad (3.4)$$

For the partial relevance, the following two ways are used to calculate the partial relevance score: the ***Overlap Score Measure*** using score Function 3.5 and the ***Vector Space Model*** using score Function 3.6 where the dot product of the query and document vectors is normalized by the product of their Euclidean length; details of the scoring methods can be found in [12] and in section 2.1.2.

$$\text{Score}(q,d) = \sum_{t \in q} w_{t,d} \quad (3.5)$$

$$\text{Score}(q,d) = \frac{\vec{V}(q).\vec{V}(d)}{|\vec{V}(q)||\vec{V}(d)|} \quad (3.6)$$

3.3.2 Convenience Services – CRN

Optimizing the use of existing roads became a necessity due to increasing demands on existing road facilities plus the economic problems which inhibit construction of new roads. In addition, congested traffic is considered the major cause of road users' dissatisfaction, air pollution and waste of resources. Therefore, in recent years, congestion detection became the most important among the applications of VANET convenience services usually known as congested road notification (CRN) [3]. More than one model is utilized for congestion detection in this application. The proposed IR-CAS CRN uses the vector space model that allows representing the context relevant to congestion severity as a vector. Two other models developed for the same purpose are compared with the proposed IR-CAS CRN model; the binary and fuzzy models.

3.3.2.1 Vector Space Model

Convenience and safety services context processing is shown in Figure 3.12. A file with optimal values for the safety and convenience services *DLLC* context is created; for example a file that represents the *DLLC* vector for the severest accident/congestion situation, see Figure 3.13. Then the distance between the current *DLLC* of the vehicle and the predefined optimal service vector is measured using Equation 3.7 to decide the degree/severity of the situation. The *Weighted Hamming distance* with normalized weight vector of dimension ***n*** is used as in Equation 3.7.

$$d(DLLC_V, DLLC_o) = \sum_{i=1}^{n}(w_i|\mathrm{a}_i - \mathrm{b}_i|) \qquad w_i \in [0,1], \qquad \sum_{i=1}^{n} w_i = 1 \quad (3.7)$$

Where the *DLLC* vector differs according to service type; For the congested road notification (CRN) service it is represented by $\boldsymbol{DLLC_V}$: $(Density_V, Speed_V)$ or $(\mathbf{a_i}, \ldots, \mathbf{a_n})$ for the **v**ehicle & $\boldsymbol{DLLC_o}$: $(Density_o, Speed_o)$ or $(\mathbf{b_i}, \ldots, \mathbf{b_n})$ for the service **o**ptimal vector or the congestion case with maximum severity: $(D_j, 0)$ where D_j is the jam density and 0 is the speed value in case of severest congestion situation. The w represents the importance of each element; equal weights of 0.5 are chosen for the CRN application as in Equation 3.8. The Severity is then calculated by deducting the resulting distance from 1 [27], see Equation 3.8.

$$Severity = 1 - \left(\frac{1}{2} * \left(\frac{\sqrt{(S-0)^2}}{FFS} \right) + \frac{1}{2} * \left(\frac{\sqrt{(D-Dj)^2}}{Dj} \right) \right) \tag{3.8}$$

S is the average zone speed and *D* is the zone density.

Figure 3.13 shows how the partial relevance is more informative than the binary relevance used in most regular congestion detection algorithms and that the IR-CAS not only calculates the severity of the congestion but also finds the certainty of the detected situation [60]. Finally, the file that has the congestion details and its severity is dispatched back to other zone vehicles as in Figure 3.13. The congestion location can also be viewed by zone vehicles using Google map. Further details of IR-CAS CRN V2V communications are in [60].

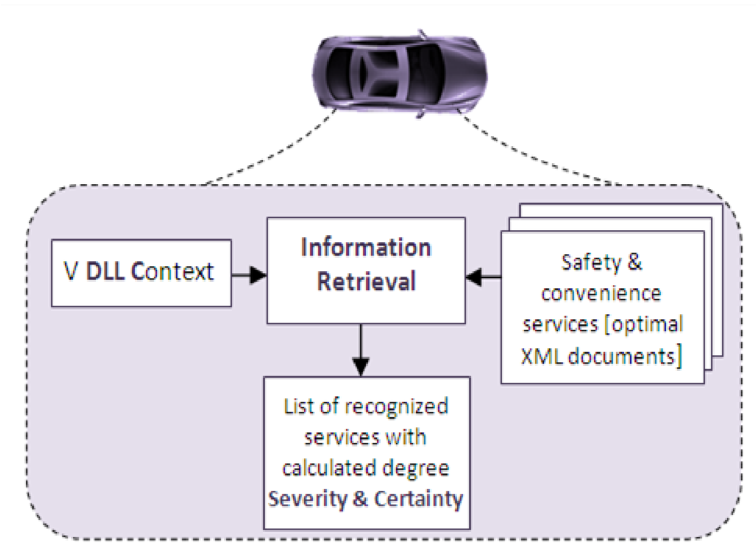


Figure 3.12: IR-CAS Context processing for safety & convenience

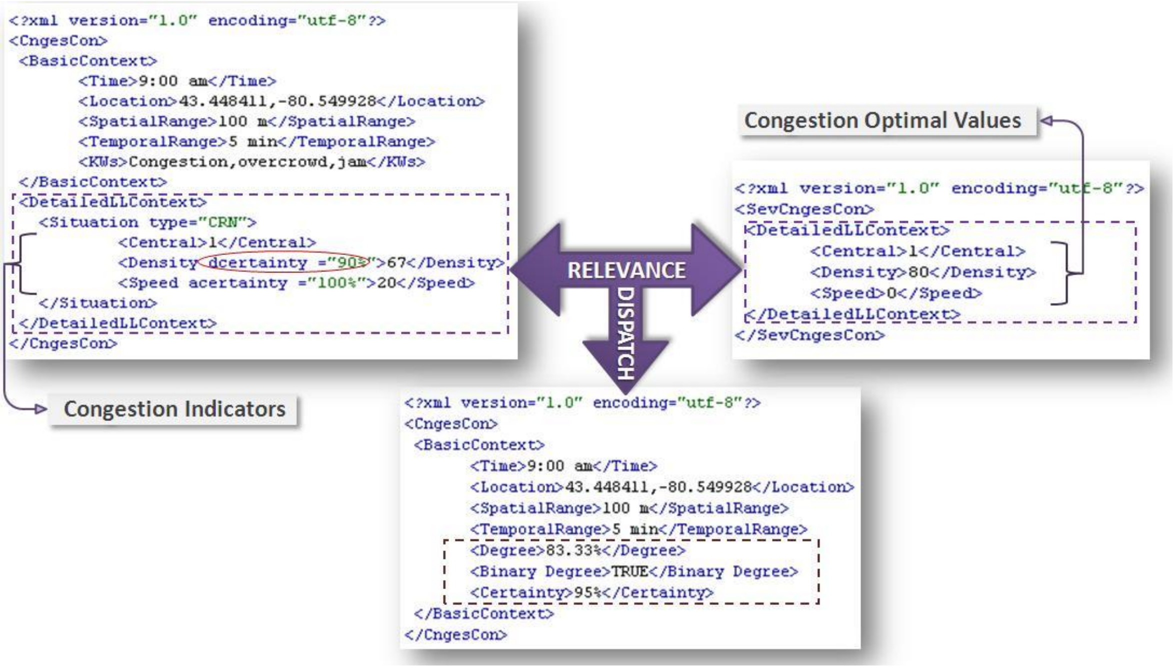


Figure 3.13: IR-CAS CRN file processing and the congestion notification as output

As can be seen in Figure 3.13, the IR-CAS doesn't only calculate the congestion degree but also the certainty of the detected congestion situation. After the congestion is locally estimated by each vehicle the zone central vehicle aggregates the results by calculating their mean value. Other aggregation methods are described in [55]; see Table A.1 in Appendix A.

3.3.2.2 Test Collection Generation

Current congestion detection systems are compared by listing their available or missing features as in [61] or against central methods over short physical and temporal ranges as in [55]. Since no simulation program is readily available to test the effectiveness of the context aware IR models utilized in VANET, a performance assessment model should be designed and implemented to fairly evaluate and measure the effectiveness of those models. This necessitates the design and deployment of large and diverse test collections then the evaluation of the results using binary and non-binary assessment measures. Therefore, a test collection for freeways in rural as well as urban areas has been developed. Methods used for estimating roadway capacities are diverse as in [62, 63], the highway capacity manual (HCM) [64] is chosen as a guide for generating the test cases and their expected congestion severity for low to moderate flow levels. From the models discussed in [65], the Greenshield model is considered for the oversaturated flow cases which are not handled by the HCM curves. This section elaborates on the methods implemented in generating the test collection for rural and urban basic freeway segments. It starts by defining important terms then the methodology of test cases generation is demonstrated.

- **Basic Concepts**

The HCM provides state-of-the-art methods that can be used in estimating the roadway capacities and deciding the level of service for transportation facilities. The Level of service (LOS) as defined by HCM in [64] is a quality measure for the traffic stream operating conditions which are described using six levels starting from A, for the best conditions, through F for the worst. While the actual number of vehicles that can be served during one peak hour is the service volume or flow. The geometric and volume factors affecting freeways flow and volume are listed in Table 3.3. Roadways have the optimal values for these factors under base conditions. HCM divides freeways into sections; a freeway section boundary occurs wherever there is a change in traffic demand or change in segment capacity. The sections within the scope are the basic freeway segments. HCM also defines three types of flows for the basic freeway segments: undersaturated, queue discharge, and oversaturated; see Figure 3.14. The undersaturated flow represents smooth traffic flow without bottlenecks. The queue discharge is the flow rate from a bottleneck where traffic accelerates to free-flow speed (FFS) after passing through a congested queue. The oversaturated flow contains slower flow where queued vehicles experience interleaved periods of stopping and movement.

The main congestion indicators considered in this work are density and speed that have inverse linear relation [64]; so as density increases speed decreases, see Equation 3.9.

$$\boldsymbol{D} = \frac{V}{S} \tag{3.9}$$

Where V is the flow rate in (passenger car (pc)/h), S is the average travel speed in (km/h), and D is density in (pc/km)

The roadway capacity is reached when the product of density and speed results in the maximum flow rate; see Figures 3.14 and 3.15. The speed and density at capacity (S_C and D_C) are sometimes called critical or optimum speed (S_o) and density (D_o) as in [64]. In speed-flow curves like the one in Figure 3.15, the density is represented by the slope of any ray line drawn from the origin of the speed-flow curve to any point on the curve. The free-flow speed (*FFS*) is the average speed of passenger cars over a basic freeway segment measured in the field under conditions of low volume. While (*BFFS*) is the base *FFS* under base conditions, see Table 3.3 for basic freeway segment base conditions. The jam speed and density is speed and density at which congestion stops all movement; i.e. S_{jam} = 0 km/h, D_{jam} = the density when traffic is so heavy that it is at a complete standstill [66].

The HCM undersaturated speed-flow and flow-density curves came from extensive field studies of free to moderate flows. Unlike free-flow, queue discharge and oversaturated flow have not been studied thoroughly for several reasons. Operating conditions, such as flow and speed, within queues and at capacity are highly unstable and variable. It is difficult to accurately predict flow rate, density, and speed at LOS F due to stop-and-start conditions. Therefore HCM methods are designed for facilities with all levels of service except the F level of service [64].

- **Methodology**

There are two methods used in constructing the IR-CAS CRN test collection: The first is the HCM basic freeway segments speed-flow curves used for generating roadways with LOS A-E. While the second is the Greenshield model utilized for freeways with F LOS.

A. HCM for A to E LOS. The relationship between speed and density presented in Equation 3.9 allows a flow rate in an infinite number of combinations. Having field experience with undersaturated roadways has helped refine this relationship to reflect this practical experience. HCM uses the field feedback in defining methods for assessing roadways capacity and LOS that differ based on the facility type. Since we are concentrating on freeways, the basic freeway segment methodology presented in HCM Exhibit 23-1 is deployed in predicting the LOS of all possible configurations of basic freeway segments.

- The methodology has three ***input*** parameters:
  1. **Geometric data** that varies over Table 3.3 ranges to get all possible road geometries in North America.
  2. Base free-flow speed [***BFFS***], in [64] it is 110 for urban and 120 for rural basic freeway segments.
  3. Random volume values (***V***) in (vehicle/h/lane) are assumed in the range of [0: Maximum Capacity]; the road Maximum Capacity is calculated as in step 3 of the following *processing* point.
- The ***output*** is LOS [A to F] for each considered road.
- The ***processing*** goes as follows:
  1. To get the free-flow speed [*FFS*] the *BFFS* is adjusted using road geometry as in HCM Equation 23-1[64].
  2. The Base Capacity in (pc/h/ln) is decided by the *FFS* calculated by HCM Exhibit 23-3.
  3. The maximum volume or capacity, used to limit the random volume generated in step 3 of the *input* section, is calculated in (v/h/ln) using Equation 3.10 by multiplying the Base Capacity by *PHF*, f_{HV}, and f_p factors in Table 3.3. Equation 3.10 is based on Equation (3) in [67] that is derived from HCM Equation 23-2 [64].

$$PeakCap = BaseCap * PHF * f_{HV} * f_p \tag{3.10}$$

  4. Volume in passenger car (V_p) results from adjusting the input volume (V) using HCM Equation 23-2.

5. The speed is decided using the resulting V_p and the speed-flow curve for the calculated *FFS* in Exhibit 23-3. Although the Exhibit shows curves only for free-flow speeds of 120, 110, 100, and 90 km/h, a curve representing any *FFS* between 120 and 90 km/h can be defined by interpolation[64].
6. The density [V_p/S] is then used to define the LOS according to LOS thresholds for basic freeway segments summarized below; see Figure 3.14 as well.

LOS	**Density Range (pc/km/ln)**
A	0–7
B	> 7–11
C	> 11–16
D	> 16–22
E	> 22–28
F	> 28

Table 3.3: Flow and Volume Adjustments as in [64]

<table>
<tr><th colspan="4">Flow Adjustments</th></tr>
<tr><th rowspan="2">Road Geometry</th><th rowspan="2">Base Condition
[No Adjustment]</th><th colspan="2">Adjustments</th></tr>
<tr><th>Range</th><th>HCM EXHIBIT</th></tr>
<tr><td>Lane Width-LW m</td><td>>= 3.6</td><td>[3.5:3]</td><td>23-4</td></tr>
<tr><td>Median/left Lateral clearance LC m</td><td>>=0.6</td><td colspan="2"><0.6 No Adjustment [Rare to find]</td></tr>
<tr><td>Right-shoulder LC m</td><td>>=1.8</td><td>< 1.8</td><td>23-5</td></tr>
<tr><td>Num of lanes-N</td><td>>= 5</td><td>[2:4]</td><td>23-6</td></tr>
<tr><td>Interchanges/Km</td><td><= 0.3</td><td>[0.4:1.2]</td><td>23-7</td></tr>
<tr><th colspan="4">Volume Adjustment</th></tr>
<tr><td colspan="4">HCM Equation 23-2 calculates the equivalent pc flow rate using the following basic freeway segments default values found in HCM EXHIBIT 13-5 & 23-8</td></tr>
<tr><td>Driver population factor [f_p]</td><td colspan="3">1.00</td></tr>
<tr><td>Peak-hour factor [PHF]</td><td colspan="3">0.88 rural 0.92 urban</td></tr>
<tr><td rowspan="5">Heavy-vehicle adjustment factor [f_{HV}]</td><td colspan="3">HCM Equation 23-3 + the default values:</td></tr>
<tr><td colspan="3">• pc equivalents for level terrain</td></tr>
<tr><td colspan="3">-Trucks and/or buses [ET]=1.5
-Recreational Vehicles (RVs) [ER]=1.2</td></tr>
<tr><td colspan="3">• Proportion in traffic stream</td></tr>
<tr><td colspan="3">-Trucks/buses[PT] =10% rural, 5% urban
-RVs [PR] = 0%</td></tr>
</table>

B. Greenshield model for F LOS. Freeway analysis and calculation of performance measures depends on the relationship among speed, flow, and density. The HCM provides curves describing this relationship in Exhibit 23-3 for *undersaturated* basic freeway segments and offers the LOS calculation methodology using these curves. For *oversaturated* or congested freeways linear flow-density relationship is suggested in HCM Exhibit A22-5 [64].

However, it is found that most of the traffic stream models like Greenberg, Underwood, Northwestern, Drew, and Pipes-Munjal in [68] are parabolic and do not use the suggested linear density-flow relationship by HCM and since it is difficult to predict the flow under the oversaturated conditions, a theoretical model is needed. Hence, the Greenshield model is used to explain the relationship among speed, flow and density in highly congested basic freeway segments, since it matches the predictive conceptual model in HCM Exhibit 13-4 for speed under queue discharge and oversaturated flow. Most of the Greenshield model drawbacks are due to its weakness in accurately matching the empirically observed flow behavior of undersaturated situations. Therefore, while generating the CRN test collection, it is used for oversaturated conditions while the HCM speed-flow curves that are based on field observations are employed for undersaturated conditions as in Figures 3.14 and 3.15.

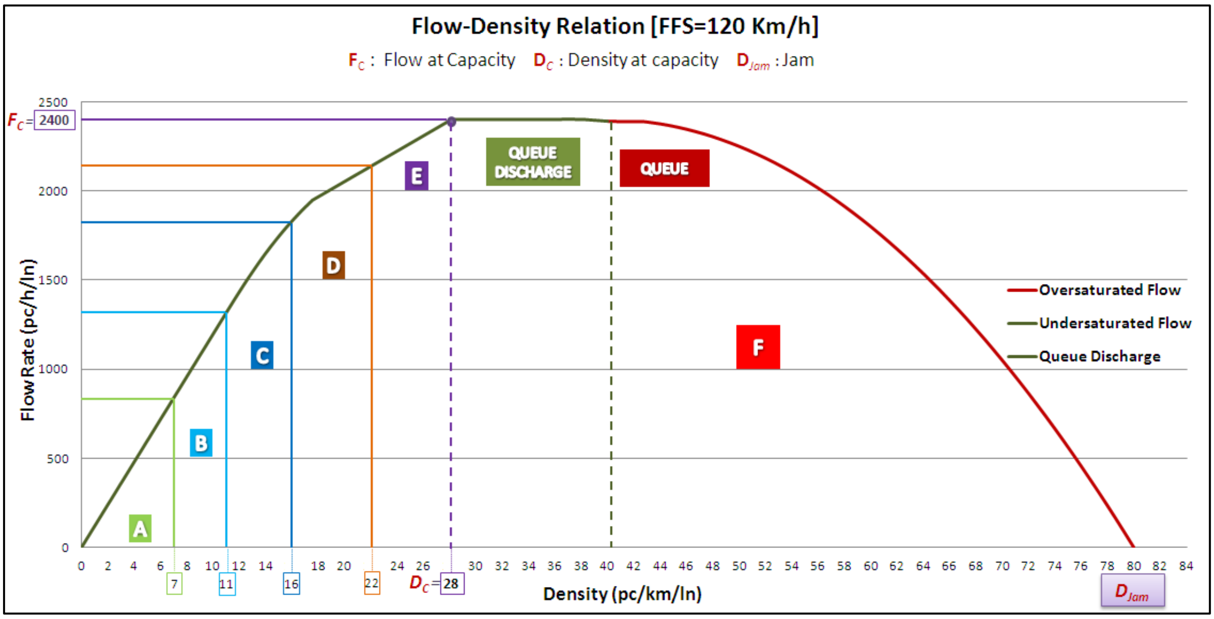


Figure 3.14: Flow-Density Relation [FFS=120Km/h]

In HCM the performance measures depend on the facility type. For freeways, speed and density are used to characterize flow conditions [64]. They are critical parameters for uninterrupted flow facilities because they characterize the quality of traffic operations. HCM EXHIBIT 7-2 gives a general relationship between these two parameters and the flow based on the Greenshield model in [69]. Since the maximum flow is often underestimated by the Greenshield model as argued in [66], it is decided to use the HCM speed flow curves in EXHIBIT 23-3 in deciding the maximum flow and then utilize the Greenshield with oversaturated flows where LOS is F as in Figure 3.14.

The Greenshield with its formulas in [69] is applied for random average passenger car speeds < speed at capacity [*Sc*] while HCM speed flow curves in EXHIBIT 23-3 are applied for random average passenger car speeds ≥ *Sc*, see Figure 3.15.

- **Input :** *S* in [0, *Sc*], *Dj*, *FFS*.
- **Output:** LOS F cases.
- **Processing:** The different flow levels are calculated using Equation 3.11.

$$V_p = D_j * S - \left(\left(\frac{D_j}{FFS}\right) * S^2\right) \tag{3.11}$$

where S is the average zone speed

Then Equation 3.9 is used to calculate the density using the assumed speed values. The resulting *D* is in the range of LOS F densities; > *Dc* and ≤ *Dj* as in Figure 3.14 that shows the flow density relationship for basic freeway segments under base conditions and with *FFS*=120.00 Km/h.

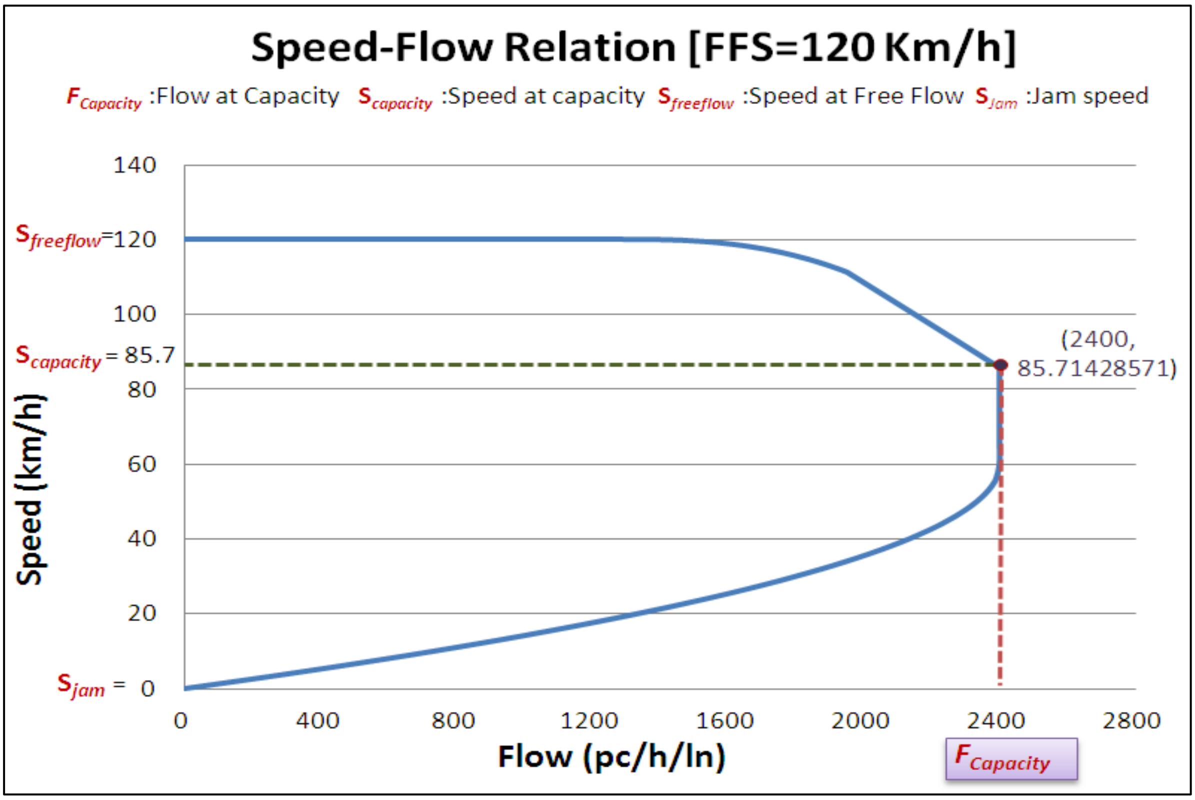


Figure 3.15: Speed-Flow Relation [FFS=120Km/h]

Two CRN systems are considered; one partial and the other binary. The first is the CoTEC system discussed in section 2.3 which distributes informative messages with estimated severity. The second discussed here disseminates binary notifications without severity degree.

- **Binary model**

The binary notifications are used in most of the current CRN applications with centralized implementations as those discussed in [3, 70], which manage congestion by monitoring vehicles status and traffic flow in a centralized way, or decentralized systems as in [1]. Therefore it is necessary to compare any proposed model with the Binary model to assess its performance. Hence a binary model is implemented and its performance, decided using the IR-CAS CRN test collection, is compared with the performance of the proposed model. The binary model relies on the speed and density parameters in predicting congestion. A threshold of 50% is chosen; any flow with average speed < (capacity speed/2) and density > (jam density/2) is considered severely congested, i.e. the congestion severity value is True, otherwise the severity value is False which indicates that the segment is not congested.

3.3.3 Safety Services – PCN/AACN

One of the main VANET safety services that attracts research attention is the Automatic Crash Notification (ACN) application. Its importance stems from its role in improving life safety which is a top goal for Intelligent Transportation Systems (ITS). As mentioned in [71], ACN enhances injury prevention and may help avoid up to 15% of traffic deaths. The chain of survival, events sequence that leads to best medical results with trauma victims, is improved by ACN since the call for help is considered to be the first link in this chain. Getting enough information about the collision case is necessary for efficient transportation of proper medical resources to the accident site and quick transfer of victims to the appropriate hospital. Missing the right hospital may lead to 25% increase in mortality as reported by McKenzie et al [71]. Therefore the speed of emergency call delivery to appropriate emergency responders plus the preciseness and accuracy of its content are crucial for victims' survival. To achieve this, the VANET IR-CAS ACN is proposed. For safety services, predicting the severity of accidents is studied and the context processing is similar to the congestion case discussed in the previous section as shown in Figure 3.12. The aim is not only to have a binary indicator for accident occurrence as TRUE/FALSE indication with location, as the case with the current PCN systems, see the GM Figure 2.8 for PCN, but to have more informative accident notifications to nearby vehicles as well as the PSAPs. Notifications to surrounding vehicles should include some *DLLC* with vehicle and accident details, along with the estimated accident severity and indicators certainty.

PSAPs notifications should have, in addition to the mentioned details, some *DHLC* like the driver's personal information. A file with optimal values for the safety services *DLLC* context is created; the *DLLC* vector for the severest accident situation. Then the distance between the current *DLLC* of the vehicle and the predefined optimal service vector is measured to decide the degree/severity of the situation. The Weighted Manhattan distance with ***n*** dimensions weight vector as in Equation 3.12 is used.

$$d(D[L/H]LC_V, D[L/H]LC_o) = \sum_{i=1}^{n}(w_i|\mathrm{a}_i - \mathrm{b}_i|), \qquad w_i \in [0,1] \tag{3.12}$$

Where the ***V****ehicle* context vector can be represented by the $\boldsymbol{DLLC_V}$: ($PadPressure_V$, $Noise_V$, $Vibration_V$, $Temperature_V$, $Speed_V$, $Belt\_Use_V$, $Multiple\ Impact_V$, $Rollover_V$, $Make_V$, $Occupants_V$, $Model_V$) with the $\boldsymbol{DHLC_V}$: (DOB_V, $Gender_V$) or $(\mathbf{a_i}, ..., \mathbf{a_n})$. While the matching ***o****ptimal* vector of the severest accident situation is represented by the $\boldsymbol{DLLC_o}$: ($PadPressure_o$, $Noise_o$, $Vibration_o$, $Temperature_o$, $Speed_o$, $Belt\_Use_o$, $Multiple\ Impact_o$, $Rollover_o$, $Make_o$, $Occupants_o$, $Model_o$) with $\boldsymbol{DHLC_o}$: (DOB_o, $Gender_o$) or $(\mathbf{b_i}, ..., \mathbf{b_n})$. All file attributes whether low or high make up together the context vector. The *w* represents the significance of each attribute to the crash severity. The weighted average of distances between the accident context and accident optimal vectors is calculated in a space with n dimensions that are equal to the number of considered attributes in the crash situation; see calculation details in Table 4.8. Lastly, a notification file with context information and estimated severity is dispatched to other vehicles and PSAPs; see Figure 3.16.

The proposed IR-CAS ACN is an improvement of the BMW Advanced Automatic Crash Notification (AACN) described in section 2.3.1 by decentralizing the severity calculation. This decentralization is achieved by doing most of the processing inside the vehicle instead of sending all the sensor readings to a central server for processing as it is the case with the current BMW AACN system; see Figure 2.10. If the degree of the accident indicates any level of injury then at this point the calculated injury level and the personal information of the driver are dispatched to zone vehicles and to the RSU as in step 1 in Figure 3.16. The personal information permissible by the user for dispatching should be pre-decided by the driver ahead of time. The RSU server should redirect the message to intended recipients like PSAP, relatives and the appropriate emergency responders as in step 2. The full proposed functionality flowchart of the modified AACN is presented in Figure 3.16.

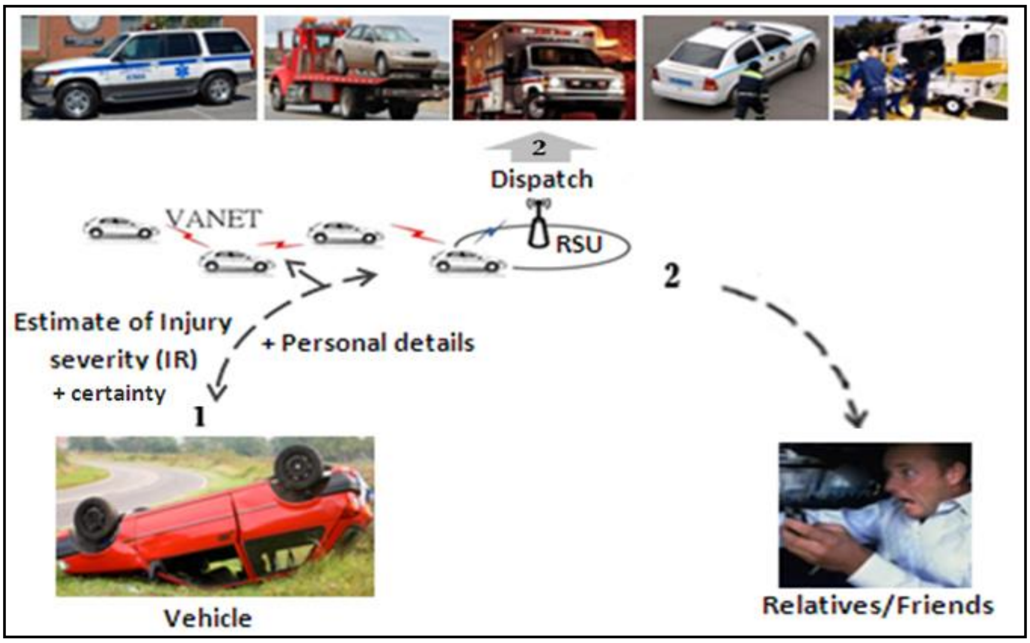


Figure 3.16: IR-CAS modified AACN dataflow

The proposed system has the following advantages:

1. It is ***decentralized*** since the sensor data is processed internally instead of sending all the sensor data to the call center server for processing. This internal calculation limits the need to connect to the central servers to those incidents where the severity level indicates injury occurrence. In the BMW AACN case all the sensor data is sent to the call center server whether the accident involves injury or not. Only then the call center can decide whether the accident led to injury or no injury has happened based on the result of the centrally executed URGENY algorithm.
2. It is a ***fully automated*** solution since it doesn't rely on human judgment. This full automation increases the notification ***efficiency*** and ***accuracy***. The electronic messages including the resulting degree and personal details are sent in one shot to the nearest vehicles as well as the RSU. The nearest vehicles forward it to other relevant vehicles and the RSU forwards it to the PSAP, preselected first contact person from the user relatives or friends, and to the nearest emergency response points. This solution is more efficient since it cancels the voice call and sensor data communication to the call center.

   In addition, avoiding voice calls and lowering the reliance on the operator's judgment in the call center reduces cases of human errors which enhances ***accuracy***. As mentioned in [11], the voice calls are not reliable and may cause fatal mistakes by delaying the transportation to trauma centers. The reasons behind this lack of reliability are as follows:

a. **Misleading response**: It frequently happens that the driver doesn't feel the severity of the injury right away so he gives false indications that may mislead the operator in the automaker call center. Florida 2006-2008 Crashes in [11] show that 23% of the drivers who were contacted by voice calls and reported no injury were later on diagnosed as having possible (C), non-incapacitating (B), incapacitating (A) or fatal (K) injury levels and 3% ending up in trauma centers.

b. **Absence of response**: Sometimes no voice is heard in the vehicle since the occupants are scared to stay in so they leave the vehicle or they are pushed them out by the accident force. In addition, the occupants may be severely injured to the extent that they are unable to respond or they might simply refuse to respond.

3.3.3.1 Vector Space Model

The accident and severity indicators deduced from readings are illustrated in Figure 3.17 [e.g. : Vibration level, Noise level, Pressure level, Deceleration (crash ΔV), Temperature level (max 150-200^{o}C), Airbag deployment, Occupant belt usage, Principal direction of force (PDOF), Crash with multiple impacts, Rollover, Vehicle make, model and Number of occupants]. These indicators can be used in addition to the driver personal information [e.g. Age or gender] to have more realistic indication of accident severity. An example of how delta-V can be used to indicate the injury severity is discussed in [10].

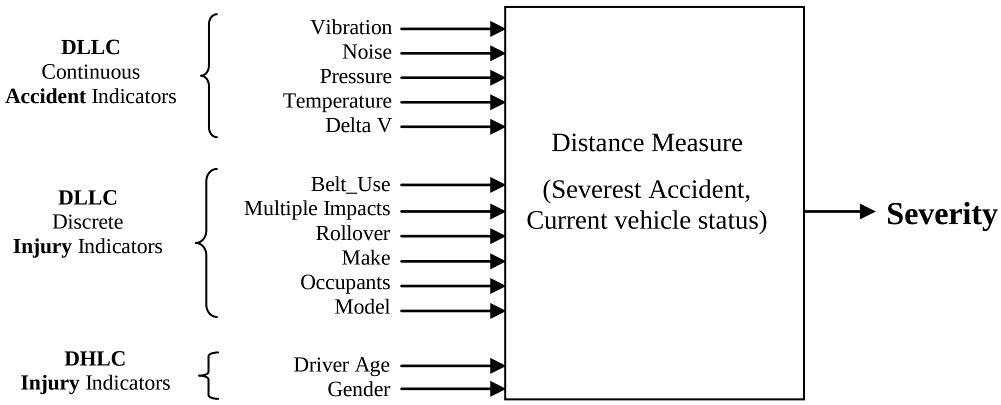


Figure 3.17: Calculating severity using *vector space model* with injury & accident indicators

3.3.3.2 Fuzzy Logic Model

With the fuzzy model increasing the number of considered variables increases the size of the problem dramatically. Therefore, decreasing the number of fuzzified variables is necessary for reducing the complexity which can only happen by increasing the level of abstraction.

To achieve this, accident indicators should pass two abstraction levels before being considered as input to the fuzzy Logic module; see Figure 3.18. The first abstraction level fuses the sensor input into 13 preliminary indicators. The second abstraction level is achieved by using the distance measures to utilize the 13 indicators, which is the output of the first stage, in deciding the injury and accident severity, which is the input to the third stage of abstraction in the severity calculation process using the *Fuzzy logic model*. The first abstraction level is done in the sensor fusion layer which is out of the scope of this work. The second abstraction level is done using the distance measuring.

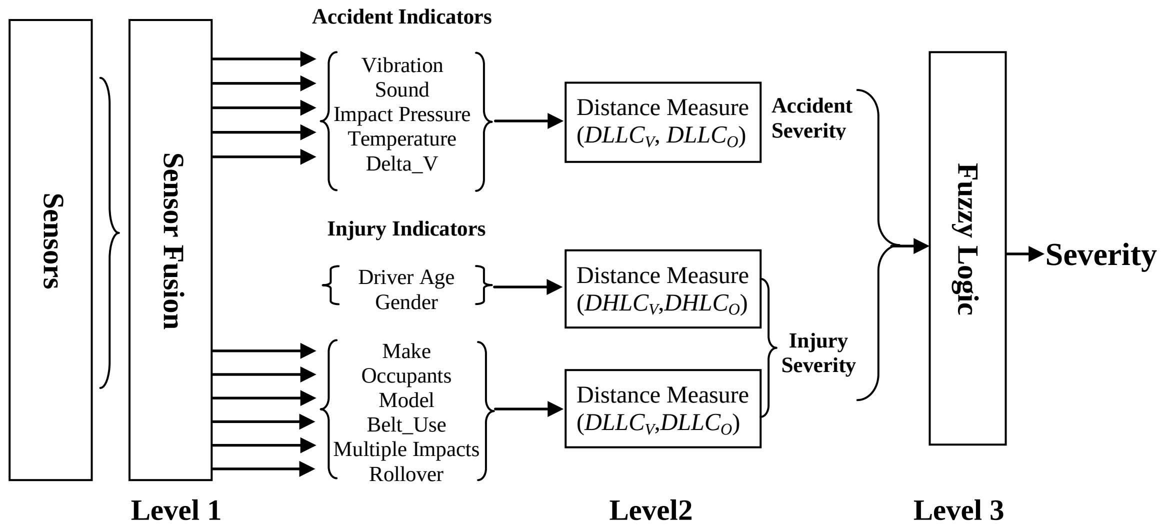


Figure 3.18: Abstraction levels for calculating severity using *fuzzy logic model* with injury and accident as input

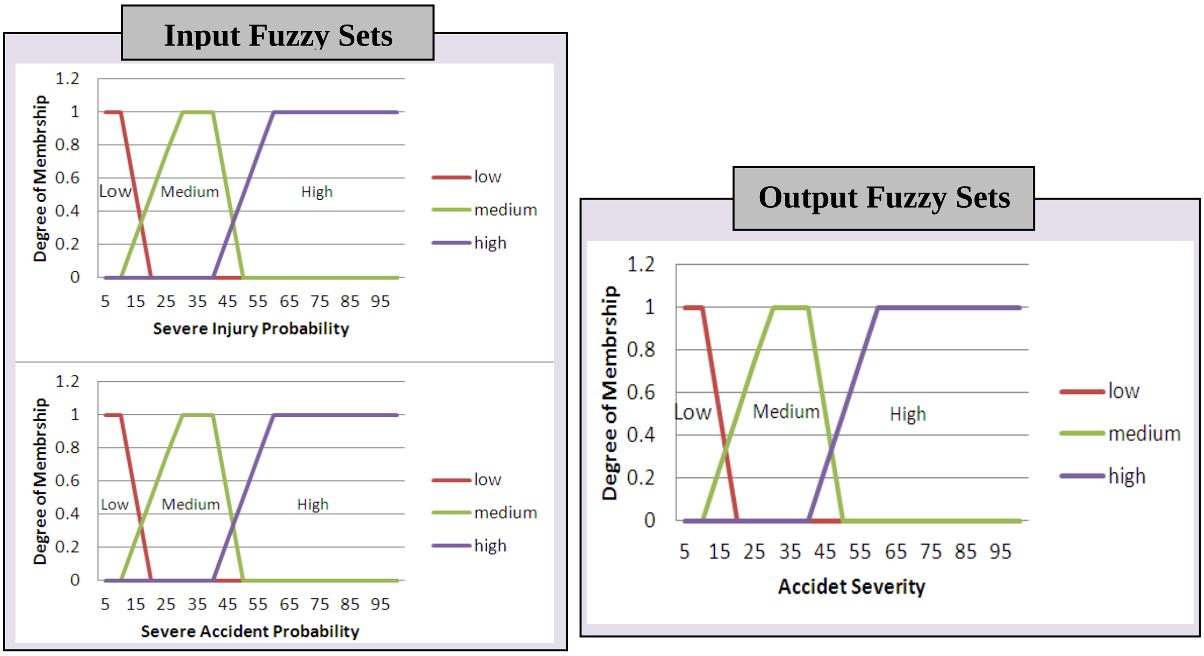
The weighted average of the distances between the accident situation vector and the accident optimal vector is calculated in a space with n dimensions that are equal to the number of considered attributes in the accident situation. These distances are normalized using the maximum range for each attribute. The steps are:

1. Calculate the distance between the current situation attribute value and the preset optimal situation value for the same attribute
2. Normalize the calculated distance using the maximum expected range for the considered attribute then scale to 100.
3. Calculate the relevance percentage of the current situation to the severest accident situation by subtracting the weighted average of the calculated attributes distances from 100. The weights used represent the importance of the attribute in accident indication.

The third abstraction level is achieved using the fuzzy logic module. The vehicle situation described by the two attribute values of the accident and injury severity are used as crisp input to the fuzzy logic system and the output is a crisp value showing the overall severity. The abstraction levels succeeded in reducing the considered variables in the fuzzy logic from many to only two. The fuzzy system rule base is shown in Table 3.4 and the input and output fuzzy sets with the defuzzification function are in Figure 3.19. The triangular and trapezoidal fuzzification functions are regularly used in most of the papers as stated in [72].

Table 3.4: Fuzzy Rule Base for the PCN

Rule#	Accident		Injury		Severity	S_H = MAX(
1:	H	AND	H	→	H	Min(HAcc, HInj)
2:	H		M		H	Min(HAcc, MInj))
	Acc		**Inj**		**S**	S_M = MAX(
3:	M	AND	L	→	M	Min(MAcc, LInj)
4:	M		H		M	Min(MAcc, HInj))
	Acc		**Inj**		**S**	S_L = MAX(
5:	L	AND	M	→	L	Min(LAcc, MInj)
6:	L		L		L	Min(LAcc, LInj))



$$Defuzzified\ Severity = \frac{(5\times S_L)+(35\times S_M)+(80\times S_H)}{5+35+80} \quad (3.13)$$

Figure 3.19: The input and output fuzzy logic sets in CRN application

3.4 Context Aware Dissemination and System Interface

The optimal goal of using the context aware layer in VANET is to achieve smart information dissemination based on the context of vehicles and services. To achieve this two communication scenarios are proposed for the services supported in VANET. For the safety services the main communication is V2V and for convenience and commercial services it is HVC which is V2I followed by V2V.

3.4.1 Dissemination

3.4.1.1 V2V Scenario

In the first scenario the convenience and safety services rely mainly on V2V. The service provider vehicle notifies the nearby vehicles of the recognized convenience providing or safety threatening situation. The notification, as in Figure 3.13, is in the form of an XML file that has the situation details (BC, degree/severity and certainty). Figure 3.20 describes two cases: the first is a case of PCN where the vehicle involved in the accident dispatches a notification file to nearby vehicles. The second is a CRN case where vehicles detecting congestion report to the central vehicle which aggregates the reported values and dispatches back the resulting aggregated congestion context, degree and certainty.

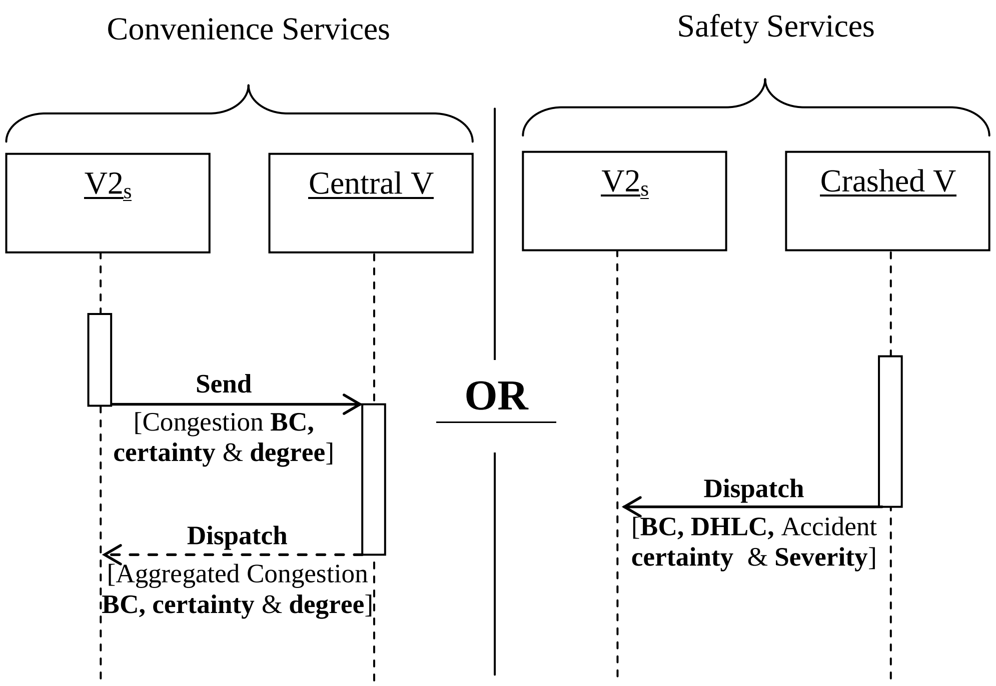


Figure 3.20: Proposed V2Vcommunication scenario for CRN and PCN Services

3.4.1.2 HVC Scenario

In the second scenario the commercial services use HVC for communication as in Figure 3.21. The service provider registers the service by sending its XML service file to the RSU. The leading vehicle uses V2I to send its BC which is used by the RSU to filter and send back relevant services. Following that V2V communication takes place to allow the leading vehicle to filter received services using the BC of the nearby vehicles and disseminate to each its relevant filtered subset of services.

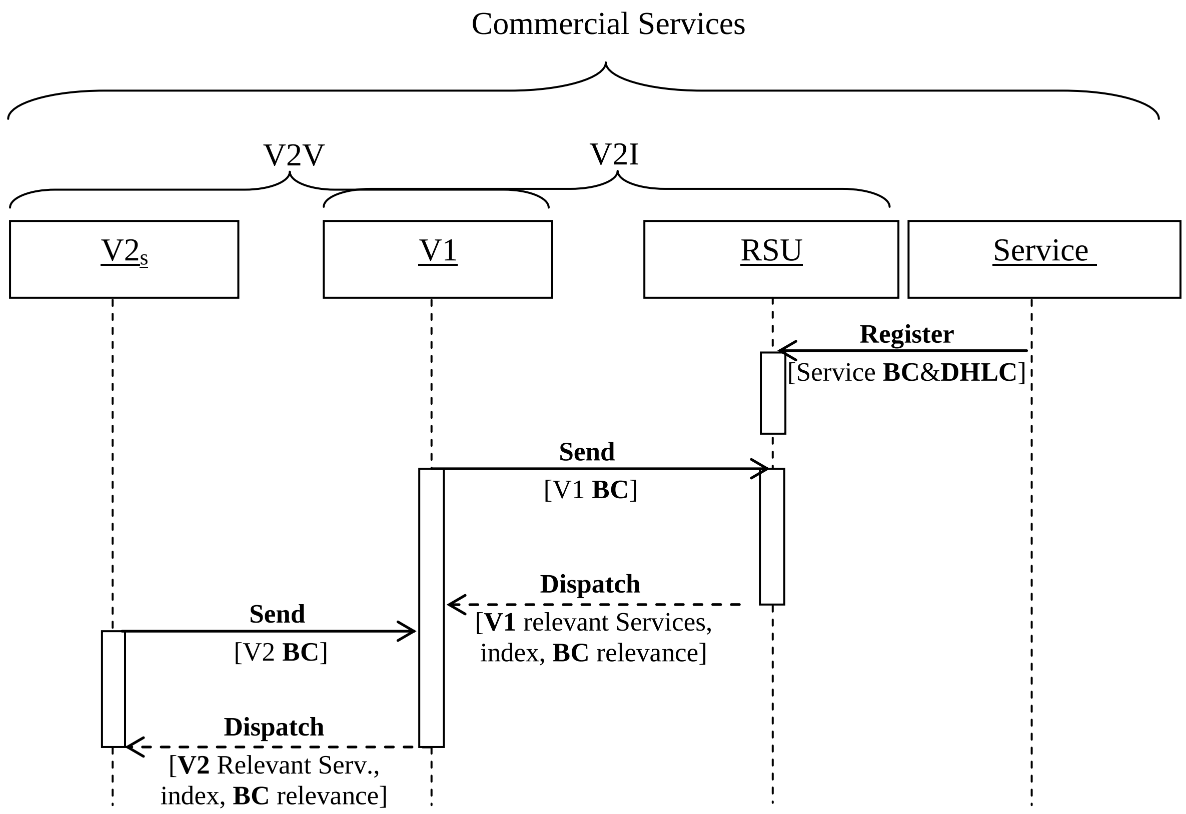


Figure 3.21: Proposed HVC communication scenario for commercial SA

3.4.2 Multimodal Interface

Unfortunately, the current crash and congestion detection systems provide low informative notifications since the severities of the detected crash or congestion incidents are not provided. Even the current IR-CAS interface appearing in Figure 4.5 shows the severity in text format which makes it very difficult for the drivers to read without being distracted from the road. In addition, the available commercial service announcement systems don't consider the interest of the user or give a binary indication of relevance to that interest which leads to either showing all the services available in the area or the ones relevant but with no ordering according to the degree of relevance to user preferences. These systems tend to overload the drivers with comprehensive unordered lists of commercial services available. Fetching the whole list to find the one that matches their interest or the one that has the highest matching rate without being distracted from the road is a very difficult task. The currently utilized interfaces for all mentioned systems are usually visual-manual interfaces that cause high level of distraction and frustration to drivers as mentioned in [73]. Having efficient, consistent and easy-to-use HCI is therefore becoming a necessity in the vehicular network with the goal of reducing distraction and enhancing safe driving [74]. The IR-CAS current interface depicted in Figure 4.5 utilizes drop down menus that are very difficult to use in the car environment therefore an alternative interface is needed. The study in [73] proved that speech-visual interfaces are the best in terms of reduction of task duration, lane deviation, eyes off road time and mental demand compared to the other types of interface. It was also mentioned that the driver focus varies according to age, driving experience, and behavior. Therefore, a user friendly multimodal HCI consistent interface should be built to help road users:

1. Have high level of safety and convenience by reducing drivers' distraction.
2. Get services customized to drivers' contexts including profiles and vehicles contexts.
3. Identify the services that best match their interest and context ordered by their degree of relevance.
4. Have on time, informative, and precise notifications of congestions and collisions with minimal distractions.
5. Have interface options adapted to match user profiles.

The following section describes alternative interface designs. Subsequent chapter overviews conducted usability tests along with a discussion of found issues and obtained results. Finally, in chapter 5 a conclusion is drawn followed by a brief on the planned future work.

3.4.2.1 Proposed Design

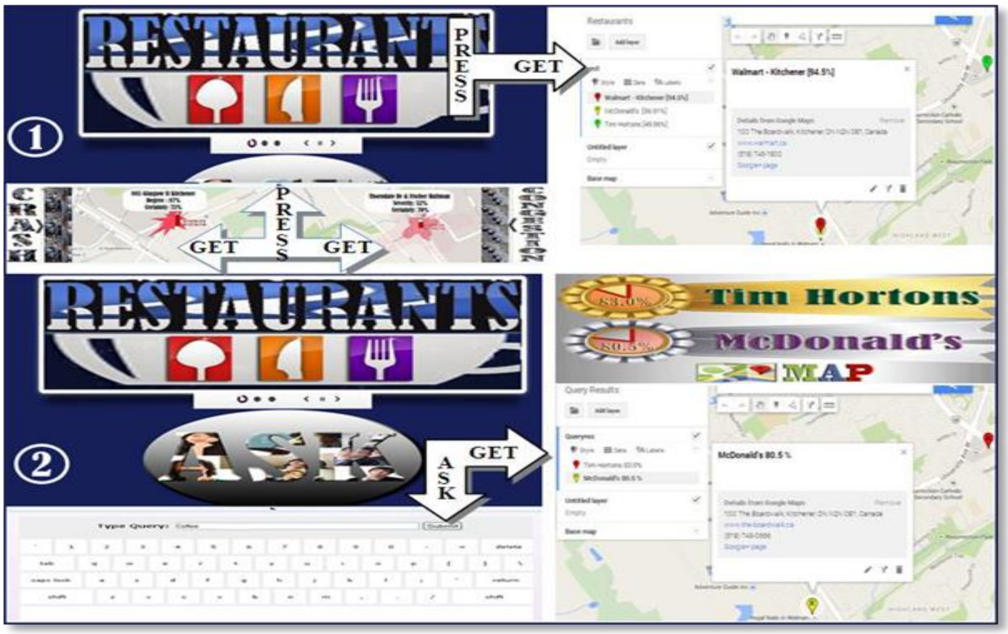


Figure 3.22: IR-CAS interface

3.4.2.1.1 Speech-Visual mode

Two interface prototypes are designed for IR-CAS systems: The first utilizes a speech–visual interface that uses vision, touch, sound, and voice modes. When a command is tapped its name is spoken to let the user press the needed option. The queries can be spoken and recognized by the system without having to type in any text. Results are read to the user using speech synthesis.

3.4.2.1.2 Visual-Manual mode

The second is a visual-manual prototype that relies on using large images for interface options that are linked to Google maps where locations of selected amenities can be found; e.g. Restaurants in Figure 3.22. The design has a large icon called ASK that is used for service querying. The congestion and crash notifications are continuously updated and can be viewed at anytime by selecting a sliding bottom bar that expands and collapses with a single touch; see Figure 3.22. The main guidelines behind the design are:

First, reduce text reading and entry by deploying images to represent the inputs and outputs; e.g. the severity numerical values are represented visually by red bars or circles where the length or area of the red sections are proportional to the values, see Figure 3.22. Second, be natural by using tapping for the traversal and touching for selection. Third, enable users to easily locate and select options blindly by having large well separated images for input. According to Fitts' Law in Equation 3.14, there is a relationship between the time taken to select an object and its size and position on screen. It states that the bigger the object and the shorter its distance from screen edges the less time it takes to select. It also recommends placing icons to the sides, bottom, top, and corners of the display to speed up their selection [75].

$$\text{Time} = a + b \log_2 (2\, D/W) \tag{3.14}$$

Where a and b are regression coefficients decided empirically, D is the distance to the center of the object and W is the width of the object [75]. According to Equation 3.14, the relationship between shape and size is represented by a curve which means that tiny increase in size for small objects makes much higher improvement to the easiness of their selection than the case of bigger objects [75]. Therefore, dividing the screen into two main sections, top and bottom, while placing large size images in each section, (top ones for service traversal & bottom one for querying), plus a bottom sliding bar with two labels pinned to bottom corners for crash or congestion notifications, as in Figure 4.20, facilitate the blind selection. Although it is argued in [76] that Fitts' law might not apply well to touchscreens, the case of blind selections using touchscreens inside the vehicles is different. The position of icons relevant to edges still matters since edges can guide drivers in placing their fingers blindly on top of the right option; see Figure 4.21.

So they can rest their four fingers over the top edge then move their thumb down a bit to choose a service. To view notifications, they just have to place their thumbs right above the bottom edge and to select the ASK icon, they stretch their thumbs a bit higher while touching the bottom border as in Figure 4.21. Finally, they can zoom into congestion notifications by holding the bottom right edge then touching the expanded map with their thumbs. For crashes they can touch the left border with their thumbs and press the expanded map with any of their other four fingers.

Chapter 4

Experiments and Analysis

The system is implemented using Java while Jena is used to manipulate the ontology. To demonstrate how IR-CAS works seven test cases are chosen. The first test case shows how the Ontology and the rule base are used to infer the near and similar service groups within varying RSU areas. The second test case shows how the HVC is used in commercial services to enhance the decentralization by reducing the reliance on the RSU; the indexing and retrieval based on user preference are also elaborated. The third test case shows how congestion is detected and reported to the vehicles using V2V communication. The fourth group of experiments tries different IR models in PCN/ACN as a sample for safety services and evaluates the results. The fifth set of experiments are for convenience services, they compare the performance of four CRN application models and assess the results. The sixth test case use the average distance measure (ADM) for evaluating the IR-CAS CRN and ACN systems against the alternative IR models using large test collections. The seventh and final test group evaluates the IR-CAS system interface using usability tests that reflect users' feedback.

4.1 Test Case1: Commercial Services - Ontology

Table 4.1: Test instances for the restaurants and the RSU nodes basic context

Node	Latitude	Longitude	Spatial Range	Time	Temporal Range
Restaurant 1	43.448335	-80.550384	20	11	11
Restaurant 2	43.442664	-80.473759	10	12	8
Restaurant 3	43.442641	-80.544891	10	6	17
Restaurant 4	43.442857	-80.54391	5	6	16
Restaurant 5	43.442793	-80.543813	4.5	6	15
Restaurant 6	43.442513	-80.473738	8	12	10
Restaurant 7	43.448183	-80.550041	20	11	11
Restaurant 8	43.442513	-80.473738	7	11	10.5
Restaurant 9	43.442857	-80.54391	20	6	8
RSU1	43.447743	-80.549649	0.5	N/A	N/A
RSU2	43.442660	-80.473490	0.5	N/A	N/A
RSU3	43.443196	-80.543794	0.7	N/A	N/A

In this section the test instances in Table 4.1 and shown in Figure 4.1 are used to test the ability to infer the RSU similar and near service groups using the Jena reasoner over the knowledge base saved in the ontology and the rule base saved in a separate file for scalability. The results obtained in Figures 4.2 and 4.3 can be analyzed as follows:

1. Restaurants 9 and 4 are in the same location but have different opening time and duration so they are near but not similar.
2. Although Restaurant 3 is near to 4, it is not similar to 4 in the opening time and duration therefore it can’t be included in the same group of Restaurants 4.
3. Restaurants 6 and 2 are not in the same group, so despite the fact that they are near they are dissimilar and hence can’t be in the same group.
4. All the three RSU groups are far apart by a distance that is greater than the preset nearness range, which is assumed to be 500 meters in this experiment, and that is why their services aren’t sharing any groups.

- **Test input**

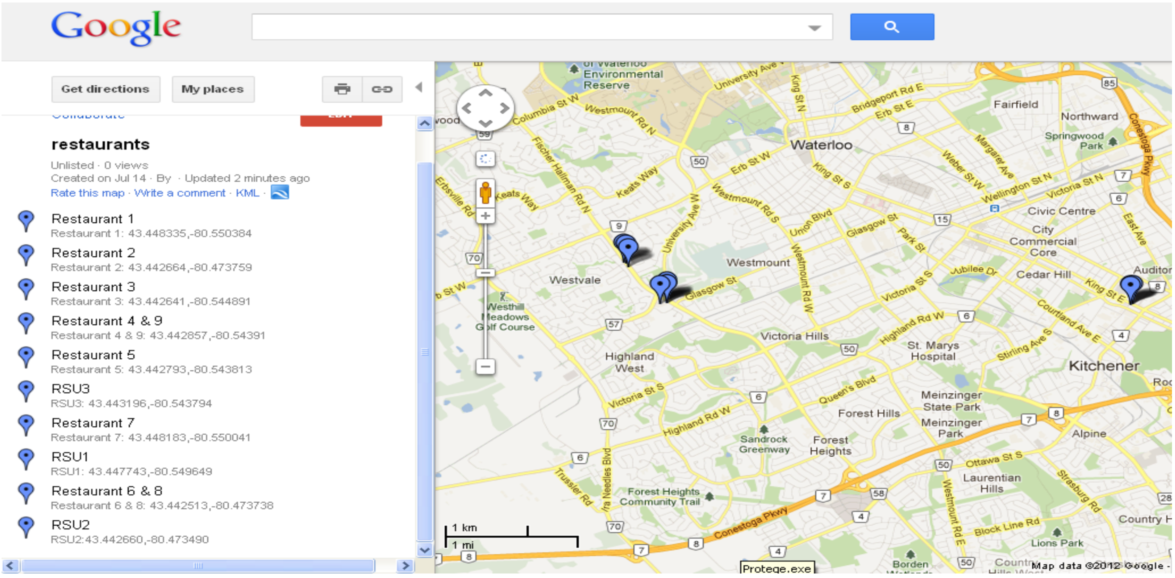


Figure 4.1: Google map locations for the restaurants and RSU test instances

- **Result**

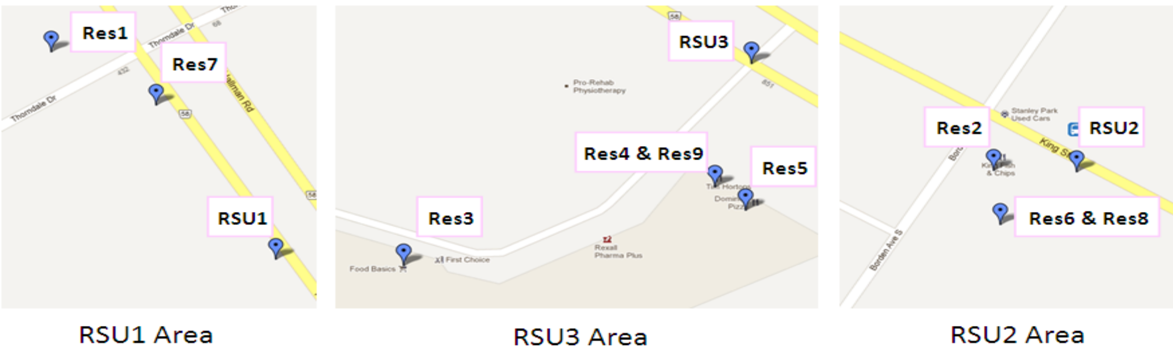


Figure 4.2: The inferred RSU areas and their near and similar services

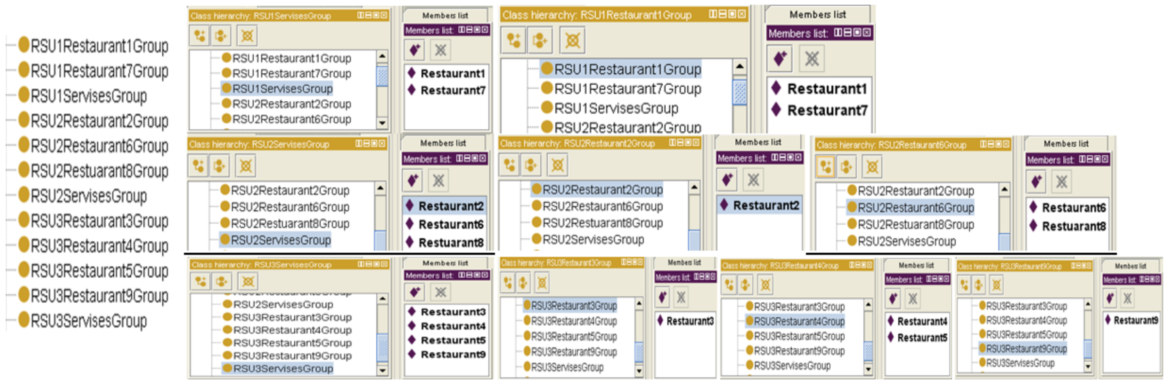


Figure 4.3: The Protégé inferred classes and their instances

4.2 Test Case 2: Commercial Services - HVC in SA

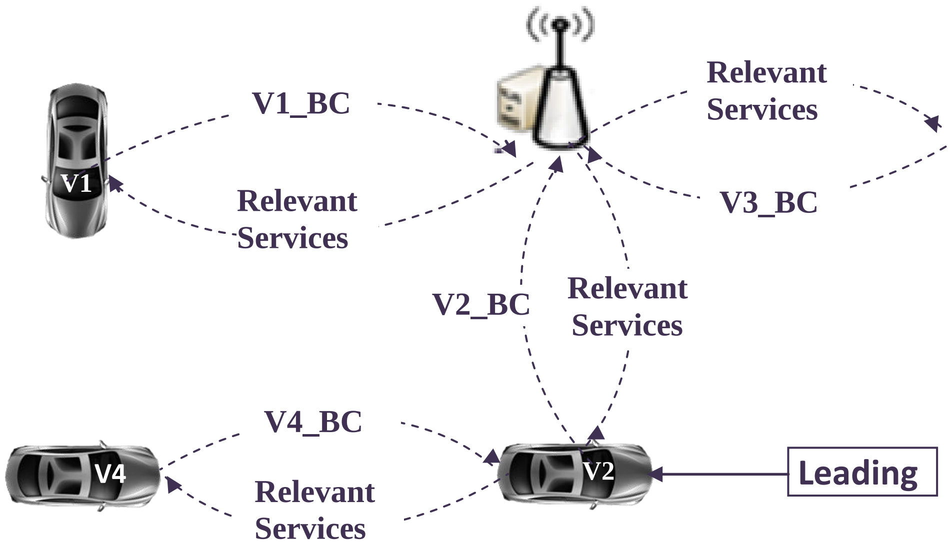


Figure 4.4: HVC test: leading vehicle V2 uses **V2I** to get commercial services then **V2V** to dispatch

V2I: Five XML service files are created and the ontology is populated with their basic contexts that appear in Table 4.2. The consistency is checked using the *Pellet* reasoner that is used with Jena. Four vehicles are considered for testing and the context of the main two vehicles appear in Table 4.3.

Table 4.2: *BC* for commercial services test instances

BC	Restuarant1	Restuarant2	Restuarant3	Restuarant4	Shopping1
Time	11:00	12:00	6:00	6:00	9:00
Location	43.448,-80.549	+43.442,-80.473	+43.442,-80.544	+43.442,-80.544	+43.433,-80.555
Temporal range	11 hr ,0 min	8 hr ,0 min	17 hr ,0 min	16 hr ,0 min	16 hr ,0 min
Range	20 Km	10 km	1 Km	1 Km	6 Km
Key Words	*Restaurant, Pizza, pasta, Italian*	*Restaurant, fish, seafood*	*Restaurant, coffee, Donuts*	*Restaurant, Burger, Salad*	*Shopping, food, toys*

Table 4.3: *BC* for V2 and V4 test vehicles

BC	V2	V4
Time	9:00	9:00
Location	+43.448411, -80.549928	+43.437978, -80.555717
Range	120 Km/hr	130 Km/hr
Key Words	*Restaurant, shopping, hotel*	*Fuel Station, shopping, hotel*

After submitting V2 *BC* to the RSU, the relevant services are dispatches back to V2. The three services available to V2 after the dispatch are shaded in Table 4.2. When Show Commercial Services option is chosen, the services presented to V2 are sorted in descending order according to their relevance to the vehicle *BC* and *DHLC* as can be seen in Figure 4.5.

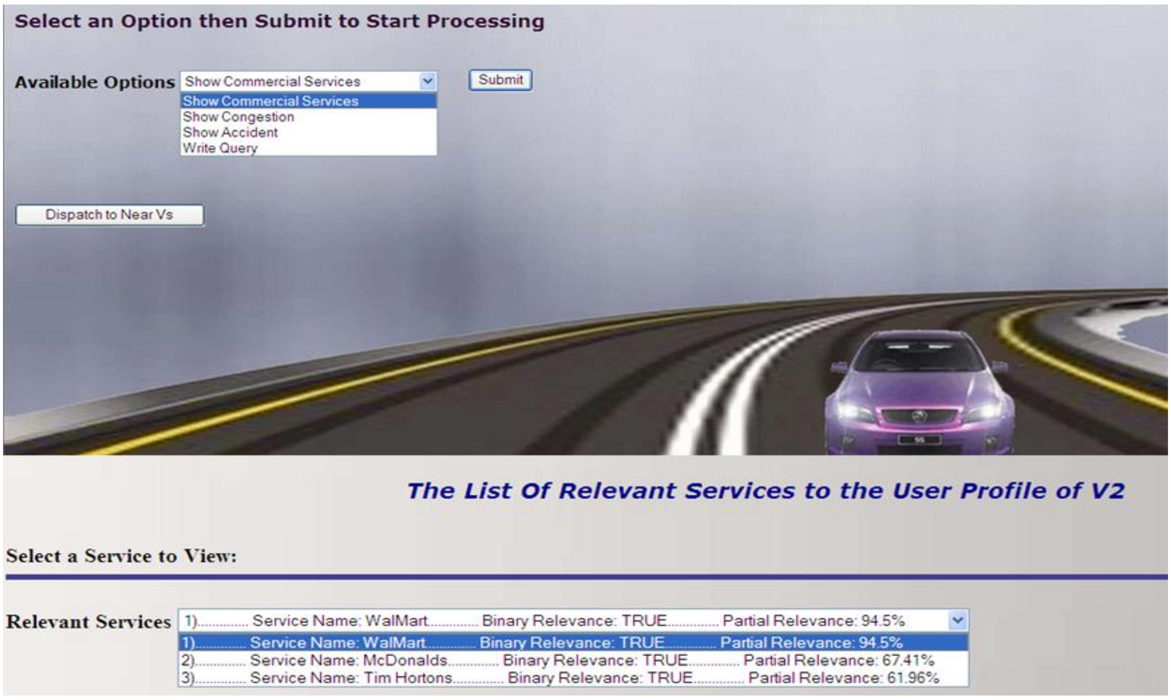


Figure 4.5: Dispatched services ranked by *BC* & *DHLC* relevance to V2

Now the user can write text queries and get a list of relevant services arranged by partial relevance. As can be seen in Figure 4.6, the partial relevance is more informative than the binary relevance. The partial relevance is calculated in two ways: the overlap score measure using Function 3.5 and the vector space model using Function 3.6.

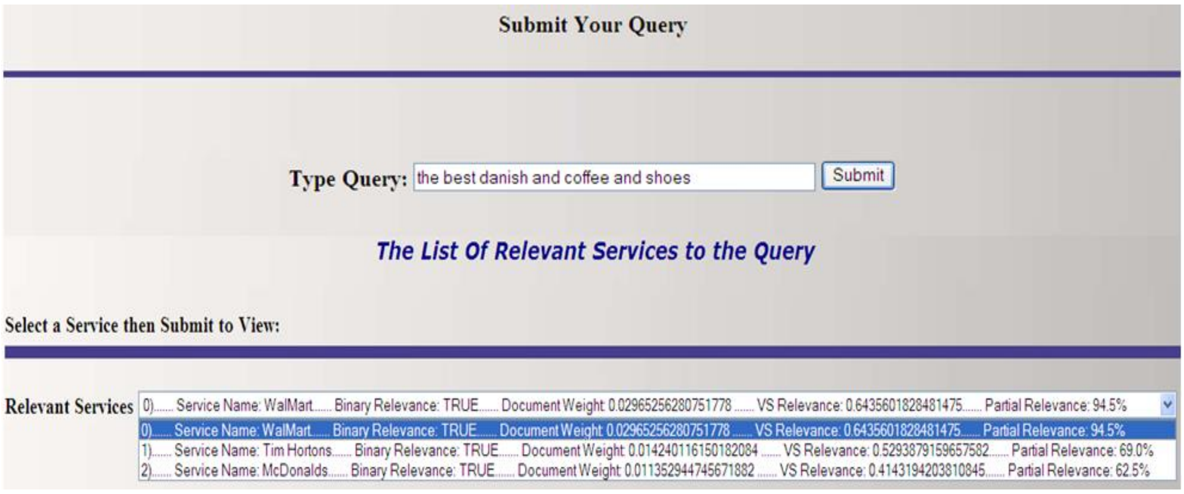


Figure 4.6: Retrieved subset of commercial services dispatched to V2 ranked by their description relevance to V2 user query

The vector space model seems to perform better when services with highly varied description lengths are considered, while the binary method failes to distinguish the services according to their degree of relevance.

- ***IR performance***

The Spearman's Rank Correlation Coefficient explained in [27] is used to evaluate the information retrieval performance. This performance measure compares rank correlations and gives a degree from -1.0 to +1.0 of association between ranks x_i *and* y_i using Equation 4.1.

$$\rho = 1 - \frac{6\sum(x_i - y_i)^2}{N(N^2-1)} \qquad \begin{cases} + & \text{Positive association (best case)} \\ - & \text{Negative or inverse association} \\ 0.0 & \text{Independent ranks} \end{cases} \tag{4.1}$$

Where ***N*** is the total number of documents, x_i represents the user ranking and y_i is the IR ranking. When this performance measure is used to check the performance of the proposed IR ranking as in Table 4.4, the resulting coefficient value was: ρ = 1 - 12/24 = + 0.5 , which means that both ranks are positively associated.

Table 4.4: Distance calculation between user and IR rank for Query: "*Best Danish, coffee and shoes*"

Services	User Rank x_i	IR Rank y_i	$(x_i - y_i)$	$(x_i - y_i)^2$
WalMart	1	1	0	0
TimHotons	3	2	1	1
McDonalds	2	3	-1	1

Table 4.5: The *DHLC* for the commercial services dispatched to V2

DHLC	Restaurant3.xml	Restaurant4.xml	Shopping1.xml
Service Name	Tim Hortons	McDonalds	WalMart
Highest Price	10	50	20
Lowest Price	1	5	10
Contact	(519)570-9181 851 Fischer-Hallman Kitchener, ON, N2M5N8	(519)571-1952 300 Highland Rd W Kitchener, ON, N2M5R2	(519)745-1800, 100 The Boardwalk, Kitchener, ON, N2N0B1
Type	dine in, takeaway	Takeaway, dine In, delivery	Superstore
Items	coffee, Donuts, Sandwiches, soup	Burger, salad	clothes, food, toys
Description	*Offers a wide selection of Always Fresh products. Specializing in Baked goods & Soups and Sandwiches & our Famous Coffee...etc*	*Menu includes Sandwiches, Hamburger ,Cheese burger, Double Cheeseburger , Quarter Pounder, Quarter Pounder with Cheese, Double Quarter...etc*	*From jeans & skirts to maternity and plus-sized, you'll find all the apparel you need for the entire family...etc*

V2I: V2 is considered the service leader for the dispatched services appearing in Table 4.5. When V4 enters the zone, V2 has to filter and dispatch to V4 the services that match its spatial context along with their index and *BC* relevance. As can be deduced from the *BC* of V4 and the *BC* of the services available to V2, see Table 4.3 and Table 4.2, the matching service is *Shopping1* which happens to be WalMart; see Table 4.5. WalMart XML file, index file as well as its *BC* relevance are dispatched to V4 as in Figure 4.7.

Dispatched files to V2	Value	Relevance
Service file1	C:\Srv\filestodispatchtoVs\Shopping1.xml	92.0%
Index file	C:\filestodispatch\toV2 \indexfiles.txt	

Figure 4.7: Files dispatched to V4 by V2

- ***Decentralization***

The performance measure described in Equation 4.2 is used to calculate the proposed solution *degree of decentralization*; with 1 as the best decentralization value and zero as the worst value. Assuming that V2 and V4 are the only vehicles in the zone receiving commercial service announcements (*SA*), then using Equation 4.2 the resulting decentralization value is: ***Decentralization*** = 1- (1/2) = **+0.5**, which is a **50%** improvement over the original case where both V4 and V2 have to connect to the RSU to get services of interest which has a decentralization value of **0**.

$$Decentralization = 1 - \frac{Number\ of\ V2I\ msgs}{Number\ of\ Vs\ getting\ SA\ in\ Zone} \begin{cases} \mathbf{+1} & \text{Best value} \\ \mathbf{0} & \text{Worst value} \end{cases} \qquad (4.2)$$

4.3 Test Case 3: Convenience Services - V2V in CRN

The second scenario shows how V2V communication is used in the Congested Road Notification (CRN) service. Four vehicles are assumed to be in the zone, V1...V4 as shown in Figure 4.8, where V4 is assumed to be the central vehicle. The non-central vehicles detect congestion situation independently and each vehicle calculates the severity internally as in Figure 4.8. All three vehicles then report the detected congestion details to V4. Finally, V4 aggregates the results and dispatches the aggregation to other vehicles within the zone, as in Table 4.6.

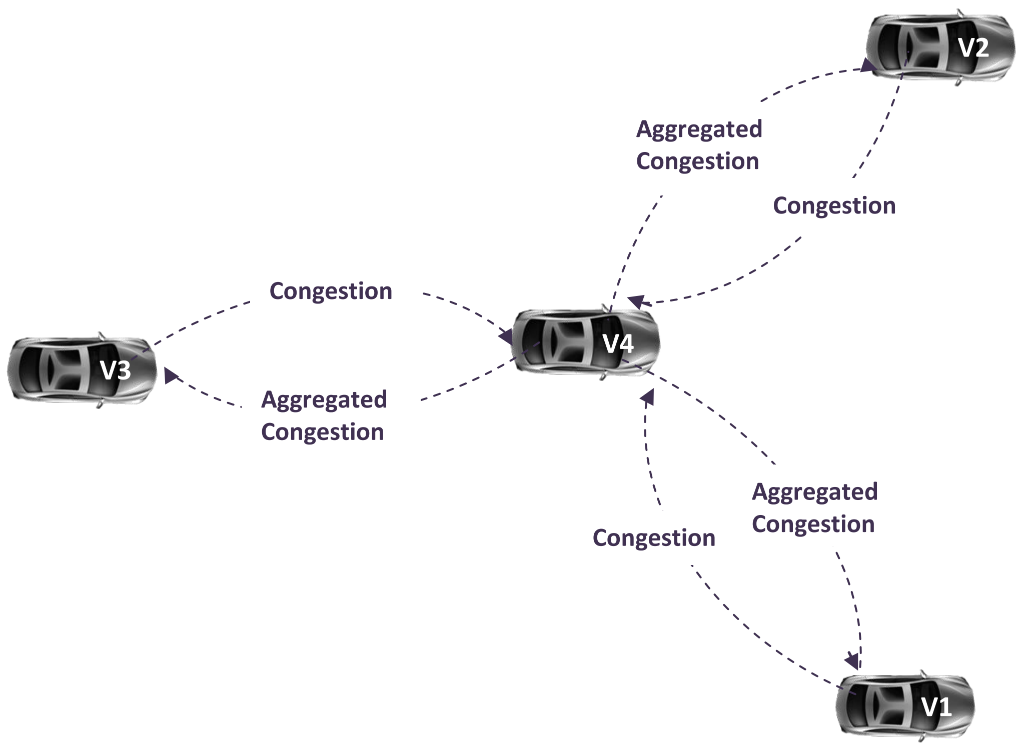


Figure 4.8: V2V test case: Central vehicle V4 aggregates V1...V3 congestion reports & dispatches the aggregated report

The uniqueness of the work comes from the fact that IR-CAS not only calculates the severity of the congestion but also finds the certainty of the detected situation as in Figure 4.9. It can be seen that the partial relevance is more informative than the binary relevance used in most regular situation detection algorithms.

Table 4.6: Congestion DLLC reported by zone Vs (V1..V3) & aggregated by central V (V4)

Name	V1	V2	V3	V4 aggregation
Time	9:02 am	9:00 am	9:05 am	9:02 am
Location	43.4484,-80.5499	43.4484,-80.5499	43.4484,-80.5499	43.4484,-80.5499
Range	100 m	100 m	100 m	100 m
Duration	5 min	5 min	5 min	5 min
Degree	49.1%	78.1%	30.1%	52.0%
Certainty	40.0%	49.0%	60.0%	49.0%
Binary degree	FALSE	TRUE	FALSE	FALSE

In IR-CAS, each vehicle has two modes, one executes when the vehicle is a central vehicle which means that its longitude and latitude are within the centre of the zone and the other mode activates when the vehicle is outside the central range of the zone. Figure 4.9 shows a drop down menu listing the two mode options; choosing the "Receiving Vehicle" option dispatches only the congestion file without aggregation. When the "Central Vehicle" option is chosen the aggregated congestion XML file is dispatched to the non-central vehicles. The file has the congestion details and its severity. The congestion location can also be viewed using Google map.

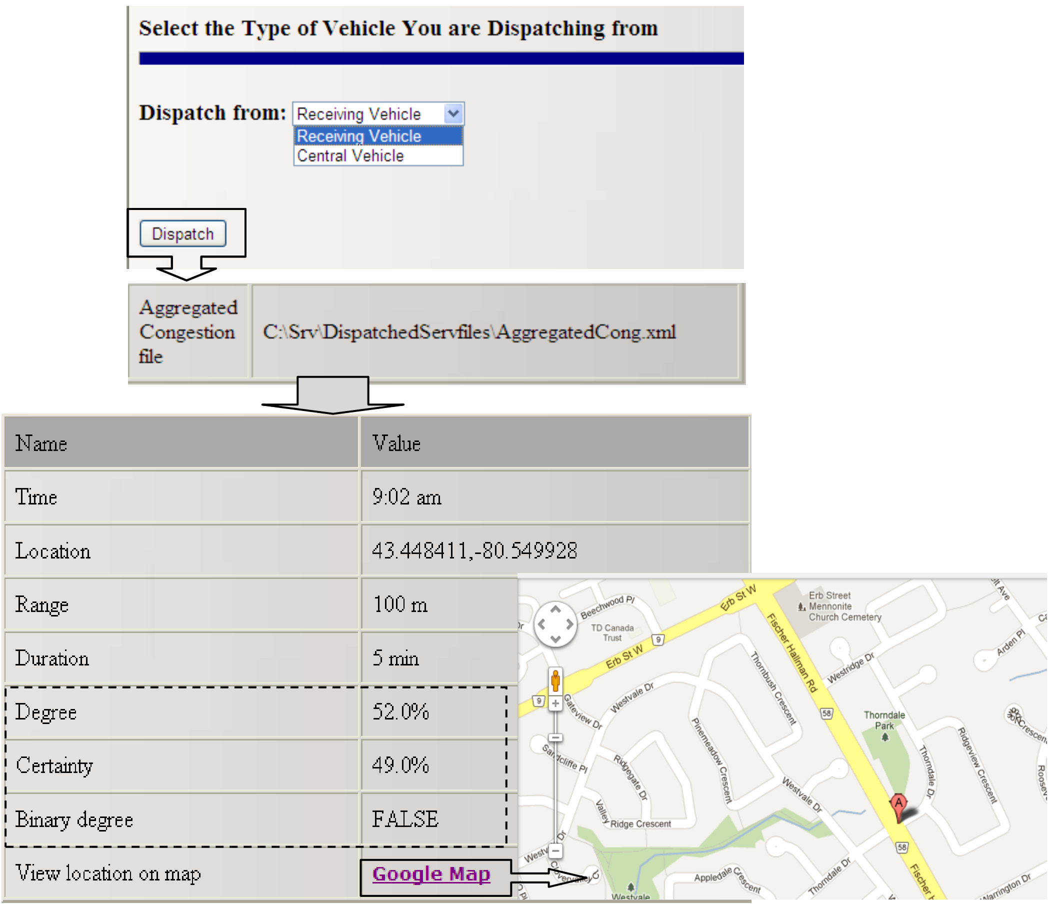


Figure 4.9: Aggregated congestion file with central location on Google map

4.4 Test Case 4: Safety Services - IR Models in PCN/AACN

A. Correlation Experiment

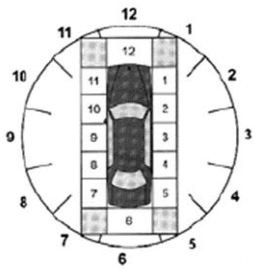
This experiment is conducted to find out if there is a correlation between the accident severity level calculated by the Manhattan distance on one hand and the learned function by George Bahouth [53], see chapter 2, on the other. To have real life data, the test records are extracted from the Fatality Analysis Reporting System (FARS) which is considered the most referenced source for U.S. fatal crash data for over thirty years [77]. The experiment considers 39 randomly chosen crashes part of them is in Table 4.7 with the considered crash indicators. A detailed example of distance and relevance calculation between the severest accident (SA) and the first crash case appearing in Table 4.7 is found in Table 4.8.

Table 4.7: Test collection from FARS 2010 [http://www-fars.nhtsa.dot.gov/ 2010]

Seating Position	Age	Belt Use	Sex	Initial Impact	Damaged Impact	Fire	Occupants	Rollover	Travel Speed	Make	Model	Speed Limit	Injury Severity
11	26	7	1	11	12	0	1	1	65	20	2008	45	4
11	51	7	2	12	12	0	1	0	55	20	2004	55	4
11	21	7	1	2	2	0	2	0	55	37	2003	55	4
11	31	3	1	12	12	0	1	0	10	35	2005	55	3
11	75	7	1	12	12	0	2	1	45	49	2000	55	4
11	37	3	1	1	12	0	2	1	55	55	2007	35	4
:	:	:	:	:	:	:	:	:	:	:	:	:	:
Severest Accident record	55	0	2	Initial Impact ≠ Damaged Impact Multiple Impact = 1		1	5	1	≥55	0	Crash year -14 = 1996	55	4

Impact point	Impact side
2,3,4	Far side impacts
11, 12,1	Frontal side impact
8,9,10	Near side impact
IS	KABCO
0	No injury (0)
1	possible injury (C)
2	Nonincapacitating Injury(B)
3	Incapacitating Injury (A)
4	Fatal Injury(K)
MK	
12	Ford
20	Chevrolet
37	Honda
Sex	
1	Male
2	Female

Principal Direction of Force (PDOF)



Seating Positions

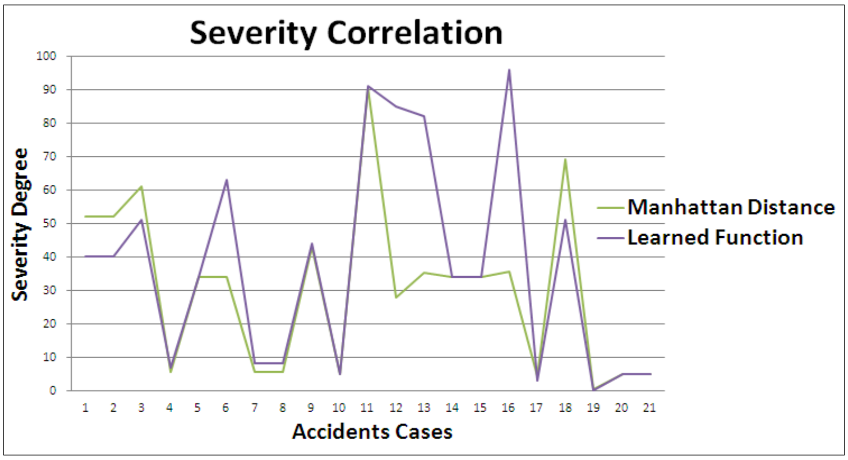


Figure 4.10: The positive correlation between the Manhattan distance measures and the URGENY algorithm

Table 4.8: Relevance of cases 1 & SA in Table 4.7

	Indicators [Long form in Table 4.7]						**Weighted Average WA**
Crash Indicators	**Belt Use**	**Sex**	**Multiple Impact**	**Fire**	**Rollover**	**Make**	
SA-Crash	**0- Belt Use**	**2-Sex**	**1- Multiple Impact**	**1- Fire**	**1- Rollover**	**Make-0**	**0.223272727** **0 Indicators-Z**
Result	**0**	1	**0**	1	**0**	**0**	**5**
Crash Indicators	**Age**		**Occupants**	**Travel Speed**		**Model**	**Distance WA/Z**
SA-Crash	**(55- Age)/55**		**(5 - Occupants) /5**	**(Speed Limit – Travel Speed) / Speed Limit**		**(1996-Model) /14**	**0.044654545** **Relevance 1–D**
Result	0.53		0.80	**0.00**		0.86	**0.955345455**

Based on crash records in [77] for years [1994-2012], descending weights are given to restrain system use, make, speed, gender, and age respectively. Distances are normalized to 1 via dividing by the largest distance if it is not equal to 1. It has to be noted that:

a. The distance is 0 for ages above 55 or when TS>SL.
b. The multiple impacts value is 1 if the initial impact is different from the damaged one and 0 otherwise.
c. BU is 1 if the restrain system use is 3 else is 0.
d. The distance is penalized by dividing it by the number of zero indicators if that number exceeds 4.
e. The worst model is 14 years older than crash year.
f. MK is 1 if it is in the safest to ride set, 0 otherwise.

As can be visually indicated from Figure 4.10 the two methods are positively correlated with low level of under estimation in magnitude for some cases while in most cases the Manhattan distance is very close in magnitude to the learned function. This learned function is found based on accidents with severity degrees 3 and 4. The factors considered by this learned function are only the rollover, speed, belt use and impacts. More factors like Driver Age, Make, Model, Gender and Number of Occupants should be added to refine the predicted severity.

B. Relevance models correlation and performance using binary metrics when 13 severity indicators are considered

Figure 4.11 shows that the prediction of the learned function matched the prediction of the Manhattan distance, recommended by the previous experiment, for eleven randomly chosen accident incidents shown partly in Table 4.7 with injury degree 3 and above. The factors considered initially are the same four attributes considered by the learned function then a generalization to all the severity indicators is done and the same results are obtained after applying the same binary effectiveness metrics to the eleven test cases.

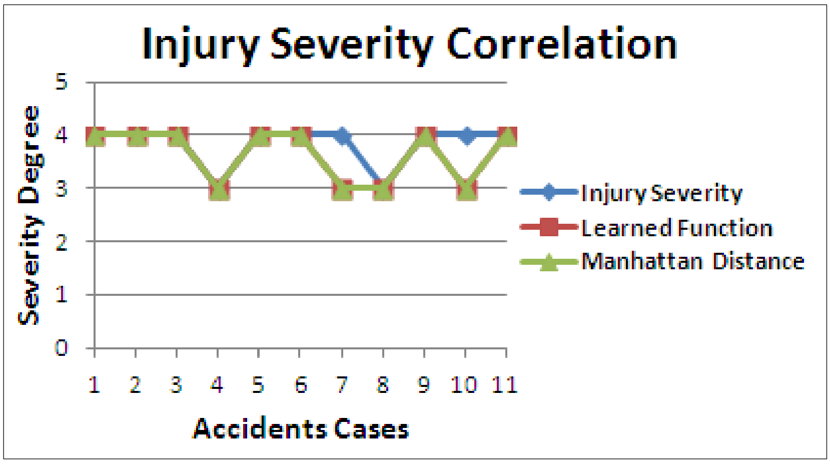


Figure 4.11: Injury severity [MAIS 3+] correlation with the Manhattan measure & learned function

Table 4.9: The number of predicted and actual injury cases with degrees 3 and 4

<table>
<tr><td rowspan="2"></td><td colspan="3">Predicted</td><td rowspan="2"></td><td colspan="5">Predicted</td></tr>
<tr><td></td><td>4</td><td>3</td><td></td><td colspan="2">4</td><td colspan="2">3</td></tr>
<tr><td rowspan="2">Actual</td><td>4</td><td>7</td><td>2</td><td rowspan="2">Actual</td><td>4</td><td>T +ve 4</td><td>T -ve 3</td><td>F -ve 4</td><td>F +ve 3</td></tr>
<tr><td>3</td><td>0</td><td>2</td><td>3</td><td>F +ve 4</td><td>F -ve 3</td><td>T +ve 3</td><td>T -ve 4</td></tr>
</table>

Table 4.10: Effectiveness measures for the Manhattan distance and the learned function

	Manhattan distance/ Learned function		
	3	4	Average
Accuracy	0.818182		
Precision	**0.5**	**1**	0.75
Recall	**1**	**0.777778**	0.888889
***F*-measure**	**0.666667**	**0.875**	**0.770833**
F_2-measure	**0.8333**	**0.81395**	**0.823625**

Precision = True positives / (True positives + False positives) (4.3)

Recall = True positives / (True positives + False negatives) (4.4)

Accuracy = True positive/ Total (4.5)

If we apply Equations 4.3, 4.4, and 4.5 to Table 4.9 we get the results in Table 4.10. The details of the calculations are as follows:

- *P*(*injury degree 3*) =2/(2+2)=0.5, *R*(*injury degree 3*)= 2/(2+0)=1
- *P*(*injury degree 4*) =7/(7+0)=1, *R*(*injury degree 4*)= 7/(7+2)= 7/9 = 0.777778
- Accuracy = 9/11 =0.818182

If we calculate the *F*-measure to have one value summarizing the recall and precision values by substituting the R and P in the equation in Table A.3 we get:

- $F(injury\ degree\ 3) = \frac{2(1*0.5)}{1+0.5} = 0.666667,$
- $F(injury\ degree\ 4) = \frac{2(0.777778*1)}{0.777778+1} = 0.875$

It has to be noted that the *Recall* measure is very important since, as mentioned in Table A.3, it is related to false negatives. In the ACN application it is important to report all severe accidents, missing a case may cause a life loss. Precision takes the second place but it is still important so that the time and effort of any rescue team are not wasted. Therefore, more attention should be given to recall over precision. To put more emphasis on recall the F_2 measure can be used as illustrated in Table A.3 by substituting values of R and P as follows:

- $F_2(injury\ degree\ 3) = (1+2^2)\frac{(1*0.5)}{2^2*0.5+1} = 0.8333$
- $F_2(injury\ \ degree\ 4) = (1+2^2)\frac{(0.777778*1)}{2^2*1+0.777778} = 0.81395$

This is an example of IR-model evaluation using real life test cases with recorded results using various effectiveness measures. It shows the high recall value of the Manhattan distance measure suggested by the first experiment. To enhance the validity of these results the non-binary test measures and a larger test sample are tried in the following experiments.

C. Finding the effectiveness of the accident severity prediction with all four severity degrees 1 to 4

The Spearman's rank correlation coefficient is calculated using 90 actual accidents used as test cases. The correlation is computed between the calculated severity using the Manhattan distance and the actual recorded severity for accidents with severity degrees 0 to 4. The *resulting correlation is +0.999349714* which is a very high correlation value between the predicted and the actual severity.

Table 4.11: Spearman's rank correlation for the Manhattan distance function & actual injury

$6^* \sum (x-y)^2$	$n(n^2-1)$	$P=1-6^* \sum (x-y)^2/n\ (n^2-1)$
474	728910	**+0.999349714**

D. IR models performance [136,709 test cases are considered with 5 seating positions]

Using non-binary performance measures with a larger test collection is recommended to confirm the previous test results. Therefore, the Spearman's correlation coefficient explained in Table A.3 is used in this experiment along with the accuracy binary measure with a larger test collection extracted from 19 years of raw FARS crash records [1994-2012]. In this experiment 136,709 cases are considered which resulted from filtering the collection to include cases with 3 or 4 injury degrees occurring to candidates while occupying one of 5 seating positions; 2 front and 3 back seats as illustrated in Table 4.7. The significance of the seating position comes from the reliance of the URGENCY algorithm on the most damaged side location relevance (whether far, near or frontal) to the position of the seat occupied by the injured candidate at the time of crash. With large test set it is decided to penalize the Manhattan distance by dividing it by the number of attributes that reached the extreme accident vector values as detailed in Table 4.8 to enhance its performance. Table 4.12 shows the 4 tested models averaged performances with emphasis on severe crashes.

Table 4.12: IR-CAS ACN & models evaluation with n=136,709 crashes [5seat positions]

Model	Accuracy	$\sum(x-y)^2$	$S=1-6^*\sum (x-y)^2/n(n^2-1)$	Precision	Recall	F	F2
Manhattan distance	**0.7**	46028	0.999999999**892**	0.7	0.7	0.7	0.7
URGENCY algorithm	**0.6**	53191	0.999999999**875**	0.6	0.6	0.6	0.6
Fuzzy	**0.5**	63282	0.999999999**851**	0.6	0.6	0.6	0.6
Binary	**0.5**	293152	0.999999999**312**	0.5	0.6	0.6	0.6

The resulting correlation of the Manhattan distance is still very high with large test collections. The rank represents the severity since the similarity is between the current set of accident documents and the severest accident document.

Having an accident wrongly ranked means it is ranked in degree 4 while its actual severity is 3 or vise versa. Surpassing the URGENCY algorithm by thousands of right estimations using such a simple function as the Manhattan distance is a feat in itself. Since severity is continuous, a threshold should be decided for transferring it to either injury level 3 or 4. It is worth mentioning that although using a percentage value is more informative when compared to only using the 0 to 4 scale for injury severity, scaling the calculated injury level according to the 0-4 scale is necessary since the real records used as bench marks are using the 0-4 or the KABCO system as in [78]; see Table 4.7. In these experiments only cases with severities 3 or 4 are considered with the threshold decided depending on the model; if the injury severity is above this threshold it is given the rank 4 otherwise it is given the rank 3. The disadvantage of using the 0-4 scale is that if a threshold of say 60% is decided, the scale doesn't differentiate between the 90% severity and the 60% severity. An alert message with a 90% versus 60% severity may increase the rescue urgency of the rescue team and surrounding vehicles even though both cases are classified as injury degree 4 using KABCO. Hence the severity continuous values are more informative than the 0-4 scale.

E. IR models performance [295,862 cases are considered with all seating positions]

The accuracy, precision, recall, *F*-measures and Spearman's rank correlation coefficient are calculated for three models using all crashes of years 1994 to 2012. All accident records with severity degrees 3 or 4 were considered regardless of candidates seating position. The correlation of predicted severity of the vector space, fuzzy, and binary models with actual recorded severities of 295,862 crashes is compared in Table 4.13 with prediction accuracy. The table also shows averaged values of binary measures with emphasis on severe crashes.

Table 4.13: IR-CAS ACN & models evaluation with n=295,862 crashes [all seat positions]

Model	Accuracy	Mismatches	Correlation	Precision	Recall	F	F2
Vector Space (Manhattan distance)	**0.7**	101474	0.999999999**976**	**0.6**	**0.7**	**0.7**	**0.7**
Binary	**0.6**	128602	0.999999999**797**	**0.5**	**0.6**	**0.6**	**0.6**
Fuzzy Logic	**0.4**	172815	0.999999999**960**	**0.6**	**0.4**	**0.4**	**0.4**

Results in Table 4.13 show that the vector space with the Manhattan distance measure performs better compared to the binary and fuzzy models. It continues to perform better even with large data sets. Despite the close correlation, the aim is not to beat the record as much as reaching comparable performance with simpler formula as the Manhattan distance. So having equal or even slightly better performance is very significant.

4.5 Test Case 5: Convenience Services - IR Models in CRN

For IR-CAS CRN application, the focus is on the effectiveness of the severity calculation method of the vehicle in the aggregation mode. After receiving the locally estimated congestion of zone vehicles, the zone central vehicle aggregates the results by calculating their mean values. It calculates the average speed and density of the zone and then measures the Manhattan distance between the current context vector with its average speed and density attributes and the jam speed and jam density attributes of the severest congestion context vector. More focus is given here to the effectiveness of the method used to calculate the congestion severity inside the central vehicle. The files that represent the context vectors for the congestion situation are demonstrated in Figure 3.13.

A. Manhattan Distance with Rural Freeways

The test collection for rural areas with 255,530 records is used to test the performance of the vector space model with the Manhattan distance measure. The results of the experiment are summarized in Table 4.14. As can be seen the system showed high performance when tested with binary as well as non-binary performance measure. The results are nearly 100% correlated with the HCM actual LOS values while maintaining a 95% accuracy level. The precision and recall levels reach 100% with severe congestion cases while the F-measure achieves an overall average of 93%.

Table 4.14: Manhattan Distance Performance using Rural Freeways Test Records

Rural							
Non binary measure							
Spearman Coefficient	**0.999999999995506**						
Binary Measures							
Congestion Level	**1st A**	**2nd B**	**3rd C**	**4th D**	**5th E**	**6th F**	**AVG**
Accuracy	**0.951099718**						
Precision	0.99	0.92	0.91	0.88	0.85	**1**	**0.92**
Recall	0.97	0.95	0.90	0.80	0.96	**1**	**0.93**
F-measure	0.98	0.93	0.90	0.84	0.90	**1**	**0.93**
F_2-measure	0.98	0.94	0.90	0.82	0.94	**1**	**0.93**

B. Fuzzy, Binary and Vector Space Models

The test collection for rural and urban freeways with 512,983 records is used to compare the performance of the vector space model with the Manhattan distance measure against the fuzzy logic model used in the CoTEC system and the binary model explained in section 3. The experiment results are summarized in Table 4.15.

If what is not F is judged as a free-flow then the precision is sacrificed for recall of free-flow. CoTEC considers all A to E levels as free-flow. This has reduced its precision dramatically despite the high recall of LOS A since any of those levels are considered as free-flow or LOS A. As can be seen its performance resembles the binary model with regard to differentiating between the six levels. They both consider the A to E flow levels as non-congested and they manage to discover the F level cases with high recall and precision. In contrast, the Manhattan distance measure has very high precision as well as recall for LOS A and is able to differentiate between the six levels of congestion with a very high overall precision and recall as seen in Table 4.15.

Table 4.15: Fuzzy, Binary & Manhattan Distance Performance using Urban & Rural Freeways

Urban & Rural										
Measure	**Fuzzy (Fz)**				**Binary (Bn)**			**Manhattan (M)**		
Non-Binary Measure										
Spearman Coefficient	0.9999999999				0.9999999999			**1**		
Binary Measures										
Accuracy	**0.549**				**0.549**			**0.917**		
Congestion Level	**1st / A**			...	**6th / F**			**Average**		
	Fz	**Bn**	**M**	...	**Fz**	**Bn**	**M**	**Fz**	**Bn**	**M**
Precision	**0.31**	**0.31**	**0.95**	...	1	1	1	0.22	0.22	0.89
Recall	1.00	1.00	0.99	...	1	1	1	0.33	0.33	0.88
F-measure	0.47	0.47	0.97	...	1	1	1	0.26	0.26	0.88
F_2-measure	0.69	0.69	0.98	...	1	1	1	0.30	0.30	0.88

C. Fuzzy model & Manhattan Distance in F LOS

The CoTEC fuzzy model claims its power from its ability to differentiate between levels of severity within the F LOS cases. Therefore, it is important to evaluate its performance against the Manhattan model in its area of strength. In this experiment, the F LOS test cases are extracted from the rural and urban test cases and both models are used to predict the degree of severity within that level. As deciding the level of service in freeways by HCM is based on the density level, see Figure 3.14, the correlation of models' predicted congestion severity with the density can be taken as a measure of the model effectiveness.

Hence, the correlation of the results with the density is used to decide the performance of both models. When the spearman correlation coefficient is calculated between the severity prediction results of both models with the density of the LOS F cases it is found that the Manhattan distance model had a slightly higher correlation value with density as in Table 4.16, which proves that a much simpler function as the Manhattan distance not only outperforms CoTEC fuzzy model in identifying the A-E levels which are considered all as free-flow (A level) by CoTEC but also has a comparable performance with even slight improvement in differentiating between the severities within the F level which is the main goal behind using CoTEC. The density is divided by the jam density to have a range from 0 to 1 and the severity is divided by 100. The ranges used to convert the F LOS continuous severities and densities to graded ones are as follows

Range	**Level**
< 2/3	Slight
< 2.5/3 – 2/3	Moderate
1– 2.5/3	Severe

Table 4.16: Fuzzy model& Manhattan distance Correlation with densities of F LOS

Measure	Spearman Correlation Coefficient
Fuzzy	0.9999999999**03286**
Manhattan	0.9999999999**99946**

4.6 Test Case 6: ADM for IR-CAS evaluation

The non-binary average distance measure (ADM) is used for evaluating three proposed IR models; the binary, fuzzy logic and the vector space model. The ADM is chosen since it is sufficient for the evaluation of the information retrieval systems and helps avoid the drawbacks of the binary measures such as the precision and recall measures [26]. Two test collections, one for the CRN application and the other for the ACN application, are used to test the models performance. To apply the ADM performance measure, the test collections are preprocessed first by scaling their severity levels to have continuous values in the [0-1] range. In [26], averaging is suggested as a way of converting the dichotomous or discrete relevance judgments that use category rating scale to continuous judgments. Similarly, the discrete severities found by using the KABCO scale or the roads A to F level of service scale found by using the HCM speed-flow curves need to be converted to the continuous 0 to 1 scale before being able to apply the non-binary average distance measure. Therefore, it is decided to convert the KABCO with its 0 to 4 graded scale by multiplying each grade level by 0.25 to get a scale that covers the continuous range from [0-1]. For the HCM A-F level of service scale, it is found that this level of service is decided based on categorizing ranges of the continuous road density. Therefore it is decided to use the density directly in finding the ADM. The density is transferred to a 0 to 1scale by dividing it by the jam density which is the maximum feasible density for the considered freeway.

Second, the ACN and CRN test collections have to be divided into separate files where each file is considered as a separate document with its own relevance score. Hence, each year in the ACN test collection is considered alone as a separate file and its relevance is first calculated then summed up with all the years and divided by the number of years or 19 before subtracting the result from one as in Equation 2.15. Similarly, for the CRN test collection each freeway is considered separately with all its tested flows as a separate file. To find the ADM, a relevance score is calculated for each freeway, summed with other freeways scores then divided by the total number of tested freeways which is 3528 and finally subtracted from 1 as in Equation 2.15.

A. ACN IR Models Performance

This experiment is conducted to assess the performance of the three proposed IR models for the ACN system by finding the average distance between the models' severity estimations and the actual reported severities for the test collection crash records.

The vector space model with the Manhattan distance proved to have very high ADM compared to the other tried models. In contrast, the fuzzy logic model is found to be the least effective severity estimation model compared to the binary and vector space models as can be seen in Table 4.17. In addition, the standard deviation is used to indicate the precision of found results. Since the average distance measure is based on averaging the differences between the system severity estimations and the actual severities, it is decided to calculate the standard deviation for the same set of values. As can be seen in Table 4.17, the vector space model has the best standard deviation among the three tested models; the lower the standard deviation, the smaller the variation and the higher the precision of the found results.

Table 4.17: ADM evaluation for ACN IR models

Model	ADM	STD
Binary	0.8623	0.016959407
Fuzzy Logic	0.6010	0.012147087
Vector Space	0.9619	0.003086265

Despite having a higher performance than the fuzzy model, the binary model fails to differentiate between the severity degrees of crashes; i.e. if two accidents are deduced to be severe the binary model gives no clue of which crash is severer. This makes continuous values for severity more informative than binary indications. A 90% severity value may increase the rescue urgency of surrounding vehicles and rescue team over the case of seeing a 70% degree although both cases may be classified as severe crashes by the binary model.

B. CRN IR Models Performance

The three models are tested using the CRN test collection with its rural and urban basic freeway segments with a total of 512,983 different road flow cases associated with their congestion levels. The ADM is calculated using the models estimated severities and the actual severities found in the test collection. The standard deviation is then calculated for the differences between these two sets of values. It is found that the vector space model with its utilized Manhattan distance between the context vectors is more effective in estimating the congestion severity when compared with the fuzzy and binary models plus having the best standard deviation value as evident in Table 4.18.

Table 4.18: ADM evaluation for CRN IR models

Model	ADM	STD
Binary	0.9571	0.004457171
Fuzzy Logic	0.9797	0.001971789
Vector Space	0.9974	0.000467632

Conversely, the binary model showed the lowest performance due to the fact that the binary scales have the disadvantage of not being able to differentiate between severity degrees of congestion; i.e. if there are two roads one is severely congested and the other is moderately congested then both are inferred to be congested but no one can tell which road has a smoother flow than the other. Some people may not mind traveling on a route with 50% congestion but would definitely mind taking a 90% congested road where vehicles are standing still most of the time.

4.7 Test Case 7: IR-CAS System Interface

The proposed IR-CAS designs are compared to two alternative visual-manual designs in [38] & [73].

- ***Alternative Design 1***

The system in [38] has the same functionalities as the IR-CAS system except for the querying and partial notifications with certainty levels features that are only available in the IR-CAS system. The common functionalities between the two systems are congestion or collision notifications and service announcement customized according to the preset user profiles and arranged in descending order of user preferences. Most of the human computer interactions of design alternative 1 depicted in Figure 4.12 rely mainly on side links and text windows which are slow to read and select from. When the links are chosen a map crowded with all available services appears to users. Text windows show the relevant amenities with relevance degree.

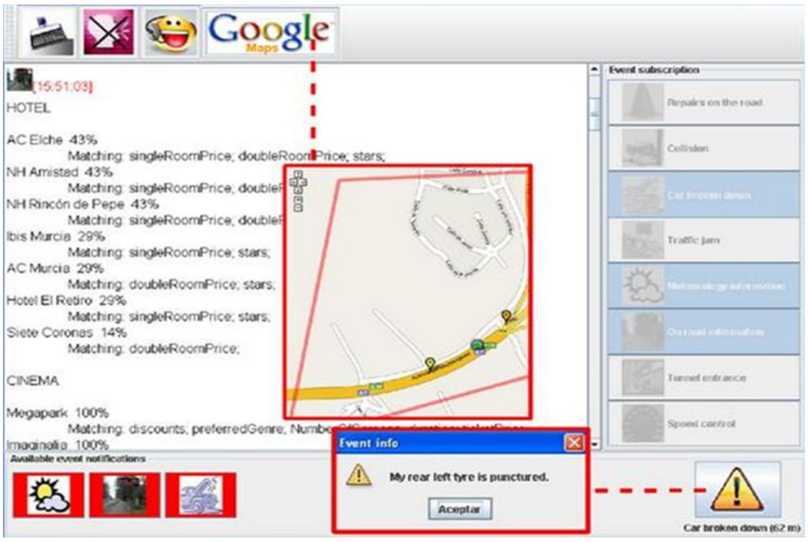


Figure 4.12: Alternative Interface 1 [54]

- ***Alternative Design 2***

A second alternative is found in [73] which is a general interface that uses icons for representing system functions. To facilitate a fair comparison among alternative designs, this interface is adopted to include icons representing the common functions between the system in [38] and the IR-CAS system; the tailored interface is illustrated in Figure 4.13. When an icon is chosen a map similar to that in [38] is shown to the user showing the location of chosen amenities. Fitts' law indicates that the smaller the icon size the slower the selection. Having separate text labels for each icon takes time to read as well. Therefore, design alternative 2 is destined to be slower than IR-CAS designs with their utilization of the bottom edge, use of large icons and fusion of text labels with icons in one place.

Figure 4.13: Alternative Interface 2 [73]

A. Usability Test 1

To assess the proposed multimodal interface prototypes proposed in section 3.4.2 they had to be compared to the alternative designs, a usability test is found to be crucial at the early stage of the design. Usability tests for early prototypes can help designers save lots of resources since the earlier the change the cheaper it is [79].Therefore a usability test that covers the main functions of the IR-CAS system is designed to test the ease of using the proposed interface for accomplishing these main tasks. In [80] it is proved that Crashes and Near Crashes (CNCs) risk increases with long eye off road glances; the longer the duration the higher the risk. They found that what matters most is the single longest glance rather than the total eyes off road time. Therefore the single longest eye off road glance time is used while describing the tasks' successful completion criteria (SCC) mentioned in [81]. Table 4.19 shows four designed test tasks covering the IR-CAS functions and 4 components for each of these tasks described as explained in [81]. Since testing with real users is essential as stated in [82], real users had to be found to conduct the designed test.

A less formal test is designed as a start, so the within-subjects testing explained in [81] is used; each user tests all tasks. In addition, as stated in [81], 4 participants can reveal up to 80% of the usability issues which account for most of the major deficiencies, therefore four first time users were randomly chosen. Since age is taken as a factor that might affect the performance, four users are picked as representatives of four different age range groups: 24-28, 28-32, 32-36, 36-40 years old; two master students, one PhD student and a research assistant. These users are given the following tasks within the mentioned scenarios.

Scenario 1: *You are driving along Fischer-Hallman road near University Av. at 9:00 am with a speed of 70 Km/hr. It is a sunny day and the weather is very clear. You wish to accomplish the following tasks with minimal distraction.*

a: *Find the favorite restaurants/hotels in the area that match your preset profile preferences*
b: *Find a nearby place that offers coffee*
c: *Find if any crashes occurred in the past 10 minutes in the surrounding area along with its severity & certainty*

Scenario 2: *You are driving on a road that you have never used before at 10:00 pm with a speed of 120 Km/hr. It is raining so you can't see clearly. You are trying to go home quickly since you are leaving your kids alone and wish to accomplish the following task while being afraid to take your eyes off the road in these risky conditions.*

d: *Locate the congestion in the surrounding area with its severity and certainty*

Each user performed all of the four *a* to *d* designed tasks using the four design alternatives. The driving is simulated using a driving game viewed on a monitor facing the user while the interface prototype occupied another screen to the right of the user and a stop watch is used to keep track of the eye off road time. For testing the IR-CAS speech-visual design, the Wizard of Oz method is used for speech recognition and synthesis [83, 84], and the think aloud method is used to understand users' actions [82].

Table 4.19: Usability test tasks

Task	***a***	***b***	***c***	***d***
Component	Description			
Description	Find Restaurant /Hotel matching the preset profile	Find a nearby place that offers coffee	Find nearby congestion /crash location, severity, & certainty	Locate congestion level in a risky road you don't know
State	Using in-vehicle software with four options for querying, service navigation, congestion, and crash notifications while driving.			
Successful completion	Locate 3 best restaurants/ hotels	Locate 1 coffee place	Locate & get severity	Locate & get severity
Bench mark	Locate ≥1 restaurant/hotel in ≤ 2sec single longest eye off road glance	Locate 1 place in ≤ 2sec single longest eye off road glance	Locate, get severity & certainty in ≤ 2s single longest eye off road glance	Locate & get severity in 0 single longest eye off road glance

A predefined user profile is assumed to be as follows: Context: Time 9:00 am, Location +43.44,-80.54, Velocity 120 Km/hr, Keywords: Restaurants, Shops, Hotels. The restaurants available in the surrounding area appear in Table 4.2 and the shaded ones are the ones relevant to the user context. The services are delivered to the vehicle based on its location.

In order to reduce the driver distraction the services are ordered inside the vehicle according to their degree of relevance to the user profile and appear to users in descending order of their relevance so he or she can pick the best matching service by one glance; see [60] for details.

The four test users tested the two IR-CAS prototypes as well as the two alternative designs; alternative 1 in [38] and alternative 2 in [73]. The findings of the usability test are summarized in Tables 4.21 & 4.22 and depicted in Figures 4.14 & 4.15.

Test 1 Results

The two IR-CAS design versions are compared to those in [73] and [38]. The following are usability issues found during the *first round of usability tests* for the proposed IR-CAS and alternative designs, for actions taken see Table 4.20:

1. The return Key in the online keyboard that is used after writing a query, see Figure 3.22, is always confused with the submit button. Therefore it is decided to redesign the return Key function so that if it is pressed it should do the same function as submit.
2. It is found that the congestion and crash notifications are very similar in shape so some users took time to differentiate whether it is a congestion or crash. Therefore this part is redesigned so that congestions can be easily differentiated from crashes from the first glance.
3. The maps showing the locations of crashes and congestions use small fonts for street names therefore it is decided to magnify the addresses and show them on top of the detected locations as in Figure 3.22.

The congestion/crash notifications are considered as main system tasks aimed at elevating the safety and convenience levels of users. They have high priority not only due to their high frequency of use but also for their essential role in achieving the system objectives. In addition, they empirically contributed highly to the longest eye off road glance time. Therefore, first priority goes to redesigning the crash/congestion notifications while the rest of the issues, including the querying feature, take the second priority. For the alternative design in [38] users found it very difficult to recognize the interface options and even to find the place where the hotel names are listed even after finding the list location. The design makes it nearly impossible to recognize where the Hotels names are from the first glance.

Table 4.20: The modifications after usability test 1

1	*Larger clearer pictures for congestion and crashes*
2	*Address is added in big font*
3	*The word congestion is in a bigger font White background is used for clarity*
4	*Congestion is moved to the far right corner to be easily recognized and distinguished from crashes*

The Coffee task or Task *b* in Table 4.19 is only applicable for the two proposed IR-CAS prototypes since they have the querying feature but can't be tested using the other two alternative designs. Therefore the performance of this task is separated in Table 4.21 for the IR-CAS versions only. As can be seen in the table the visual-manual version failed to facilitate the task completion within the 2 sec longest eye off road glance bench mark. Therefore, the speech-visual is the best choice when activating the query or ASK feature.

Table 4.21: Comparing the visual-manual & speech-visual IR-CAS designs using the Coffee Query [task *b*] in test 1

IR-CAS	**Coffee Query task time (sec)**	
Criteria	Longest eye off road glance	Total eyes off road
[V- M]	3.1	10.73
[S - V]	0.5075	0.5075

Figures 4.14 and 4.15 compare the performance of all the considered designs evaluated using tasks *a*, *c* and *d* once with the single longest off road glance as the criteria and another using the total eyes off road time.

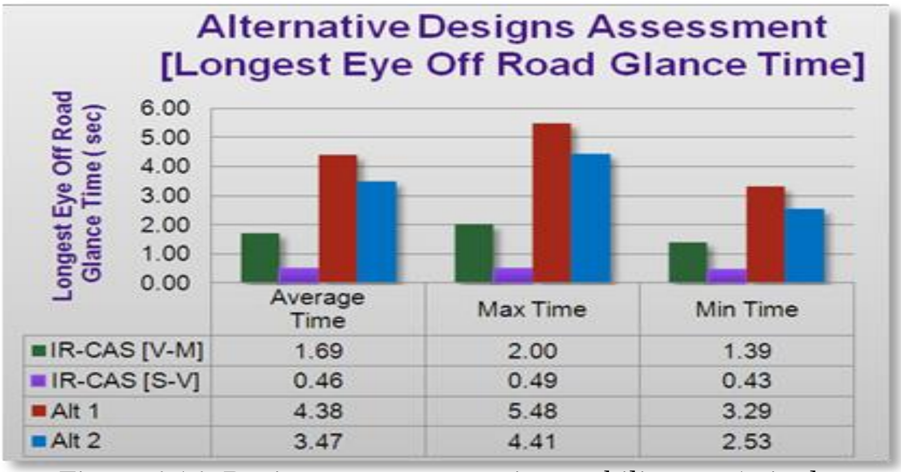


Figure 4.14: Designs assessment using usability test 1 single longest eye off road glance time

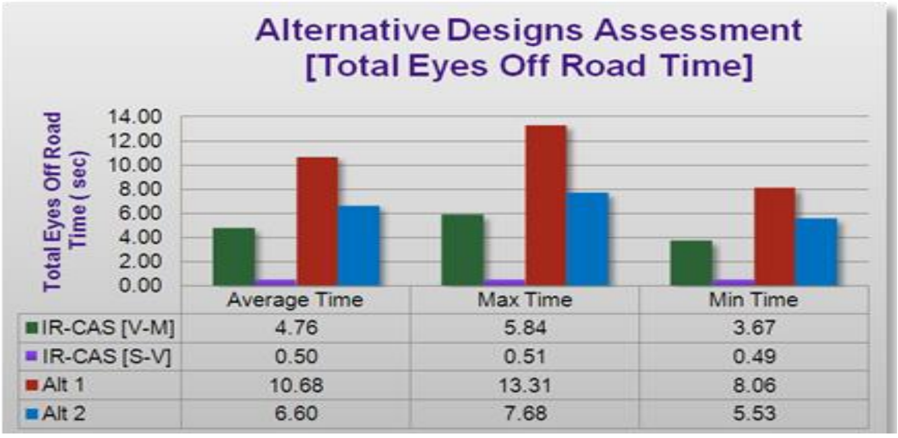


Figure 4.15: Designs assessment using usability test 1 total eyes off road time

Table 4.22: Alternative designs assessment

Designs	Type	Single longest glance Time (sec)	Total eyes off road Time (sec)	Modes utilized	Extra features	Accurate blind selection %
Text & Side links in [38]	Visual-Manual	3.47	6.60	Vision, Touch	-	0%
Icons in [73]	Visual-Manual	4.38	10.7	Vision, Touch	-	25%
IR-CAS Large Image links	Visual-Manual	**1.694**	**4.76**	Vision, Touch	Querying, Partial relevance, certainty	100%
IR-CAS Speech Synthesis & Recognition	Speech-Visual	**0.463**	**0.5**	Speech, Sound, Vision, Touch	Querying, Partial relevance, certainty	N/A

In both cases the two IR-CAS prototypes proved to be successful since on average all users were able to accomplish the designed tasks within the 2 seconds longest single eye off road glance bench mark and the least total eyes off road time as well; with an exceptional success for the speech-visual version over all other designs. Table 4.22 summarizes the differences in features and performance levels among all the four tested design alternatives.

B. Usability Test 2

The system is redesigned after taking into consideration the initial usability test users' feedback. A second round of evaluation took place with 9 additional users who tested the modified prototype; 6 graduate students (2 Master, 4 PhD), a postdoctoral student, a research assistant, and a stay home mother, see Table 4.23 for details. To have more precision in calculations a car driving simulator shown in Figure 4.16 is tried with the new users to give more realistic environment for conducting the test. In addition to the age factor considered in the previous experiment, the driving experience factor is taken into account this time since the machine simulates an actual car driving experience.

Table 4.23: Usability test 2 users' description

User #	Driving Experience	Age group	User #	Driving Experience	Age group
1	0-5	20-24	**6**	5-10	32-36
2	0-5	24-28	**7**	10-15	24-20
3	0-5	28-32	**8**	10-15	28-32
4	0-5	32-36	**9**	15-20	32-36
5	5-10	28-32			

4 age groups are used 20-24, 24-28, 28-32, 32-36 years old plus 4 driving experience year ranges: 1-5, 5-10, 10-15, 15- 20. 16 different combinations of age and experience are possible out of these groups; 9 of them are represented with the 9 users in Table 4.23. The 2 scenarios are translated into the following 2 sets of driving settings using the simulator.

Scenario 1 settings (see Figure 4.16 left side):

Weather conditions are set to sunny
Time of the day is set to morning time
Traffic is set to average traffic with average pedestrians
Cars' attitude is set to normal

Scenario 2 settings (see Figure 4.16 right side):

Weather conditions are set to rainy
Time of the day is set to night time
The traffic is set to high traffic with high pedestrians ratio
Cars' attitude is set to highly unexpected & aggressive

Figure 4.16: The driving simulator with *Scenarios 1 & 2*

Test 2 Results

The following are the usability issues found during the *second round of usability tests* for the proposed IR-CAS and alternative designs with actions taken, see Table 4.24:

The bottom part of the screen where the congestion and crash indicators reside is usually minimized as a default state to save screen space and it expands only if the user needs to see the crash and congestion indicators. The problem is that for first time users there is no indication of what the bottom bar represents when it is minimized.

So it is decided to have horizontal labels always visible even when the frame is minimized with the word crash to the left and the word congestion to the right as mentioned in Table 4.24. The word congestion and crash are vertically aligned and users found difficulty in recognizing the vertically aligned text. Therefore the top labels that are mentioned in point 1 are horizontally aligned for reading clarity.

The crash and congestion indicators appear next to one another and have a similar color which is red. This was very confusing so even when the bottom part is expanded, the users couldn't differentiate the crash case from the congestion one. So using different colors for the congestion and crash is decided; red for crash and dark green for congestion; Figure 4.17 shows these modifications.

The relocation of the Ask icon and services was recommended to simplify blind selections. The ASK icon was suggested to be placed at the top left corner of the screen while placing the services at the top right corner.

As mentioned earlier the crash/congestion notifications have the highest priory for their essential role in safety and convenience improvement, their high frequency of use as well as their noticeable empirical impact on the longest eye off road glance time. Therefore the first priority goes to the redesign of the notification bar and the second priority goes to changing the ASK icon place since it is less frequently used compared to the congestion and crash notification bar.

Table 4.24: The modifications after usability test 2

1	*The Green color is used to represent the congestion to clearly differentiate it from the crash red color*
2	*Two labels with red background color for crash and green one for congestion are added to screen bottom to indicate the place to click to expand the crash/congestion window*
3	*The labels' text are horizontally aligned for easier reading*

The accurate blind selections stayed 0% for alternative design 1 since none of the 9 users were able to locate the options without looking directly to the screen. On the other hand, only 2 out of the 9 users, which form 22% of users, were able to blindly locate the options shown in Figure 4.13 for alternative design 2. For the IR-CAS prototypes, 89% of the users, 7 out of the 9 users, successfully did the blind selection of prototype options. This supports the main guideline behind the design and proves that having large well separated images for input options enables the users to easily locate and select options blindly. This feature is essential especially in emergency situations where it is impossible or risky to have the eyes off road; see Figure 4.21.

Figure 4.17: The modified system after usability test 2

As can be seen in Table 4.25, the Coffee task (Task *b*) is still taking >2 sec longest eye off road glance using the visual-manual IR-CAS prototype and <1 sec with the speech-visual. This speech-visual time has even improved since it went from 0.5075 sec in usability test 1 down to 0.3 sec in usability test 2, see Tables 4.21 & 4.25. Hence, the speech-visual persists to be the most effective when querying using the ASK feature.

Table 4.25: Comparing the visual-manual & speech-visual IR-CAS designs using the Coffee Query [task *b*] in test 2

IR-CAS	Coffee Query task time (sec)	
Criteria	Longest eye off road glance	Total eyes off road
[V- M]	3.24	9.69
[S - V]	0.3	0.3

Figures 4.18 and 4.19 compare the performance of all the considered designs evaluated using tasks *a*, *c* and *d* once with the single longest eye off road glance as the criteria and another using the total eyes off road time. Figure 4.18 shows how the two IR-CAS prototypes continue to be the most effective since on average the nine users successfully completed the three tasks within the 2 seconds longest single eye off road glance bench mark. This target is unachievable using the other two design alternatives. In addition, the closeness of the IR-CAS visual-manual prototype version to the 2 sec threshold is due to the excess of time spent by confused users on the crash and congestion tasks (tasks *c* and *d* in Table 4.19). This time is expected to be lower after the interface redesign presented in Figure 4.17. On top of that, the IR-CAS prototypes have the least total eyes off road time among the tested designs as illustrated in Figure 4.19. Again, the speech-visual version proved to have an exceptional performance with users' task completion speed that surpassed all the tested designs.

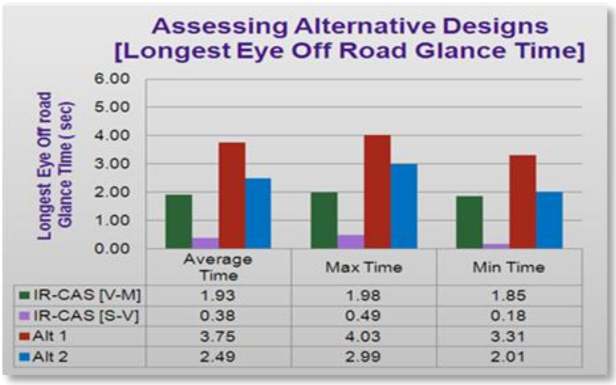


Figure 4.18: Designs assessment using usability test 2 single longest eye off road glance time

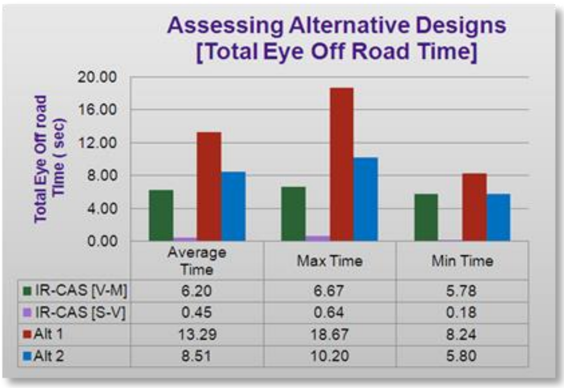


Figure 4.19: Designs assessment using usability test 2 total eyes off road time

C. Usability Test 3

After modifying the interface according to usability test 2 users' feedback, a third round of evaluation took place with 5 additional users who tested the modified prototype; 4 graduate students (4 PhD) and a working mother. The users varying ages and driving experiences are listed in Table 4.26.

Table 4.26: Usability test 3 users' description

User#	Driving Experience	Age group
1	0-10	17-25
2	0-10	25-33
3	10-20	25-33
4	10-20	33-41
5	20-30	41-49

This test was only designed to test the redesigned part that affects only the crash and congestion tasks (Tasks *c* and *d* in Table 4.19) for the proposed IR-CAS visual manual version. Test 3 uses the same 2 scenarios deployed in the previous tests. The time values for tasks *c* and *d* are updated and compared to the rest of unaffected values obtained in test 2.

Figure 4.20: The modified system after usability test 3

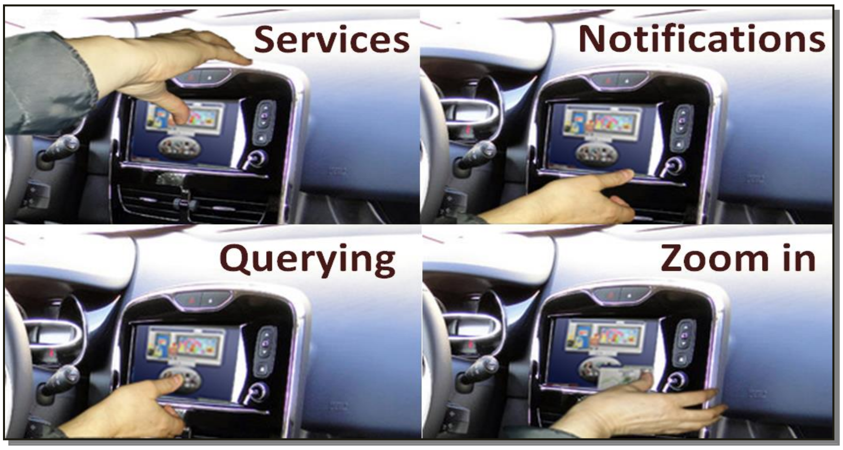


Figure 4.21: Edge guidance for blind selection of options

Test 3 Results

As can be noticed from Figures 4.22 and 4.23, the new design has helped reduce the driver distraction compared to the previous one; the minimum and average longest eye off road glance time went down far from the 2 sec threshold.

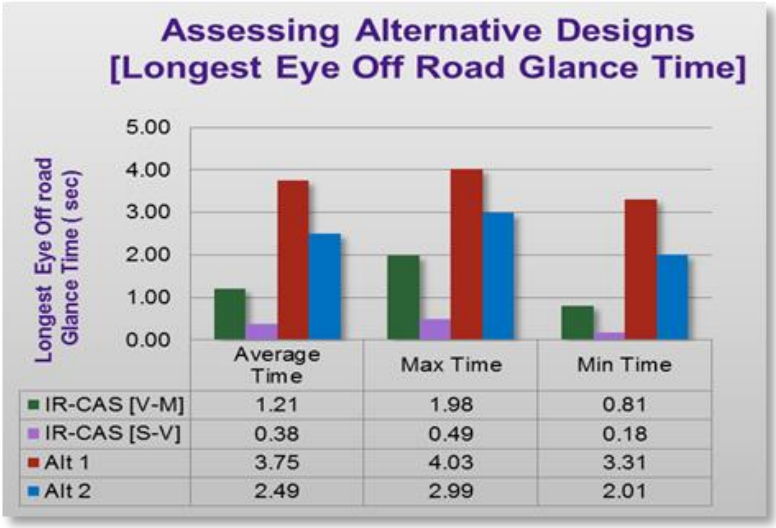


Figure 4.22: Designs assessment using usability test 3 single longest eye off road glance time

Nevertheless, after the third round of usability tests for the IR-CAS tasks *c* and *d*, the alternative design in Figure 4.20 is decided to close the door on any lingering confusion between crash and congestion notifications. The design expands each notification separately so that they never coexist in one display at any moment. Figure 4.21 shows how the main four functions of the IR-CAS design can be blindly selected using the guidance of screen edges.

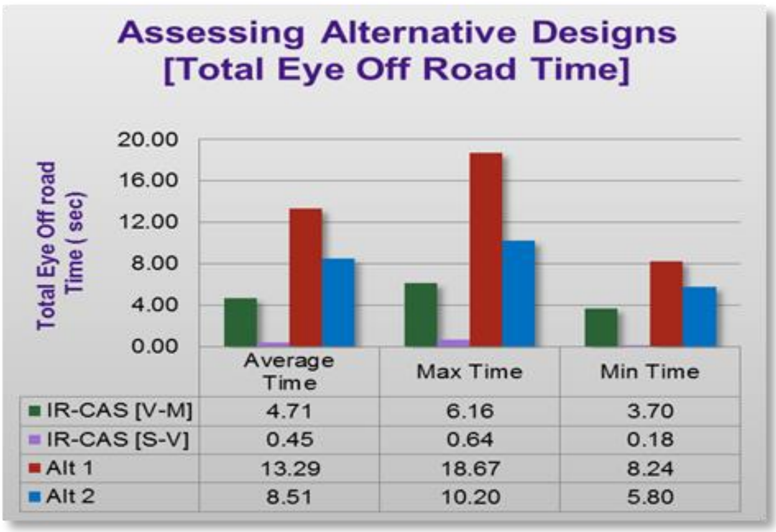


Figure 4.23: Designs assessment using usability test 3 total eyes off road time

Chapter 5

Evaluation of IR-CAS Systems

5.1 Commercial Services

The iConAwa system described in [38] is a centralized context aware multi-agent system where the ontology is used to save user context and points of interest/services context. The user is then presented with the attraction points relevant to his/her profile by submitting his/her location. Although the solution has a high level of abstraction since it uses OWL, it is a totally centralized system where all the calculations are performed at the server side. This type of system has low privacy since the user profiles are kept at the server and used by the agents to provide the context aware information. The second issue is that this system is designed for mobile devices and not for VANET which is different since vehicles might have higher processing power. Thirdly, the calculated relevance is a discrete value representing the number of overlapping keywords between user preferences and points of interest. Finally, the user preferences are represented with a limited number of keywords.

In [1], the proposed solution is basically a pure vehicle grouping based on interest using V2V communication. The ontology is used only to design the exchanged preference messages among the vehicles, but it is not represented in OWL DL. The degree of similarity is not calculated, a binary decision is taken of whether the vehicle belongs to the interest group or not. Furthermore, the user preferences are represented by a basic triple containing his/her location, main interest and sub-interest, without providing any detailed user profile.

In [54], a publish/subscribe method is deployed where vehicles subscribe to some services then receive asynchronous notifications. The main drawback of this work is its highly centralized processing. All user profiles are kept at the server side where inferences of relevant services take place. Moreover, the user needs to subscribe to the provided services. Discrete relevance is used where the matching is done by counting how many user preferences are satisfied by the service. This value is then divided by the total number of preferences to convert the discrete relevance into a percentage; which is yet an accumulation of a set of binary relevance measures.

In [39] the hierarchical context modeling is proposed in general not in VANET context. So in our work we customize the proposed model to fit our processing objectives for VANET.

The originality of IR-CAS is that it makes use of IR techniques to support dissemination of relevant information to prospective users. The users enjoy higher level of privacy by keeping their profiles saved locally. It uses well studied partial relevance measures that not only count the number of matching preferences but also determine how high each preference is satisfied by services; hence providing more accurate and precise relevance and severity.

A hybrid context model is utilized with a high level of abstraction for better reasoning. In addition, the ontology rules enable deduction of the service groups reachable from the RSU instead of fixing the RSU area by specific dimensions that decide the reachable services which enhances the scalability and adaptability to different areas. Deciding the near and similar RSU service groups by applying the rules on the VANET knowledge base increases the level of abstraction since the groups are considered high level knowledge inferred from the low level knowledge of the road nodes like the RSU and the road services like the SA commercial service. Deducing the relevance of a group of similar and near services based on the relevance of one of these services to the user context enhances the efficiency of the retrieval process from matching *n* services to matching *m* groups where m is definitely less than or equal to *n*. This reduction in the processing time leads to reduction in the connection time to the infrastructure which is a high priority with applications with high mobility nature like the VANET information dissemination to vehicles traveling in high speed. Moreover, decentralization is enhanced by employing HVC for free commercial services and V2V communication for safety and convenience services. A comparison between IR-CAS and other discussed related works is further demonstrated in Table 5.1.

Table 5.1: IR-CAS comparison to other related work

Work	**Field**	**Decentralization**	**Privacy**	**Relevance**	**Context model**	**Notification**	**Abstraction & Scalability**
[54]	VANET	Low (V2I)	Low	High	POI + context Ontology	Discrete	High
[39]	Context Modeling	N/A	N/A	N/A	Hierarchical hybrid context model	N/A	High
[38]	MANET	Low (M2I)	Low	High	POI + context Ontology	Discrete	High
[1]	VANET	Very High (V2V)	Medium	Medium	Basic Ontology	Discrete	Medium
IR-CAS	VANET	High (HVC)	High	High	Hierarchical hybrid context model	Partial	High

5.2 Safety and Convenience services

For safety services, if the proposed IR-CAS ACN is compared with the BMW AACN described in [52], it can be found that IR-CAS has improved the BMW system in many aspects: First, the decentralization of the severity calculation. This decentralization is achieved by doing most of the processing inside the vehicle instead of sending all the sensor readings to a central server for processing as it is the case with the current BMW AACN; see Figure 2.10. Second, the high automation of the solution that doesn't only enhance the solution efficiency but also lead to high reduction in errors due to human factors which enhances the solution accuracy and life safety. Third, using the more informative partial relevance, calculated with the simple Manhattan distance measure, to represent severity instead of using the 0 to 4 relevance graded scale or KABCO used in [11, 78], the MAIS scale by BMW in [11] or the binary relevance explained by General Motors in [3]. The discrete and binary scales have the disadvantages of not differentiating between severity degrees within one injury level; i.e. if two accidents have the severity degree 3 or (A) then both are inferred to have incapacitating injury but no one can tell which injury is severer than the other. This makes the continuous value more informative than the 0 to 4 scale. In many cases seeing a 90% severity value may increase the rescue urgency of the surrounding vehicles in addition to the rescue team over the case of showing them a degree of 70% although both cases may be classified as injury degree 3 using the KABCO scale. Forth, the Manhattan distance outperformed other tested IR models in its severity prediction accuracy and simplicity.

For convenience services, the proposed IR-CAS CRN is an improved version of the common CRN centralized implementations with binary notifications used in most of the current applications as those discussed in [1, 3] or the system provided in [70] which can help manage congestion by monitoring vehicles status and traffic flow in a centralized way. First, the partial relevance and the continuous severity degree are used in IR-CAS. Therefore, the disseminated messages are more precise and informative especially that the severity is accompanied by its certainty degree. Second, the IR-CAS CRN enhances the decentralization by utilizing the V2V instead of the V2I communication. This makes it a more efficient solution compared to the centralized CRN in [85, 86] where the congestion information has to be collected by the RSU from zone vehicles, processed and then broadcasted back to all zone vehicles from the RSU.

The rural test collection proved the system high performance; the results are nearly 100% correlated with the HCM actual LOS values while maintaining a 95% accuracy level. The F LOS test cases extracted from the rural and urban test cases show that the Manhattan distance model has a slightly higher correlation value with density. This proves that the simple Manhattan distance function not only differentiates precisely between the six congestion levels while maintaining high overall recall but also differentiates between the degrees of the F level with a comparable performance to the CoTEC system which is developed mainly for this purpose.

5.3 System Interface

According to the usability tests in section 4.7, the updated IR-CAS interface succeeded in achieving the objectives behind its design. The design proved to be easy to use and to provide high level of comfort and safety for drivers while guiding them to available amenities relevant to their context and informing them of the surrounding congestion/crash incidents along with their severities and certainties.

1. It improves safety by reducing distraction by having the least eyes off road time.
2. Its well placed large icons and its utilization of screen corners highly increase the convenience and speed of pointing to options. The drivers can even use the interface blindly without having to remove their eyes off the road which is useful in case of emergencies or under risky conditions; on average 95 % of the users are able to blindly select the options. The speech-visual version which outperforms all other designs can be the best to use under these conditions. Yet, the visual-manual version can still be useful in other situations; when the level of noise is very high which might lead to erroneous voice recognition, when vehicle drivers suffer from hearing problems or incase quietness is required inside vehicles.
3. The interface adapts to users' profiles and contexts which speeds up the selection process and enhances users' convenience. The service categories displayed to the users to choose from are matching those listed in their profile preferences while the service files are dispatched to them according to their context. Using the interface users can then visually view services that best match their interest and context ordered by degree of relevance.
4. The congestion and crash notifications are continuously updated and available in the screen bottom sliding bar. Their new design enables clear and quick view of their severity, certainty and locations with minimal distraction.

Chapter 6

Conclusion and Future Work

6.1 Conclusion

Experimentations show that the proposed IR-CAS fulfills its intended purpose. It outperforms the relevant existing systems by its precise partial relevance calculation methods, which are based on IR techniques, and its highly abstract model.

For commercial services **IR-CAS SA** system as in [87], it succeeds in decentralizing the information processing in VANET by delegating some retrieval tasks to vehicle nodes to reduce the load on the RSU and the connection cost to infrastructure. This is realized by assigning a service group leading vehicle that is responsible for dispatching the retrieved services from the RSU to other relevant zone vehicles. A high level of abstraction is deployed by building the VANET ontology. In addition, scalability is enhanced by adding context handling rules in a separate file from the ontology. Moreover, the user privacy is higher compared to other related systems since their profiles and preferences are kept in the vehicle not at the server side.

For safety and convenience services in [60, 88], a good level of abstraction is achieved that simplifies the reasoning. In addition, a more reliable detection system for safety threatening situations is designed which enables higher level of accuracy and safety. This is accomplished by proposing a fully automated situation detection system, **IR-CAS ACN,** capable of disseminating more informative notifications of detected situations with precisely calculated severity degrees and certainty levels. Experiments proved that the IR-CAS ACN application can be considered an improvement to the state of the art by: first, its simplicity and high performance obtained from using measures like the Manhattan distance. Second, its accuracy and efficiency attained from eliminating the human involvement in the severity estimation and notification dispatching process plus the decentralization of the severity calculation. Third, its precise and informative notifications gained from including partial relevance coupled with certainty values. For the convenience **IR-ACS CRN** system, different models for congestion detection are built, like the binary in [3] and fuzzy logic in [55], to enable the comparison of the IR-CAS CRN model performance to the state of the art models.

Fair evaluation of these models became handy and feasible after the design and generation of a test collection for rural and urban basic freeway segments with a total of 512,983 cases. Diverse values covering the ranges of road attributes are assigned to generate the test cases constrained by the HCM speed-flow curves for undersaturated flows and the Greenshield's model for oversaturated flows. Binary assessment measures like precision and recall as well as partial measures like the Spearman's rank correlation coefficient and the average distance measure are utilized in the assessment.

Results show that for convenience services, the proposed IR-CAS CRN prevails over state of the art models, such as the binary and fuzzy CoTEC models, not only by the decentralization of severity calculation and dissemination of precise informative messages with continuous severity and certainty, but also by precisely identifying the service levels of undersaturated freeways plus accurately differentiating levels of oversaturated ones via deploying the simple Manhattan distance function. After using the non-binary average distance measure **ADM** for evaluating the safety ACN and the convenience CRN systems it can be deduced that using the vector space model for the severity estimation by calculating the Manhattan distance outperforms the fuzzy logic and binary tested models. The vector space model persisted high performance with an ADM above 96%.

Lastly the proposed **Interface** prototype proved to be the least distracting to drivers among the tested designs. Therefore it is the safest to use not only in terms of having the least maximum eye off road glance and total eye off road time but also by enabling users to have the blind selection of options needed under risky driving conditions.

6.2 Future Work

- **IR-CAS SA:** For the future, it is still crucial to build up a large test collection containing the contexts of highly diverse population of vehicles and services. Using such a collection can help fairly evaluate the proposed VANET context aware IR models. Generalization to other commercial services and testing the effectiveness and efficiency of the employed IR models using multiple services are necessary for more prominent results.
- **IR-CAS ACN**: The future planned research direction is first, to compare models using more non-binary test measures. In addition, the accuracy of the calculated severity must be improved since sets of actions rely on this calculation such as notifying authorities.

Therefore, further tests using all the 0 to 4 severity degrees cases with possible variations in the retrieval models are essential to avoid biased results and improve accuracy. These variations may include finding relations between the crash vector attributes and using these relations in enhancing the severity prediction functions, considering the seating position as an attribute that affects severity by the vector space, fuzzy and binary models, and improve the fuzzy model possibly by amending its rule base and functions. Some systems are tested by performing the crash experiments in centers like the Applus + IDIADA [1]. Since using real cars for testing is considered expensive these centers usually offer assessment programs that model different types of vehicles and enable testing crashes under different traffic conditions. It’s planned to test the system in the future in equivalent labs with similar assessment programs to avoid testing cost using real vehicles.

- **IR-CAS CRN:** More attention is given to the basic freeway segments as a sample of uninterrupted facilities considered in HCM. However, comprehensive test collections with consideration of other facilities with uninterrupted flows, like multilane highways, and interrupted flows, as signalized intersections, should be developed in the future. In addition, diverse assessment measures should be considered with more non-binary metrics to broaden the range of served researchers with wider variety of topics. More IR models should be experimented and compared as well. Finally, explore methods other than the mean for congestion severity aggregation to collaborate the per vehicle detected levels and reach a single congestion severity value for the zone.
- **Assessment Measures**: Although many binary measures are used, basing a conclusion using two non-binary measures such as the spearman correlation coefficient and the average distance measure ADM might not be sufficient. Therefore, the planned research direction is to assess and compare the performance of more IR models in the future. In addition, more non-binary and binary measures should be utilized to confirm the results found.
- **The IR-CAS interface:** The future plan is to implement a fully functioning system with the IR-CAS visual-manual and speech-visual interface modes. Then deploy the system in vehicles and have tests run in more realistic environment. Finally, compare the IR-CAS system with its two interface modes to other deployed single mode speech-visual systems.

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[1] Applus + IDIADA is an official center for approval of new car systems under the European New Car using A Platform (EuroNCAP). Sophisticated crash test laboratories are available and comprehensive state-of-the-art automotive testing and approval services are offered independent from manufacturers; [http://www.applusidiada.com/en/].

Appendix A

1. Detailed Algorithms

- **Task1: New Service Launching**

- **Algorithm:**
    - Upload an XML file OR fill a form
    - Populate the ontology with the instance of service context [BC]
    - Check consistency
    - Update index [Description element]

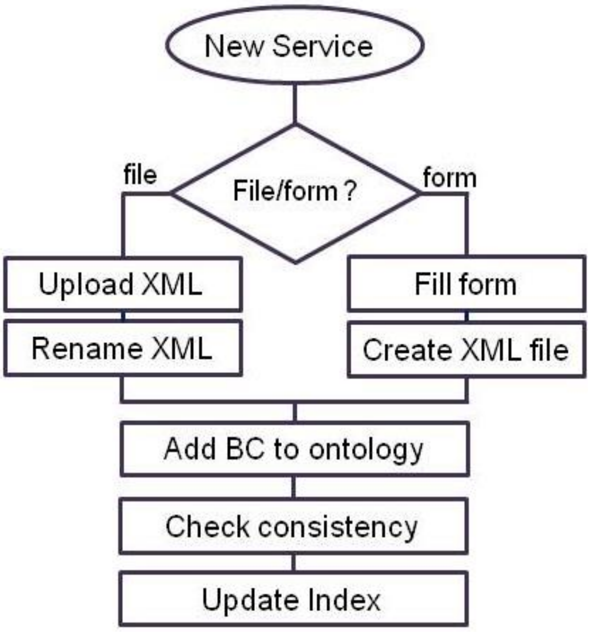


Figure A.1: Flowchart for service launching process

- **Task2: Structured Retrieval [BC]**

- **Algorithm:**
    - Get V[BC]
    - Use spatial filtering for services based on the car context
    - Calculate BC relevance [the distance between the Service & V BC]
    - Retrieve relevant XML service files and disseminate them with the BC relevance.
    - Disseminate the relevant indexes

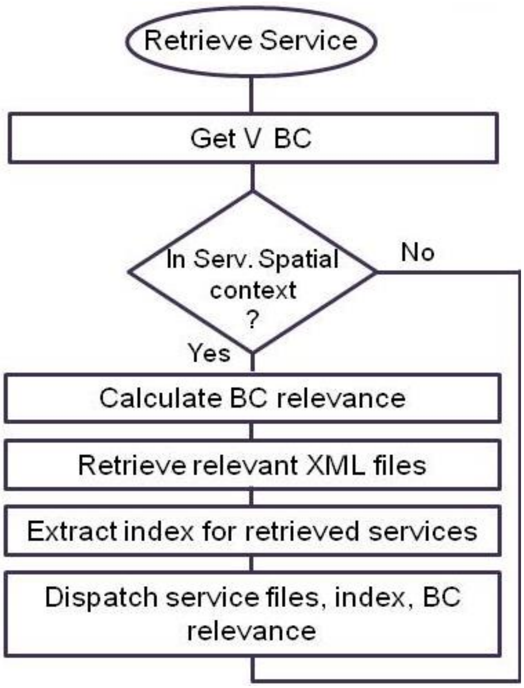


Figure A.2: Flowchart for the structured retrieval

- **Task3: Sorting disseminated Services by relevance to user preferences [V-DHLC]**

- **Algorithm:**

[Structure Retrieval]

For each dispatched Service file

- Retrieve the corresponding V-DHLC
- Calculate DHLC relevance [distance between service and V DHLC vectors]
- Relevance = (DHLC rlv + BC rlv)/2
- Write Service & relevance to result file

End

Sort in descending order by Relevance

Show the chosen service by the user

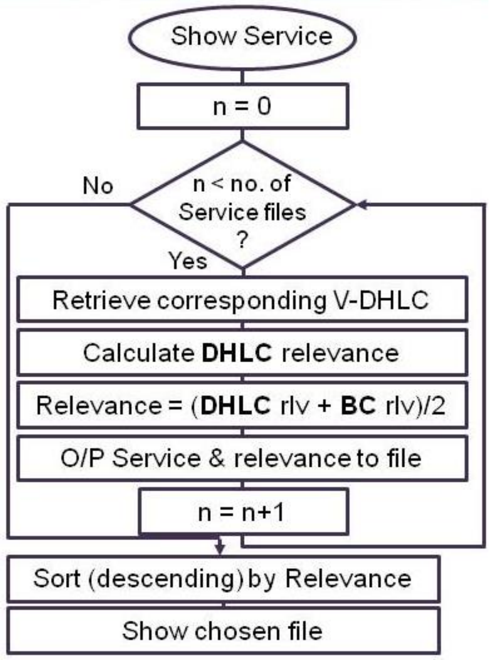


Figure A.3: Flowchart for sorting disseminated services

- **Task4: Unstructured Retrieval [User Query]**

- **Algorithm:**

- Stem user query
- Calculate relevance of dispatched documents to the query using the dispatched description tag index
- Sort Results according to relevance
- Retrieve chosen documents and show content to the user

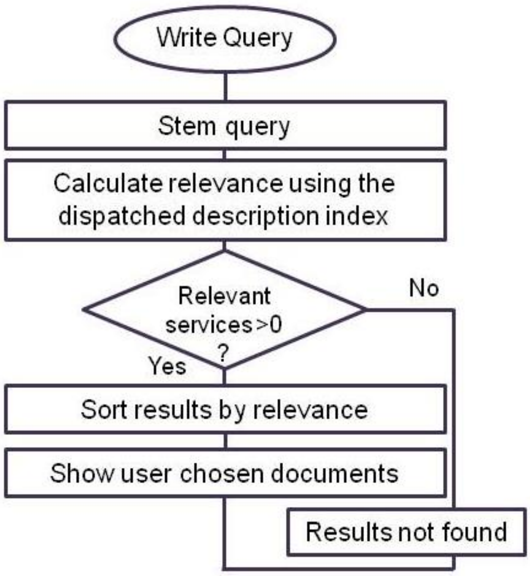


Figure A.4: Flowchart for the unstructured retrieval process

- **Task5: Dissemination to near Vs**

- **Algorithm:**

  For each V_n in near V_s

  - Get V_n Basic context
  - Filter the available services based on relevance to Services and V_n-BC
  - Disseminate relevant service files and indexes

  End

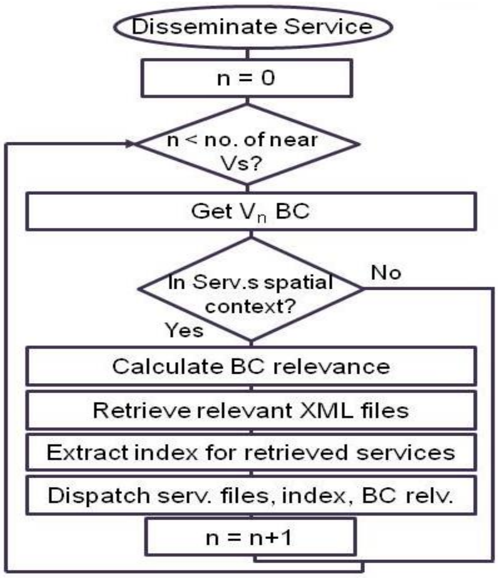


Figure A.5: Flowchart for dissemination to near Vs process

2. Congestion Detection

- CoTEC **(Cooperative Traffic congestion deTEction)**

Table A.1: Methods to cooperatively calculate the congestion level [55]

CTE: *Cooperative Traffic Estimation* exchanged when a traffic congestion situation is detected

Name	Method	CTE packet content
Mean	[Vehicle Estimation_n + (n-1)* Mean $_{n-1}$]/ n	mean_{n-1} and n
Median	the Vehicle after the rear end of the traffic jam calculates the median	list of locally estimated congestion level per vehicle
Congestion intervals: [C_{th}, 1] with intervals 0.1		
Median intervals	Increment the interval matching current vehicle estimation by the count of vehicles surrounding the current vehicle.	list of intervals with count of vehicles per interval
Median intervals neighbors	Increment the interval matching current vehicle estimation by 1.	list of intervals with count of vehicles per interval
Centralized method: is used as the optimal values		

- **Fuzzy logic and CRN**

Table A.2: Rule base for detecting the congestion level [55]

Fuzzy Rules		**Traffic density**			
		Low	**Medium**	**High**	**Very High**
Speed	**Very Slow**	Slight	Moderate	Moderate	Severe
	Slow	Free	Slight	Moderate	Moderate
	Medium	Free	Slight	Slight	Moderate
	Fast	Free	Free	Free	Slight
Congestion rating		**Density rating** veh/km/ln		**Speed rating** km/h	
LOS A-E	**Free – Near capacity**	Below 29	**Low**	Above 81	**Fast**
HCM LOS F Rating	**Slight**	[29-37]	**Medium**	[48-81]	**Medium**
	Moderate	[37-50]	**High**	[24-64]	**Slow**
	Severe	Above 50	**V. High**	Below 40	**V. Slow**

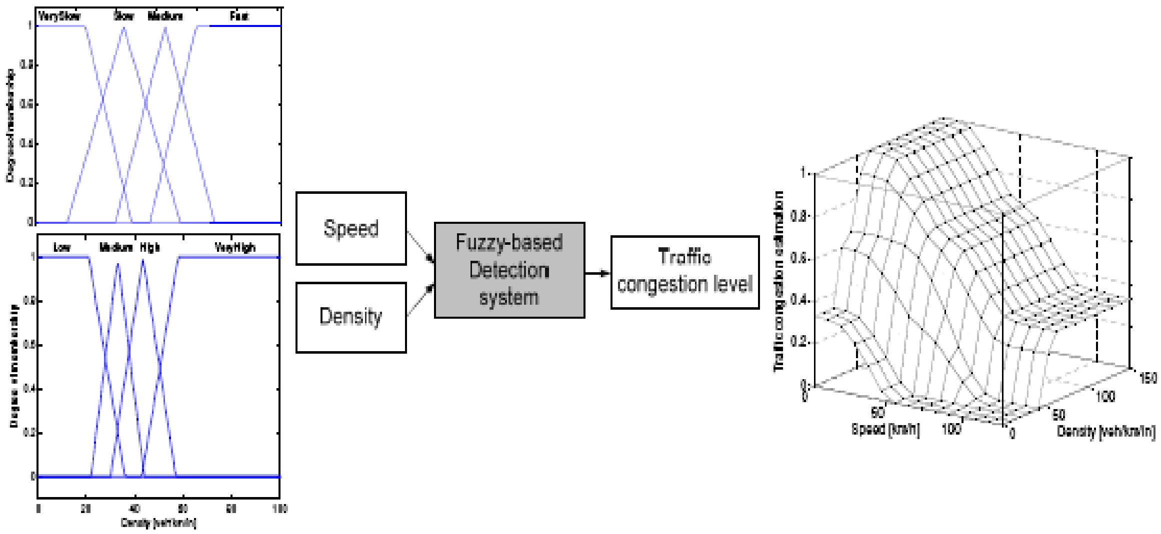


Figure A.6: Fuzzy based local congestion detection as in [55]

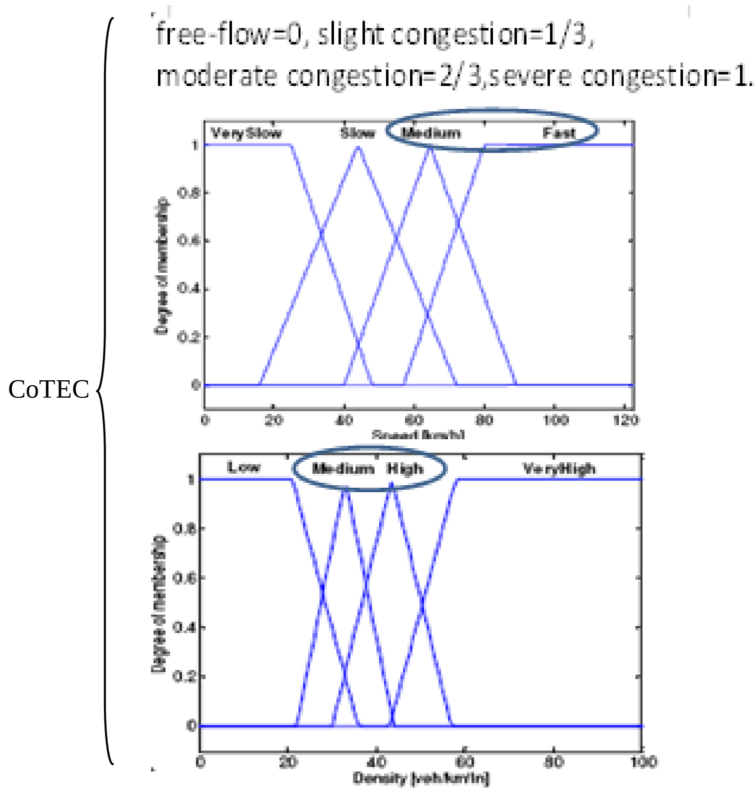


Figure A.7: The CoTEC fuzzy sets for CRN

3. TREC

Sample TREC 2012: Contextual Suggestion [89]

// 50 possible contexts

<context number="1">
<city>New York City</city>
<state>NY</state>
<lat>40.71427</lat>
<long>-74.00597</long>
<day>weekday</day>
<time>afternoon</time>
<season>summer</season>
</context>
…
<context number="50">…</context>

// 49 examples [document set]

<example number=”1”>
<title> Dogfish Head Alehouse </title>
<description>Craft Brewed Ales and tasty wood grilled food</description>
<url>http://www.dogfishalehouse.com/</url>
</example>
…
<example number=”49”>….</example>

// 34 user profiles

<profile number=”1”>
<example number=”1” initial=”1” final=”1”/>
<example number=”2” initial=”0” final=”-1”/>
…
<example number=”49” initial=”0” final=”-1”/>
</profile >
…
<profile number=”34”>…</profile >

//Run

<suggestion **profile**=”1” **context**=”1” **rank**=”1”>
<title>Deschutes Brewery Portland Public House</title>
<description> Deschutes Brewery’s distinct Northwest brew pub in Portland’s Pearl. District has become a convivial gathering spot of food lovers since it’s 2008 opening.
</description>
<url>http://www.deschutesbrewery.com</url>
</suggestion>…..

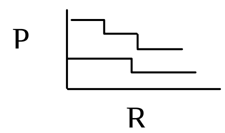
Figure A.8: Sample of TREC 2012 test collection [89]

4. Effectiveness measures

Table A.3: Effectiveness measures description

<table>
<tr><th>Name</th><th>Meaning</th><th>Equation</th><th>Reason</th></tr>
<tr><td colspan="4"><u>Binary Relevance</u> Judgment not multi-grade relevance [relevant / not relevant][13]
A: relevant $\bar{A}$: non-relevant B: retrieved $\bar{B}$ not-retrieved R: recall P: precision</td></tr>
<tr><td>Precision (P)</td><td>Represents specificity in classification & shows how well the retrieval algorithm is doing in rejecting non-relevant documents. Used if relevant documents set is unknown</td><td>$\frac{|A \cap B|}{|B|}$</td><td rowspan="3">Why P & R Not fall-out and R?
P more meaningful to the user
If most of the corpus not relevant evaluating retrieval algorithms as a classifier is counter intuitive [classifying a doc. as not relevant is always good while this results in having the retrieval algorithm retrieve nothing]</td></tr>
<tr><td>Recall (R)</td><td>Related to false negatives or relevant not retrieved. Shows how well the IR algorithm is doing in finding all relevant documents. Used if relevant documents set is known</td><td>$\frac{|A \cap B|}{|A|}$</td></tr>
<tr><td>Fall-out</td><td>Related to false positives: proportion of non-relevant retrieved. Represents effectiveness in classification, measured by R & fall-out.</td><td>$\frac{|\bar{A} \cap B|}{|\bar{A}|}$</td></tr>
<tr><td>F-measure
- Balanced F-score
- F_1 measure
- Harmonic mean</td><td>In IR retrieval effectiveness is measured by Recall & Precision. The F-measure combines P & R in a single measure.</td><td>$F = \frac{1}{\frac{1}{2}\left(\frac{1}{R}+\frac{1}{P}\right)} = \frac{2RP}{R+P}$</td><td rowspan="2">Harmonic mean is better than arithmetic mean: It gives better summary of retrieval effectiveness. E.g.: if R = 1 and P = 0 → A. Mean = 0.5, while H. Mean = 0
Two other commonly used F measures are the FF_2 measure, gives recall higher weight than precision, and $F_{0.5}$ measure, emphasizes precision over recall.</td></tr>
<tr><td>The general formula for positive real β
Weighted Harmonic mean</td><td>Effectiveness is represented in a single number; measures the effectiveness of retrieval with respect to a user with β times as much importance to R as P.</td><td>$F_\beta = (1+\beta^2)\frac{RP}{(\beta^2 P)+R}$</td></tr>
</table>

RANKED OUTPUT : **Methods to summarize ranking effectiveness for a single query [e.g. compare two ranks][13]**			
P@ n rank position	P@n calculates the precision so far. Conversely, recall requires knowing the total number of relevant documents so it can't be found gradually. P@n finds most relevant documents at a given rank. P @ cut-off rank 10 or 20	P@n $= \frac{\sum_{k=1}^{n} rel(d_k)}{n}$ ***rel*(*d**k*)** = **1** [relevant] or **0** [not relevant]	Doesn't distinguish differences in rankings at positions 1 to n. Useful when considering only the topmost n results returned by the system. In Web search the k is usually chosen to represent the number of pages people usually look at. 10 is the usual no. of pages considered therefore P@10 is important for the Web.
P @ fixed R levels	Summarizes ranking across all relevant documents not just the top ranks. 11 Recall levels per ranking; from 0 to 1 at 0.1 increments.	Each ranking is represented by 11 precision values	Some recall levels are not available (0,0.1,0.2,0.3,0.4,0.5,0.6,0.7,0.8,0.9,1) That is why interpolation is needed.
Average. P @ each n where R changes	Shows the contribution of a retrieved document to the average. R increases when a relevant document is retrieved.	AveP $= \frac{1}{R}\sum_{k=1}^{n} rel(d_k)P(d_k)$ ***rel*(*d**k*)** = **1** [relevant] or **0** [not relevant]	The precision is recorded whenever a relevant document is found: if the n^{th} document in ranking is the k^{th} relevant document so far, then precision @k is k divided by n then we average all recorded precisions to get Average P (AP) then across the whole set of queries to get Mean AP (MAP) [12].So the AP is the mean of the P scores obtained after each relevant doc is retrieved, using 0 as the P for relevant docs that are not retrieved.

<table>
<tr><th colspan="4">RANKED OUTPUT : Methods to summarize ranking effectiveness across a <u>collection of queries Q</u>
Averaging an Interpolation techniques[13]</th></tr>
<tr><td>MAP [Mean AP]</td><td>P & R are single-value metrics based on the whole list of documents returned</td><td>$MAP = \frac{\sum_{q=1}^{Q} AveP(q)}{Q}$
Q is the total number of tested queries</td><td>Doesn’t distinguish differences in ranking positions</td></tr>
<tr><td>P(R)</td><td>computing a P and R at every position in the rank Interpolation using P(R) function</td><td>P(R)= max{P’:R’≥R ∧(R’,P’)∈ S
S set of observed (R,P)

</td><td>An optimal retrieval system may mean precision and recall values of 1, while in real world systems, precision decreases with greater recall [90]. P(R) Results in sets of docs with best possible precision values.</td></tr>
<tr><th colspan="4">Interested in Top rank results: Shows how well the IR algorithm does at retrieving documents at very high ranks
Evaluation of IR using [non-binary relevance or degree of relevance]</th></tr>
<tr><td>MRR</td><td>Mean Reciprocal Ranks over query sets</td><td>$MRR = \frac{1}{|Q|}\sum_{i=1}^{|Q|} \frac{1}{(rank\ of\ 1st\ rel\ d)i}$</td><td>MRR is sensitive to the rank position, not as P @n rank.</td></tr>
<tr><th colspan="4">Graded Relevance Scale</th></tr>
<tr><td>DCGp</td><td>Discounted Cumulative Gain at rank p is a popular measure for web search and more sensitive to the rank position.</td><td>$DCG_p = rel_1 + \sum_{i=2}^{P} \frac{rel_i}{log_2 i}$</td><td rowspan="2">- The gain is reduced at lower ranks
- uses a graded relevance scale of docs
rel_i is the graded relevance level at i on scale 0-3
Queries result set may vary in size to compare performances the normalized version of DCG uses an ideal DCG</td></tr>
<tr><td>nDCG</td><td>Normalized DCG at rank p
The nDCG values for all queries can be averaged to obtain a measure of the average performance of a ranking.</td><td>$nDCG_p = \frac{DCG_p}{IDCG_p}$</td></tr>
</table>

User Preferences [NO STANDARDARD EFFECTIVENESS MEASURE BASED ON PEREFERENCE][27]		
Distance performance measure	IR system performance = 1 – distance function.	Relevance evaluation function
Spearman's rank correlation coefficient	$$\rho = 1 - \frac{6\sum(x_i - y_i)^2}{N(N^2-1)}$$ ***N***: number of docs, ***x:*** user ranking, ***y***: IR model ranking, ***i***: is the ranking position	Compares user ranking ***x*** and IR model ranking ***y.*** + ve $\boldsymbol{\rho}$: + ve association, -ve $\boldsymbol{\rho}$:-ve association, $\boldsymbol{\rho}$ =0 means independent ranks.
Kendall Tau Rank Correlation Coefficient	$$Tau = \frac{C^+ - C^-}{\frac{1}{2}N(N-1)}$$ The denominator is the total number of pairs in a rank out of ***N docs***, $\boldsymbol{C}^-$ contradictory and $\boldsymbol{C}^+$ agreeing pairs	The ***Tau*** value ranges from -1 to +1 as the previous Spearman's rank coefficient.
Sliding Ratio (*sr*)	$$sr = \frac{\sum_{i=1}^{n} d_i}{\sum_{i=1}^{n} d_{I(i)}}$$ The *sr* value ranges from 0, non-relevant, to 1, highest relevance.	Where $\boldsymbol{d_{I(i)}}$ is the relevance score of the *i*th ranked doc. in the ideal ranking. This measure is not sensitive to document order
Modified Sliding Ratio (*msr*)	$$msr = \frac{\sum_{i=1}^{n} \frac{1}{i} d_i}{\sum_{i=1}^{n} \frac{1}{i} d_{I(i)}}$$	The modified version *is sensitive to document d order i*
Generalizations of Average Precision	$$wap = \frac{1}{R}\sum_{n=1}^{N} rel(d_n)\frac{cg}{cg_I}$$	Cumulated gain (cg) = sum of di relevance. Used for graded relevance scale.

Average Gain Ratio	$$agr = \frac{1}{R}\sum_{n=1}^{N} rel(d_{l_{(n)}})\frac{cg'}{cg'_I}$$ where cg' and cg'_I denote the cumulated gain and the cumulated gain of an ideal ranking calculated by $d_{l(i)}$	The *agr* is designed for giving more credit to systems for their ability to retrieve the few most relevant documents. $$d'_{l(i)} = d_{l(i)} - \frac{R_l}{R}(d_{l(i)} - d_{(l-1)(i)})$$ Where l denotes the relevance level, $d_{l(i)}$ denotes the relevance score for finding an l-relevant document at rank i, and R_l denotes the number of l-relevant documents.
Normalized Distance Performance Measure	$$ndpm(\succ_u, \succ_s) = \frac{ndpm(\succ_u, \succ_s)}{ndpm(\succ_u, \succ_u^c)} = \frac{2C^- + C^u}{2C}$$ $$C^u = \lvert \succ_u \cap \sim_s \rvert, C^s = \lvert \sim_u \cap \succ_s \rvert, C^- = \lvert \succ_u \cap \succ_s^c \rvert = \lvert \succ_u^c \cap \succ_s \rvert$$ C: denotes the total number of document pairs qualifying the user preference relation in the user ranking.	Measures the distance between ≻u and ≻s rankings by examining their agreement and disagreement. For d & d': *Agreeing*(C^+): same order [distance 0] *Contradicting*(C^-): opposite order[dist. 2] *Compatible*: one has *d* or *d'* higher & the other has them tied [distance 1]
Average Distance Measure	$$adm = 1 - \frac{\sum_{d \epsilon D} \lvert s_i - u_i \rvert}{\lvert D \rvert}$$ where D is the whole document collection	Measures the distance between user ranking & system ranking by examining the absolute differences between system relevance estimation and user relevance estimation.

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