Adaptive Wireless Biomedical Capsule Localization and Tracking

by

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

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Abstract

Wireless capsule endoscopy systems have been shown as a gold step to develop future wireless biomedical multitask robotic capsules, which will be utilized in micro surgery, drug delivery, biopsy and multitasks of the endoscopy. In such wireless capsule endoscopy systems, one of the most challenging problems is accurate localization and tracking of the capsule inside the human body. In this thesis, we focus on robotic biomedical capsule localization and tracking using range measurements via electromagetic wave and magnetic strength based sensors. First, a literature review of existing localization techniques with their merits and limitations is presented. Then, a novel geometric environmental coefficient estimation technique is introduced for time of flight (TOF) and received signal strength (RSS) based range measurement. Utilizing the proposed environmental coefficient estimation technique, a 3D wireless biomedical capsule localization and tracking scheme is designed based on a discrete adaptive recursive least square algorithm with forgetting factor. The comparison between localization with novel coefficient estimation technique and localization with known coefficient is provided to demonstrate the proposed techniques efficiency. Later, as an alternative to TOF and RSS based sensors, use of magnetic strength based sensors is considered. We analyze and demonstrate the performance of the proposed techniques and designs in various scenarios simulated in Matlab/Simulink environment.

Acknowledgements

Dedication

This is dedicated to my family.

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AOA . . . . . angle of arrival

BW . . . . . . bandwidth

CE . . . . . . capsule endoscopy

CT . . . . . . computed tomography

GI . . . . gastrointestinal

GPS . . . . . global positioning system

IBD . . . . . . inflammantory bowel disease

IR-UWB . . . impulse-radio ultra wideband

L-M . . . . . . levenbergh-marquard

MCS . . . . . multilevel coordinate search

MRI . . . . . magnetic resonance imaging

MSTU . . . . mobile sensor triplet unit

RFID . . . . . radio frequency identifier

RF . . . . . . radio frequency

RSS . . . . . . received signal strength

WBC . . . . . wireless biomedical capsule

WBCR . . . . wireless biomedical capsule robot

TOA . . . . . time of arrival

TOF . . . . . time of flight

TDOA . . . . time difference of arrival

UWB . . . . . ultra wide band

Chapter 1

Introduction

Each year in the U.S., 147,000 new cases of colorectal cancer are diagnosed and more than 57,000 people die from the disease and 233,000 Canadians, 1 in every 150 Canadians (over 11,900 dolar per person with IBD) every year, suffer from inflammantory bowel disease (IBD). Today, diagnosis and treatment of gastrointestinal disorders such as obscure bleeding, irritable bowel syndrome, Crohns disease, chronic diarrhea, and cancer are extremely challenging problems for the physicians [1,9].

Also, conventional methods such as colonoscopy are often painful and uncomfortable for patients, who undergo these procedures, due to difficulty of accessing such a complicated environment, such as small intestine. For instance, the colonoscope,the equipment for colonoscopy, is approximately a long, flexible, relatively large tube housing a camera and a source of light at its tip. The tip of the colonoscope is inserted into the anus and then is advanced slowly, under visual control, into the rectum and through the colon usually as far as the cecum [33]

Over the last decade, wireless capsule endoscopy (WCE) has established itself as a valuable tool for diagnosis of gastrointestinal bleeding, Chrohn disease, small intestine tumors, Celiac disease and other disorders which happen in the gastrointestinal (GI) tract. WCE does not only help to diagnose and treat these diseases, but also provides a safe and relatively easy procedure that can provide valuable data in the diagnosis of GI tract conditions. WCE involves swallowing a small capsule that will pass naturally through your digestive system while taking pictures. The images are transmitted to monitoring system, that are placed outside the body.

It is indicated that over 1,250,000 patients have taken advantage of WCE test all over the world [28]. This statistics demonstrates that WCE technologies are extremely important and bring about a revolution in diagnosis of GI diseases [28].
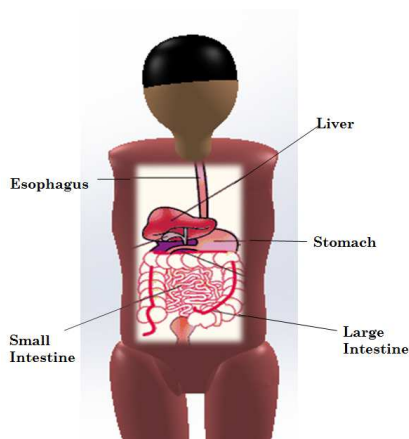
Figure 1.1: GI track of the human body

Developing technologies and miniaturization of the large electronic components have enabled to produce sufficiently small medical devices such as radio telemetry capsules that are small enough to swallow and hence more patient friendly, decreasing the discomfort. GI physiological parameters such as temperature, pressure or pH can be measured by the

capsules. Fig. 1.1 illustrates a typical wireless biomedical capsule (WBC), which consists of an image sensor, an illumination module, a radio-frequency transmitter, and a battery. A typical WCE system comprises of a 3D cartesian robot with a sensor unit attached to its end effector as illustrated in Fig.1.2 or a bell-shaped sensor unit attached to the body with a real time viewer as shown in Fig.1.3.
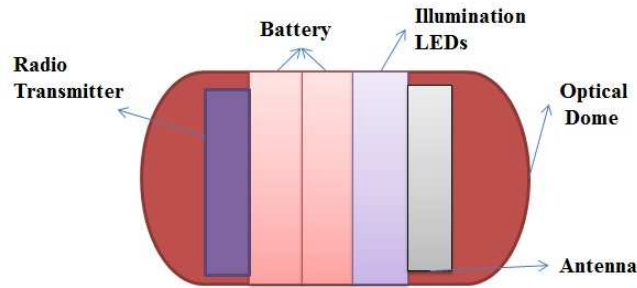
Figure 1.2: Structure of an endoscopic capsule robot [28]

Today, three companies in the world produce small-bowel WCE systems (see some of the commercial capsules and their properties in Table 1.1). However, these technologies still do not provide exact location of the capsule associated with the problems such as tumor diagnosis precisely [9, 33]. WCE offers a feasible noninvasive way to monitor the entire GI tract and particularly middle part of the small intestine, where traditional endoscopy is not able to reach. GI track is a long particularly curled path in the human body (Fig. 1.4. Therefore, the movement of the capsule inside the GI track is very complicated. Capsule endoscopy (CE) starts with the patient swallowing the capsule. The natural peristalsis force helps capsule movement through GI track without any harm or pain. In general, main idea of the CE is to allow the physician to visualize the whole GI track and if possible to release the medicine without scope trauma [33].

WCE is a novel breakthrough in the biomedical industry. However, exact location of the

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Capsules Photo	PillCam SB2	EndoCapsule	MiroCam	OMOM
Diameter	11mm	11mm	11mm	13mm
Length	26mm	26mm	24mm	27.9mm
Weight	3.4g	3.8g	3.4g	6g
Frame rate	2fps	2fps	3fps	0.5-2fps
Image Sensor	CMOS	CCD	CCD	CCD
Field of View	156	145	150	140
Illumunination	6 whiteLEDs	6 white LEDs	6whiteLEDs	6whiteLEDs
Anntennas	8	8	9	14

Figure 1.3: Different WCE examples and their some of the properties [33].
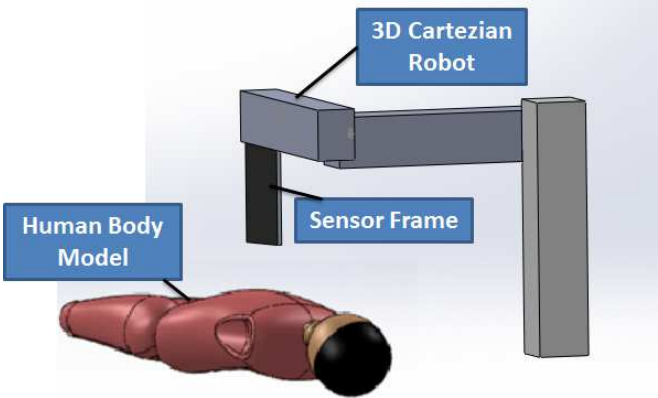
Figure 1.4: 3D endoscopic capsule robotic platform [28]

capsule, image resolution, wireless power transmission, and limited working time are still bottlenecks for the researchers and physicians. Finding location of the capsule is one of the most essential problems since capsule position does also provide information on location of the tumors, bleeding or other problematic issues in the GI tract. In addition, without position information, finding solutions for other problems on the capsule endoscopy is nearly impossible, such as tracking of the capsule or arranging working time of the capsule inside the body. Therefore, there is a need for further research in localization technologies

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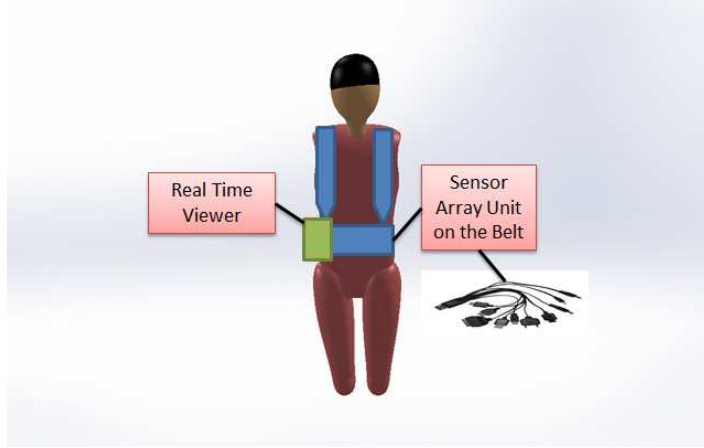
Figure 1.5: Wireless Capsule Endoscopy Reciver Set [33]

and algorithms of the capsule endoscopy.

Our purpose is to provide an overview on the capsule endoscopy technologies to localize and track a capsule inside the human body with a novel cost effective and non complex environmental coefficient estimation method. Nowadays, most of the research have focused on two step positioning systems in electromagnetic based capsule localization problems; first step is to estimate of the environmental coefficients, such as relative permittivity for TOF or path loss coefficient for RSS based techniques, with a prori data on the environmental coefficient of the each organ or medium, and then, second step is to develop a localization and tracking algorithm based on the parameters that are found in the first step [12,58]. In this dissertation, however, we propose a novel geometric method for finding environmental coefficients without any priori information on it. Later, we apply an adaptive recursive least square algorithm to find the exact location of the capsule and a tracking control law for electromagnetic and magnetic capsule localization problems.

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1.1 Outline of the Thesis

This dissertation mainly focuses on the localization and tracking problem of the capsule endoscopy depending on an environmental coefficient estimate of TOF, RSS, and magnetic strength sensing based methods. In Chapter 2, we first introduce summary of the existing localization techniques and algorithms as well as with challenges in capsule endoscopy(CE) in the literature. In Chapter 3, we present a novel geometric environmental coefficient estimation technique for TOF and RSS based WCE localization with a particular 3D scenario inside the human body. In Chapter 4, tracking problem of the WBC with a specific TOF localization scenarios is presented. In Chapter 5, we introduce a novel adaptive magnetic sensing based WBC localization technique to compare proposed electromagnetic and magnetic based methods effectiveness. Results of simulations and and discussion are given based on proposed CE localization and tracking technique depending on the environmental coefficient estimate at the end of Chapter 3,4 and 5. Finally, we conclude the dissertation in Chapter 6 and give some idea about future work.

Chapter 2

Background and Problem Definition

There exist various measurement methods and estimation algorithms for WBC localization. Measurement methods are classified in two sections in the literature; magnetic-field strength based methods and electromagnetic- wave based methods [28, 53]. Magnetic strength based methods have some drawbacks, for instance, significant weight and size, conflicts between actuation and localization systems, some health risk for the patients associated with increased magnetic field and magnetic field interference with other magnetic applications such as magnetic resonance imaging (MRI) systems. On the other hand, rather than aforementioned measurement methods, computed tomography (CT) or x-ray can be used for localizing a WBC inside the GI track by inserting radiation opaque material into the WBC. However, using CT and x-ray is very expensive and there exist some health risks for the patient. Therefore, since electromagnetic wave based location estimation provides easier, natural, less sensitive toward outside influences and cheaper solutions, it has been selected for localization with Smartpill, M2A and Microcam [18, 33].

2.1 Electromagnetic Waves Based Localization Methods

The essential merit of electromagnetic-wave based methods is that they are not affected by the magnetic field generated for the actuation purpose. Fig. 2.1 demonstrates the distinctive areas of the electromagnetic spectrum. However, only radio waves, visible waves, x-ray and gamma ray have been used for capsule tracking because microwaves, infrared waves and ultraviolet waves have very low transmissivity through human tissue [20]. Transmitted signal of the capsule is recieved by the sensors on the patients abdomen. The capsule location is estimated using data of these sensors at any given time. The sensor in the closest proximity to capsule recieves the strongest signal. Using strength of the signal or arrival time of the signal and location of the sensors, an approximate location of the capsule can be calculated [33].

Figure 2.1: Different electromagnetic wave for WCE localization

2.1.1 RF Based Techniques

Radio frequency (RF) based localization techniques include: received signal strength indicator (RSSI), angle of arrival (AOA), time of arrival (TOA), time difference of arrival (TDOA), and radio frequency identification (RFID) [28]. There are unique problems exist for in-body localization due to the complicated structure of the human body, such as multipath caused by the boundaries of the organs, shadowing effect, and variable signal propagation velocity and path loss parameters in the whole human body. In addition, the use of high-band or high power signals for capsule localization is restricted by defined standards (i.e., MICS) [14]. Furthermore, models of RSS and TOF are fairly complex since the recieved signals from the body mounted sensors is damaged with multipath reception caused by the refraction at the boundary of organs and tissues in the human body [33]. Some preliminary two dimensional (2D) RSS and TOA localization techniques for inside the human body have been reported in [10, 62].

RSS Based Techniques

RSS - received signal strength or RSSI - RSS indicator [37, 41] is a distance measurement technique based on the signal power (or strength) measured by a receiver located at the sensor. In a generic RSS setting, the target signal source, which is required to be localized, emits a signal with original power P_T. The power P_S received by S follows an exponential decay model, which is a function of P_T, the distance d_T between S and T, and a coefficient η modeling the signal propagation behaviour in the corresponding environment, called the *path loss coefficient (exponent).* The widely used corresponding mathematical model is

$$P_S = K_l P_T d_T^{-\eta}, \tag{2.1}$$

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where K_l represents other factors that include effects of antenna height and antenna gain. K_l is often considered to be log-normal, and is often ignored in algorithm design leading to the simplified model

$$P_S = P_T d_T^{-\eta}. \tag{2.2}$$

RSS technique often provides cost saving over deploying localization-specific hardware and all current standard radio technologies such as Wi-Fi and ZigBee provide RSS measurements. However, RSS can have multi-path effects that include shadowing, reflection, diffraction, refraction due to unpredictable environmental conditions, particularly for indoor applications [37]. In modeling, these affects are also lumped and included in the coefficient K_l of (2.1).RSS is a power measuring data received by a radio receiver from a radio transmitter for localization and supplies the data as to the imminence of the transmitter depending on some factors such as distance from the transmitter and attenuation. The use of the transmitter and receiver provides to transmit a signal from the object to some receivers placed on the abdomen, and to own those receivers return the signal strength in order to determine the correct location of the object [20].

The authors in [38] introduce an algorithm based on a lookup table which includes previous 2D position via corresponding signal strength for position estimation. During the experiment, fresh data is compared with the data stored in the lookup table to determine the closest match and thus to chose the most appropriate position.

In addition, the studies [39, 40] consider both the distance dependence of the signal strength and the influence of the antenna orientation factor and tissue absorption to build a compensated attenuation model.

The researchers in [42] take into account the effect of different organs and sensor-arrays topology on the position error in localization systems based on the RSSI technique.

TOF Based Techniques

In the time of flight (TOF) based techniques, sensor node is composed of a transmitter unit, a receiver unit, and a precision timer; the transmitter emits a signal, which is reflected by target and received by the receiver; and the time of flight is used to deduce the distance. The environmental characteristics is summarized in the electromagnetic (e.g., radio-frequency- RF) signal propagation velocity

$$v = \frac{c}{\sqrt{\varepsilon}}. \tag{2.3}$$

Range is calculated by multiplying this propagation velocity and the measured TOF value. The corresponding mathematical model [25] can be formulated as

$$t_F = \frac{2d_T}{v_{ave}} = d_T\sqrt{\bar{\varepsilon}} \tag{2.4}$$

where

$$\bar{\varepsilon} = \frac{4\varepsilon}{c^2} = \frac{4}{v_{ave}^2}.$$

There exist three widely known techniques for TOF based localization systems. Firstly, DLOS, direct line of sight, can provide higher accuracy for outdoor applications. However, a huge measurement error can be seen due to the severe multipath environment for indoor applications. It is a direct impression of the distance between transmitter and receiver. Second, DSSS, direct sequence spread sequence,demonstrates better performance for compressing systems. For these systems, a known pseudo-noise,PN, signal is multiplied by the carrier signal. This method is chosen always to achieve better ranging accuracy due to

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inability of the available bandwith in real application. Lastly, UWB, ultra wide band, is capable latest accurate and promissing method [33]. In this method;

$$d = \frac{c}{BW} \tag{2.5}$$

where d is the absolute resolution and BW is the bandwidth of the signal.

Large bandwidth of UWB system is capable to resolve multiple paths and combat multipath fading and interference. But, this systems have a limited range and building penetration due to high attenuation. One of the main problems for UWB systems is interference between UWB devices and other services such as GPS systems, operating at 1.5 GHz.

In addition, the authors in [12] use a mobile sensor unit for TOF based measurements and take into account the effect of electrical properties for different organs and tissues. For this purpose, they divide the human body four subareas and calculate the avarage relative permitivity values for each region. However, this method does not provide precise data on relative permittivity of the human body.

The study in [33] compares the number of capsules and sensors influences on localizations accuracy and it is demonstrated that the number of receiver sensors on body surface has more affect on the accuracy of localization than the number of capsules in cooperation inside the GI tract based on both TOF and RSS methods.

A widely known benet of TOA based techniques is their high accuracy compared to RSS based techniques [28]. The TOA based technique relies on measurements of travel time of signals between the known reference nodes and unknown terminal nodes. Ranging information is calculated by multiplying the propagation velocity of RF signal and the measured TOA value. The TOA value can be measured not only measuring the phase

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of received narrowband carrier signal, but also directly measuring the arrival time of a wideband narrow pulse [33].

The study in [46] shows that time-based methods need strict time synchronization and high bandwidth for desired precision, which is hard to achieve in the MedRadio band (401-406 MHz). It could be used for ultra-wideband (UWB) based localization [2]. Hence,field strength methods based on the received signal strength indicator (RSSI) have been used for M2A and Smartpill technologies.

2.2   Wireless Capsule Antennas

Another essential issue in WCE systems is antenna design since an efficient communication link between the in-body capsule and the ex-body receiver unit is extremely important. Acording to the study in [47], the antenna has vital importance in transmitting and recieving signals in WCE systems. Image quality is related with transmission efficiency of the antenna in real time. Therefore, the ideal WCE antenna should have insensitivity to human tissues, enough bandwidth to transmit high resolution images and large amount of data, lower power consumption and high data rate transmission. Also, the researchers mentioned that recently, there are two type of antenna structures that are studied mostly: embedded and conformal antennas.

The antenna design must fulfill several requirements to be an effective capsule antenna such as miniaturization to save precious space in the capsule cavity, omnidirectional, multidirectional, radiation pattern in order to maintain data transmission regardless of the orientation and location of the capsule or receiver, as well as tuning adjustment to compensate for in-body effects [47].

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The dispersive properties of the human body suggest that signals are less vulnerable when they are transmitted at lower frequencies. Therefore, a modified design is proposed to provide ultra-wide bandwidth (UWB) at a lower frequency range [48].

In addition, the authors in [49] state that RSSI based localization algorithm accuracy heavily depends on antenna radiation pattern analyzing radio propagation in distinctive human tissues by calculating path loss values ,that are compensated related both distance and azimuth angle, in different frequencies.

Moreover, the study in [48] focuses on improving power consumption and performance of a wideband antenna,insulating glycerin based gel form, using IR-UWB comunication system, RX5500. Here, IR-UWB signals in the frequency range of 3.5 to 4.5 GHz are used to sent images from inside the body to a reciver placed outside of the body and in order to prevent complexities due to IR-UWB reciver, a norrowband reciver is utilized inside the capsule. Use of a narrowband receiver in the capsule provides less power consumption in high data rate and resolution since synchronization of narrow IR-UWB pulses requires extensive signal processing leading to additional power over heads. Also, here,a microcontroller, PIC18F14K22, communicates with a camera module to set image resolution and signaling format and also control LED(light emitting diod) that turns on only when the camera requires images to preserve power.

2.3 Magnetic-Field Strength Based Localization Methods

Magnetic tracking method has gained increasing attention in the last decade since static and low frequency magnetic signals can pass through human body without any reduction

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of the signal amplitude. The composition of capsule endoscopy is shown in Figure 2.1. In this method, the capsule does not need to be in line of sight with magnetic sensor in order to be detected. Here, a localization system is not only used to localize the diseases, also it is used to provide feedback for an actuation system. Therefore, the localization and actuation system must be considered together. However, a conflict between these two system due to interference of two magnetic field can be very challenging problem [54], so some research groups ignore the effect of the actuation system on the localization problem [44].

2.3.1 Magnetic Localization for Passive Capsule Endoscopy

In a magnetic tracking system, a magnetic source and sensor module are the most significant elements. According to magnetic source situation, whether the capsule behaves as a field generator or a sensing module, the localization systems in this group are usage of a permanent magnet inside a capsule, usage of a secondary coil embedded in a capsule and usage of a 3-axis magnetoresistive sensor mounted inside a capsule as three distinctive study areas [28].

Most of the researchers focus on usage of a permanent magnet inside a WBCR in the literature since this technique provides generation of magnetic field and depending on magnet location and orientation, magnetic sensors that are outside of the patients body can measure magnetic flux intensities signals [28,31]. Since the magnets magnetic field can be defined by a mathematical model, magnets position and orientation can be computed by using the sensor data and an appropriate algorithm. Here, in order to compute 5D localization and orientation parameters, five or more sensors must be used. Levenbergh-Marquard (L-M) method provides satisfactory tolerance for initial guess parameters almost zero computation error. In the following example, application of LM methods is demonstrated [53].

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$$B_l = \frac{\mu_T \mu_0 M_T}{4\pi} \left[\frac{3(H_0 P_l) P_l}{R_l^5} - \frac{H_0}{R_i^3} \right] \tag{2.6}$$

$$B_l = B_T \left(\frac{3(H_0 P_l) P_l}{R_l^5} - \frac{H_0}{R_i^3} \right) l = 1, 2, 3, ..., N \tag{2.7}$$

where, the magnets position is represented by

$$(a, b, c)^T \tag{2.8}$$

and the magnets orientation is represented by

$$H_0 = (m, n, p)^T \tag{2.9}$$

. $[x_l, y_l, z_l]^T$ is position of magnetic flux. The flux intensity is invariant to the rotation of the circular magnet along its central axis. Hence the magnets orientation H_0 is in two dimensions, in other words, the length of vector (m,n, p)T can be any fixed value. Therefore we add following constraint for (m,n, p)T :

$$m^2 + n^2 + p^2 = 1 \tag{2.10}$$

Here, μ_T is relative permeability of the medium. μ_0 and M_T are air magnetic permeability and magnetic intensity of the magnet respectively. $\mu_0 = 4\pi \text{x} 10^- 7$ T.m/A

$$M_T = \pi \sigma^2 L M_0 \tag{2.11}$$

σ, L and M_0 represent radious of the magnet, length of the magnet and magnetization strength in return. For Nd-Fe-B magnet; $M_0 = 1,032 \text{x} 10^6$ A/m . $H_0 = [m, n, p]^T$ is the direction of the magnet.

Last, $P_l([x_l - a, y_l - b, z_l - c])$ is the spatial point of lth sensor [53].

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2.3.2 Magnetic Localization for Active Capsule Endoscopy

These systems are designed to work effectively with their own magnetic actuation mechanisms. Accordingly, many research groups are studying to develop active locomotion devices and platforms [28, 31, 32, 55]. A recent address: Maglev Microrobotics Lab, Department of Mechanical Engineering, University of Waterloo.

Localization based on high frequency alternating magnetic field

This technique uses a spiral structure on the surface of a capsule in which a permanent magnet is integrated with 3 pairs of coils were placed in three perpendicular axial directions to generate an external rotating magnetic field around the patients body. The spiral structure rotates the capsule by applying this magnetic field on the magnet can propel it forward and backward. The frequency of rotating magnetic field should not be higher than 10Hz [28].

Localization Based on Inertial Sensing

Magnetic Steering, utilizes a 6 degree of freedom robotic arm to carry a permanent magnet on end efector. 4 Cylindirical magnets are mounted uniformly on the body of a capsule in order to create a magnetic link between body and the external permanent magnet. By this design, the capsule can be dragged and sterred effectively with the assistance of the magnetic interaction. For localization purpose, a 3- axis accelerometer is inserted into the capsule [28].

Localization Based on Measuring a Rotational Magnetic Field by Rotating an External Permanent Magnet.

This method includes an endoscopic capsule with a helical architecture, created an external rotational magnetic field to rotate 2 permanent magnets embedded in the endoscopic

device. Instead of utilizing 6 bulky coils around the patients body, the authors rotates a big parallel piped permanent magnet made by 7 smaller rectangular magnets to generate a rotational magnetic field. Here, an electrical motor mounted on a manipulator helps to generate the magnetic field , so that it could spin and its position can be changed during the control process of capsule [28].

In addition to the WCE localization methods, WCE localization algorithms are also categorized under some subgroups in the literature: linear and nonlinear localization algorithms and those are also can be divided under magnetic and electromagnetic sensing based localization algorithm.

The study in [51] indicates that the non linear algorithm has its drawbacks(e.g., low speed, high complexity and dependence on the initial guess of the parameters) for magnetic sensing based methods. However, linear algorithm can provide better solution in terms of rapidity and real time tracking system.

There exist several minimization algorithm such that Powells Algorithm [57], Downhill Simplex Algorithm [57], DIRECT [59], Multilevel Coordinate Search (MCS) [64] and Levenberg-Marquardt method [21] to solve high order nonlinear localization equations. The Levenberg-Marquardt method is a general nonlinear downhill minimization algorithm. It dynamically mixes Gauss- Newton algorithms and the gradient iterations. The authors in [53] indicate that perfect localization and orientation accuracy is found by this algorithm. Trilateration method is very popular among electromagnetic wave based localization algorithms and applied to calculate the capsule position the distances from the transmitter to the receivers. Proximity data from the last section is converted into position information generally by applying triangulation that takes the features of triangles into account to calculate distances. The distance from one reference point to an object with knowledge of the angles between both references and the object and also the distance between the

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access points can be calculated by giving any two reference/access points (AP1, AP2) (Fig. 2.7) [7].

In this approach, the system degree will be reduced using a linearizing technique.

$$d = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2 (z_i - z_j)^2} \tag{2.12}$$

is the distance between sensors i and j. (i = 1,2,...j 1, j + 1,...,n).

The linear system of equations can easily be written in matrix form as:

$$A\vec{x} = \vec{b} \tag{2.13}$$

where b is related the distance between sensors i and j. From above equations, unknown parameters can be manipulated(3 equations and 3 unknown) and theoretically only three sensors are necessary to determine the unique position of the object in 2D.

There are many localization algorithms and methods in the literature for localizing a sensor inside the human body. Among these technologies, RF signal based localization systems have the merits of application and relatively low cost for implementation. Hence, the systems have been selected for use with the Smartpill, Microcam and the M2A [33]. A widely known benefit of TOA based techniques is their high accuracy compared to RSS and AOA based techniques. However, the strong absorption of human tissue causes large errors in TOA estimation and the limited bandwidth (402-405MHz) of the Medical Implant Communication Services (MICS) band prevent us from high resolution TOA estimation. In addition, due to variable relative permittivity of the human body, large errors are shown.The peristalsis movement resulting in unpredictable ranging error is made the problem even worse [33].

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2.4   Specify Problem Definition and Approach

Although TOF and RSS based techniques have more popularity on WBC localization problems, due to variable environmental coefficients, permittivity of the human body (ε) for TOF or path loss coefficient (η) for RSS based techniques, these methods are not precisely reliable to obtain position of the capsule inside the body. Not only for WBC localization, also for general localization problems, in both RSS and TOF based tecniques, η for RSS and ε for TOF have vital effect on the accuracy of the localization. In many practical settings these parameters are unknown, and even variable in some due to influences of variances on the weather conditions, human behavior, actuator effect at the anchor nodes [43]. It is shown that using a wrong data on path loss coefficient, η, has huge effect on accuracy of the position estimate [63].

Finding accurate estimation of these parameters is studied in the literature [12, 24, 50, 58, 63]. Most of the relevant works follow recursive algorithms involving training by data off-line or two step on-line coefficient estimation and localization based on the estimate coefficients [12, 58]. In the off-line identification approaches, large amount of training data is needed for obtaining accurate estimates of the coefficients. The two-step on-line iterative approaches, on the other hand, may not lead to a successful level of accuracy during the joint coefficient estimation and localization process. In the next section we propose a technique that would overcome these issues via static or instantaneous calculation based on certain geometric relations. The required additional cost is use of triplets of sensors at the nodes of the WSN or the sensory mobile agent of interest in place of single sensors.

The novelty of this thesis is a more direct and static calculation technique for estimating the environmental coefficients ε and η using a mobile sensor triplet unit during adaptive WBC localization of a signal source by a 3D cartesian robot equipped with this sensor

triplet unit. The triplet is designed to have a fixed rigid geometry where the z-coordinates of the sensors are equidistant.

In addition, a non-complex magnetic strength based linear localization algorithm, is established in 2D. Since the main purpose of WCE visualize the GI tract and send the images to physicians using RF signals, we can apply same signal to obtain position of the capsule. Also, usage of omni-directional antenna for video transmission provides orientation data of the capsule inside the body. Using this data, a magnetic strength based localization algorithm can be developed easily. Moreover, a comparison between magnetic strength and electromagnetic wave based localization provides use of more reliable data on tracking algorithm.

Chapter 3

Electromagnetic Wave Based Capsule Localization

Much research on the development of the WCE has been performed for diagnosis of the GI tract disorders. However, exact location of the capsule is still bottleneck for the researchers and physicians. Although, most of the popular localization methods, that include TOF, RSS, time difference of arrival (TDOA) for capsule localization, have enabled to find exact location of the capsule, these techniques have some limitations in real applications since, variation of propagation velocity and path loss coefficient of human organs, due to complicated structures and electrical properties of the GI tract, are dominant source of error for RF based capsule localization techniques inside the human body. Accordingly, these common capsule localization methods are used based on estimating some position-dependent signal parameters like signal propagation velocity (v) for TOF or path loss coefficient (η) for RSS based methods. In many WCE applications, the localization algorithms are vulnerable since the signal propagation speed due to relative permittivity of the medium or

path-loss coefficient, which are often unknown in practical scenarios, and cause unreliable location estimation. Recently, localization using estimation of these parameters has received much attention since it provides reliable results in location estimate of WCEs applications. However, these studies in general has recursive nature, some initial assumptions and require significant computational complexity for training and estimation algorithms.

In this chapter, we focus on the distance estimation based capsule localization problem depending on a novel estimation technique of the environmental coefficients v and η using a mobile sensor triplet unit(MSTU), assuming a spatial motion for this triplet and fixing the interval differences of the z coordinates between sensor contents. Here, a parametric model can be established by a geometric relationship between the MSTU and the capsule for estimation of environmental coefficient [15, 56].

3.1 Problem Definition and Proposed Design

Consider a WBC-robot C at an unknown position $p_T(t)$ at time $t = t_k$, where $t_k = t_0 + kT$, $k = 1, 2, ..., T$. Also, consider a triple of mobile sensors S_1, S_2, S_3, that move only parallel to the $x - y$ plane of a pre-defined fixed coordinate frame, having a fixed separation in z direction. That is, denoting the positions of S_1, S_2 and S_3 at time step k by,

$$p_i[k] = [x[k], y[k], z_i[k]]^T \tag{3.1}$$

where $z_1[k] = z[k] + \bar{z}$, $z_2[k] = z[k]$ and $z_3[k] = z[k] - \bar{z}$ for some constant z. Note that, the spacing $\bar{z}$ is known since it is a design constant. We are interested in estimating the value of $p_T[k] = [x_T[k], y_T[k], z_T[k]]^T := p_T(t_k)$, where $p_T(t)$ will be initially assumed to be constant. We further consider a device setting where z_2 and hence z_1 and z_3 are known

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and constant. The task is to generate estimate $\hat{p}_T[k]$ of the unknown WBC position, p_T, aiming to satisfy;
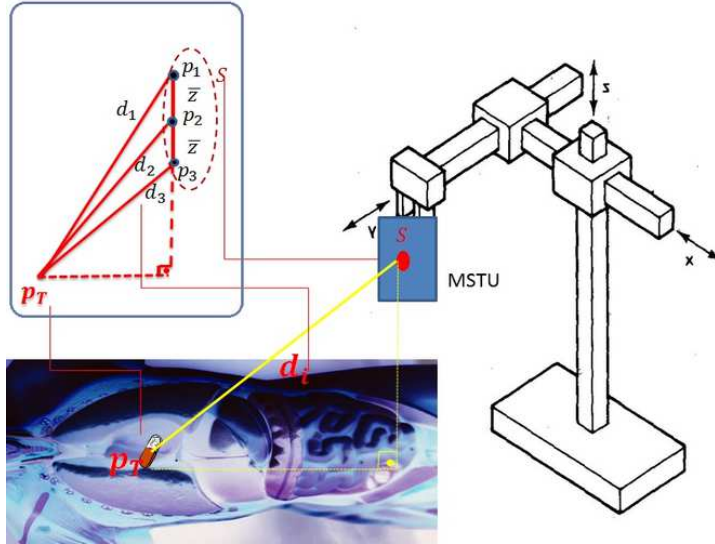
Figure 3.1: A demonstration of the wireless WBC localization task setting and the proposed sensor array geometry.

$$\lim_{k \to \infty} \|\hat{p}_T[k] - p_T\| = 0 \tag{3.2}$$

using only the geometric relationships between the sensor and WBC locations and the measurements of the distances Fig. 3.1.

$$d_i[k] = \|p_i[k] - p_T[k]\| \tag{3.3}$$

$i = 1, 2, 3$. At each step k, note that

$$d_1^2 - d_2^2 = (z + \bar{z} - z_T)^2 - (z - z_T)^2 = \bar{z}^2 + 2\bar{z}(z - z_T) \tag{3.4}$$

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$$d_3^2 - d_2^2 = (z - \bar{z} - z_T)^2 - (z - z_T)^2 = \bar{z}^2 - 2\bar{z}(z - z_T) \tag{3.5}$$

Adding (3.4) and (3.5), we obtain

$$d_1^2[k] - 2d_2^2[k] + d_3^2[k] = 2\bar{z}^2 \tag{3.6}$$

[15]. We propose use of (3.6) for estimation of environmental coefficient, $\eta[k]$ for RSS or $\bar{\varepsilon}[k]$ for TOF. Time dependence of these coefficients comes mainly from time variations in the position of $\bar{S}$ (and p_T if the target is not stationary) and hence the time variation in the environment between T and $\bar{S}$.

More specifically, in the case of TOF, using (2.4), (3.6) can be rewritten as

$$\bar{\varepsilon}[k] = \frac{t_{F1}^2[k] - 2t_{F2}^2[k] + t_{F3}^2[k]}{2\bar{z}^2} \tag{3.7}$$

[15]. Similarly, in the case of RSS, using (2.2), for each sensor S_i we have

$$\frac{P_T}{P_{Si}} = d_i^\eta, \tag{3.8}$$

where P_{Si} denotes the signal power received by S_i. Hence, (3.6) can be rewritten as

$$\zeta_1^{\bar{\eta}} - 2\zeta_2^{\bar{\eta}} + \zeta_3^{\bar{\eta}} = 2\bar{z}^2, \tag{3.9}$$

[15], where $\zeta_i = \frac{P_T}{P_{si}}$ and $\bar{\eta} = \frac{2}{\eta}$.

In the RSS case, although we cannot obtain a closed form solution for the coefficient η (or $\bar{\eta}$) similar to (3.7), there exists pre-calculated look-up tables for (3.9) can be used (if preferred, together with some iterative accuracy fine-tuning methods) to solve (3.9) for $\bar{\eta}$. Here, the WCE system consists of a IR-UWB transmitter inside of the human body, a receiver outside and a multi-directional antenna on the WBC.

In WCE localization problems, another important issue is severe multipath effects due to two different mediums, air and body or an organ and another organ. According to

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Snell's law, radio waves refract when they go from one medium with refractive index, n_1, to another with refractive index, n_2. However, in our proposed design, it is not a problematic issue for localizing a WBC inside the GI track (Fig.3.2 and Fig.3.3). In our calculation part, $\bar{\varepsilon}$ is used and

$$\sqrt{\bar{\varepsilon_1}} \cong \sqrt{\bar{\varepsilon_2}} = \frac{t_f}{d_T} \tag{3.10}$$

For first agent S_1;

$$\sqrt{\bar{\varepsilon_1}} = \frac{2}{c} \frac{a_1\sqrt{\varepsilon_1} + b_1\sqrt{\varepsilon_2}}{a_1 + b_1} \tag{3.11}$$

Similarly, for second agent S_2;

$$\sqrt{\bar{\varepsilon_2}} = \frac{2}{c} \frac{a_2\sqrt{\varepsilon_1} + b_2\sqrt{\varepsilon_2}}{a_2 + b_2} \tag{3.12}$$

Let prove it with a visible example; Let $a_1 = 10$, $a_2 = 8$, $b_1 = 5$ and $b_2 = 4$ also $\varepsilon_{air} = 1$ and $\varepsilon_{body} = 40$. In this case, it is clear to see that $\bar{\varepsilon_1} \cong \bar{\varepsilon_2} \cong 10$.

Therefore, we can get average relative permittivity of the medium from the proposed design and ignore the refraction between body and air or similarly between organs since $\bar{\varepsilon_1} \cong \bar{\varepsilon_2}$ and the part of the signal waves outside of the body is much smaller than the part inside the human body (Fig.3.2 and Fig.3.3). Here, the WCE system consists of a IR-UWB transmitter outside of the human body, a narrowband receiver in the capsule and a multi-directional antenna on the capsule.

3.2 Adaptive Source Localization Algorithm

In this study, a recursive least square algorithm (RLS) with forgetting factor is considered to estimate $\hat{p}_T$. Similarly to [25], first the unknown position vector, $\hat{p}_T$, is assumed to be
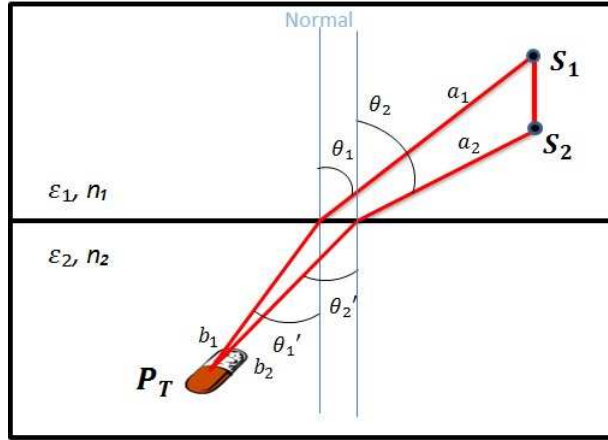
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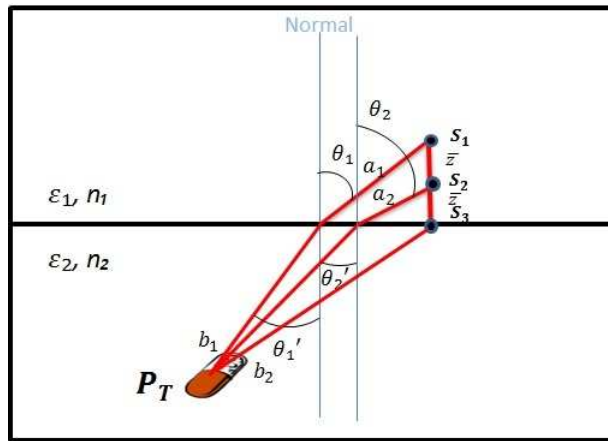Figure 3.2: Representation of Snell Law for proposed design.

Figure 3.3: Representation of Snell Law for proposed design.

constant and then a drifting target case is considered based on the RLS algorithm. The localization algorithm is based on a linear parametric model derived in the sequel. From

(3.6) and (4.2), we have

$$
\begin{aligned}
d_2^2[k] &= (p_2[k] - p_T)^T (p_2[k] - p_T) \\
&= \|p_2[k]\|^2 + \|p_T\|^2 - 2p_T^T p_2[k].
\end{aligned}
\tag{3.13}
$$

Then, evaluating (3.13) at steps k and $k-1$ and taking the difference, we obtain

$$
d_2^2[k] - d_2^2[k-1] = \|p_2[k]\|^2 - \|p_2[k-1]\|^2 - 2p_T^T(p_2[k] - p_2[k-1]),
\tag{3.14}
$$

which can be written in the SPM form as

$$
\begin{aligned}
z[k] &= p_T^T \phi[k], \\
\phi[k] &= p_2[k] - p_2[k-1], \\
z[k] &= \frac{1}{2}\left(\|p_2[k]\|^2 - \|p_2[k-1]\|^2 - (d_2^2[k] - d_2^2[k-1])\right).
\end{aligned}
\tag{3.15}
$$

Based on the SPM (3.15), various estimators can be designed to produce the estimate $\hat{p}_T$ of p_T. Next, we design an RLS based on-line estimator based on the parametric model (3.15). Following the design procedure in [26], we obtain the following RLS adaptive law:

$$
\begin{aligned}
\hat{p}_T[k] &= Pr(\hat{p}_T[k-1] + \Gamma[k]\phi[k]\epsilon[k]), \\
\epsilon[k] &= z[k] - \hat{p}_T^T[k-1]\phi[k], \\
\Gamma[k] &= \frac{1}{\beta}\left(\Gamma[k-1] - \frac{\Gamma[k-1]\phi[k]\phi[k]^T\Gamma[k-1]}{\beta + \phi[k]^T\Gamma[k-1]\phi[k]}\right),
\end{aligned}
\tag{3.16}
$$

where $\Gamma(0) = \Gamma_0$ (and hence $\Gamma(k)$, $\forall k > 0$) is an 3×3 positive definite matrix, $0 < \beta < 1$ is the forgetting factor coefficient, and $Pr(.)$ is the parameter projection operator keeping $-20 \le \hat{p}_{T3} \le 20$ based on a priori information.

Stability and Convergence of the Algorithm

The adaptive localization algorithm (3.16) is a discrete-time RLS algorithm with forgetting factor and parameter projection. Such algorithm is studied in detail in [26]. It is

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also established there and the references therein that if $\phi[k]$ is persistent excitation (PE), i.e., if it satisfies

$$\lim_{K \to \infty} \lambda_{min} \sum_{j=0}^{K} \phi(j)\phi(j)^T = \infty$$

or

$$\sum_{j=K}^{K+L-1} \phi(j)\phi(j)^T \leq \alpha_0 L I$$

for some $\alpha_0 \geq$, $L \geq 1$ and for all $K \geq 1$, then $\theta(k) \to \theta^*$ as $K \to \infty$.

Also, in order to avoid covariance wind-up problem, we modify the RLS algorithm using a covariance setting modification. The following modified RLS algorithm with forgetting factor is used;

$$\hat{p}_T[k] = (\hat{p}_T[k-1] + \Gamma[k]\phi[k]\epsilon[k]) \tag{3.17}$$

$$\Gamma[k] = \begin{cases} \frac{1}{\beta}\left(\Gamma[k-1] - \frac{\Gamma[k-1]\phi[k]\phi[k]^T\Gamma[k-1]}{\beta+\phi[k]^T\Gamma[k-1]\phi[k]}\right) & \text{if} \|\Gamma\| \leq R_0 \\ 0, & \text{otherwise} \end{cases} \tag{3.18}$$

3.3   A Simulation Case Study

In this section, we analyze the proposed adaptive localization scheme with combination of the RLS algorithm (3.17)and the coefficient estimation technique (3.1). We consider a MSTU localization scenario, where the MSTU is equipped with a TOF based range sensor triplet. The task of the MSTU is to estimate the position of the p_T of (and track) a certain target T. For, this task, the MSTU uses the localization algorithm(3.17) and, in order to guarantee estimation convergence and eliminate the wind-up convergence problem at the end of the (3.2), it follows a PE path , a path satisfying ϕ to be PE and modified LS algorithm. Such a PE path follows the path, whose x and y coordinates, as shown in Fig.

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4.2:

$$x(t) = 30\sin(0.1t + \pi/2) + 50cm,$$

$$y(t) = 20\cos(0.2t)cm,$$

$$z(t) = 5\sin(0.01t) + 22cm.$$

We consider the following design parameters for the algorithm (3.17):

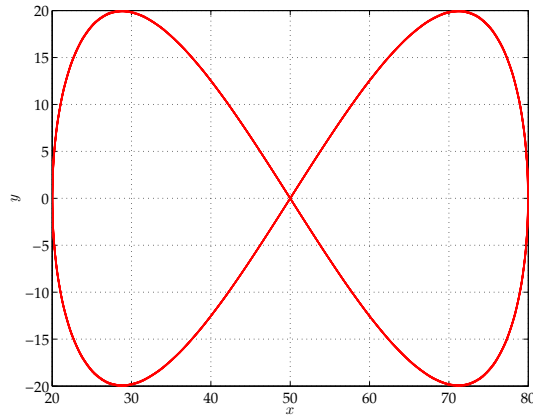

Figure 3.4: Lateral trajectory $(x(t), y(t))$ of the sensor S.

$$\beta = 0.9$$

$$\Gamma[0] = I$$

$$\hat{p}_T(0) = [5, 5, 5]^T cm$$

Stationary and drifting WBC cases are considered in the following subsections.

3.3.1 Stationary Capsule Case

First, the performance of the proposed technique is demonstrated for stationary WBC case in MATLAB/Simulink environment. A stationary WBC located at

$$p_T = [50, 30, 10]cm \tag{3.19}$$

The position estimation results for this case are shown in Fig. 3.5 and Fig. 3.6. The

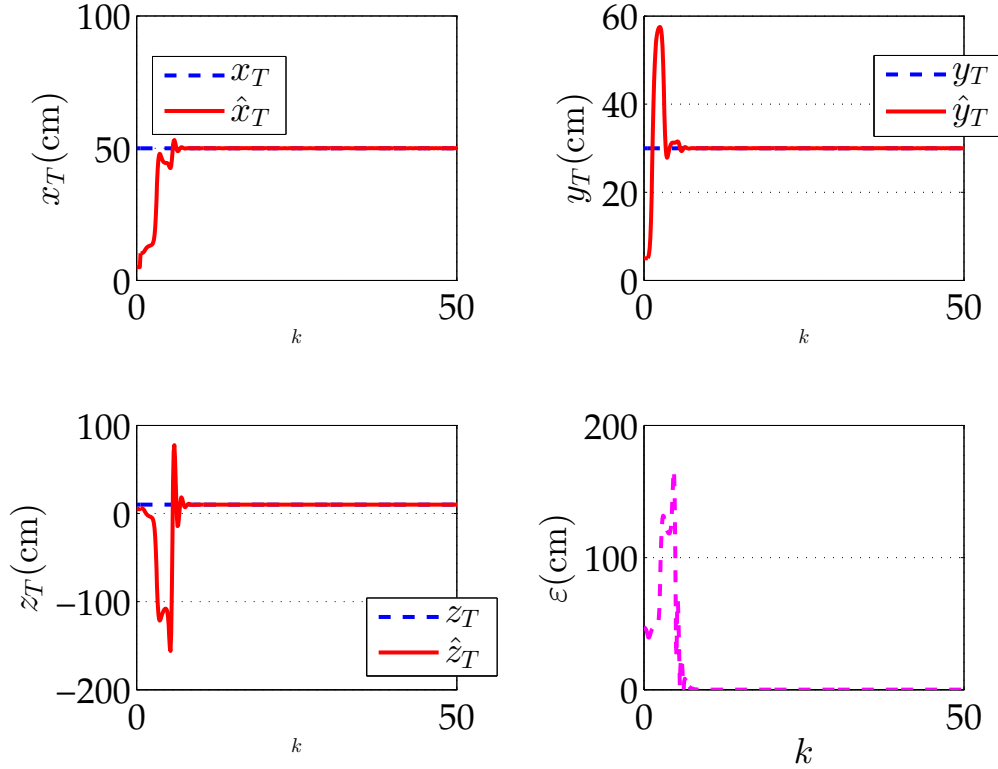Figure 3.5: Location estimate $\hat{p}_T[k]$ and estimation error $e[k] = \|\hat{p}_T[k] - p_T\|$ for stationary WBC case localization with proposed environmental coefficient estimation. technique.

figures shows that all the coordinates of the position estimate $\hat{p}_T[k]$ rapidly converge to their actual values, leading the estimation error $e[k] = \|\hat{p}_T[k] - p_T\|$ to converge zero.

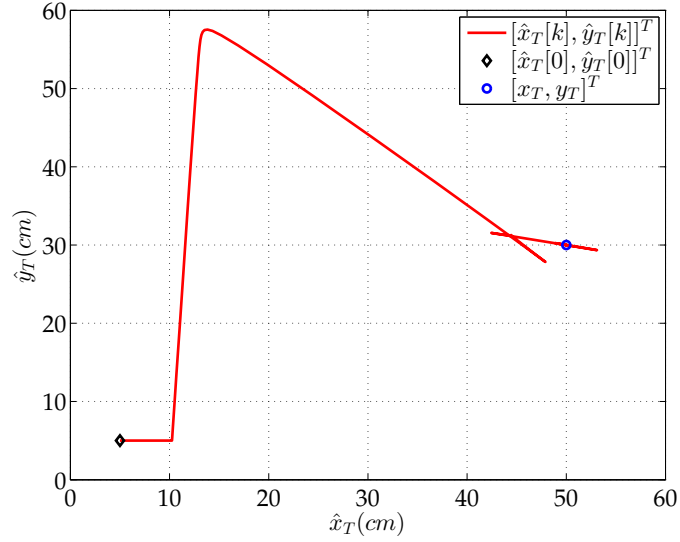Figure 3.6: Lateral coordinate estimates $(\hat{x}_T[k], \hat{y}_T[k])$ for stationary WBC case.

Fig. 3.5 shows the resulting average localization error (cm) around $5.5x10^{-8}$ without any random noises, where the distance between the WBC to the sensor plane is around 30cm and time step $t_k = k = 0.001$. One can further enhance the performance of the localization by fine-tunning the design parameters given above.

3.3.2 Drifting Capsule Case

In this scenario, we assume all design parameters same as given before and consider the WBC point is moving with a constant speed, V_t. In this case;

$$x_T(t) = 0.1t + (2\sin(0.05t) + 100)cm$$

$$y_T(t) = 0.05t + (2\sin(0.05t) + 75)cm$$

$$z_T(t) = (0.5\sin(0.01t) + 8)cm$$

$$V_T = [(0.1 + 0.1\cos(0.05t)), (0.05 + 0.1\cos(0.05t)),$$

$$(0.005\cos(0.01t))]^T cm/s$$

$$t_k = k = 0.1$$

The simulation results for drifting WBC case are shown following: The average
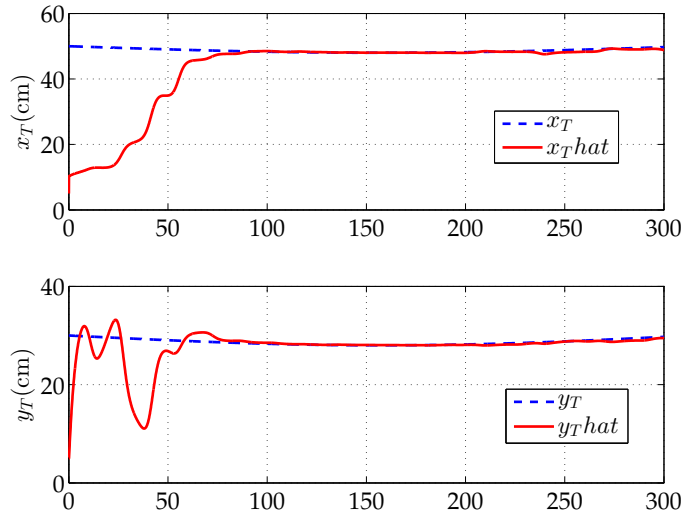

Figure 3.7: Location estimate $\hat{p}_T[k]$ and estimation error $e[k] = \|\hat{p}_T[k] - p_T\|$ for drifting WBC case.
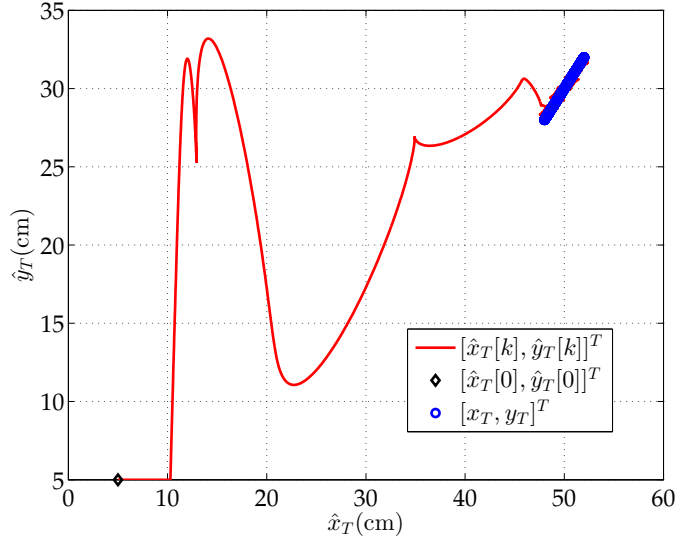
Figure 3.8: Lateral coordinate estimates $(\hat{x}_T[k], \hat{y}_T[k])$ for drifting WBC case.

localization error (cm) in Fig. (3.7) is around 0.05 without any random noises, where the distance between the WBC to the sensor plane is around 30cm. It is clear to see from the above figures, perfect convergence is not possible due to the motion of the WBC except the case, v_T is known as a priori data.

Also, Fig. 3.9 and Fig. 3.10 illustrate location estimate, estimation error and lateral coordinate estimate for stationary WBC localization with a given relative permittivity. Here, it is clear to see from Fig. 3.9 and Fig. 3.5 that localization with the proposed coefficient estimation technique is as effective as the localization scenario with a given relative permittivity of the medium. In addition, the simulation case studies in this paper are adaptable to medical communication bands such as MICS bandwitdh at $402-405$ MHz as well as with Ultra Wideband (UWB) frequencies from 3.1 to 10.6 GHz since the time step (0.001) for the proposed scenarios is fast enough to handle TOF or RSS data.
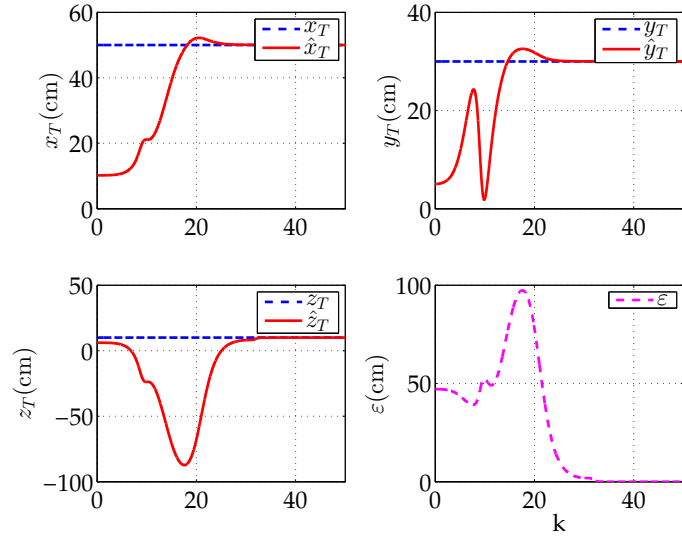
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Figure 3.9: Location estimate $\hat{p}_T[k]$ and estimation error $e[k] = \|\hat{p}_T[k] - p_T\|$ for stationary WBC case localization with a given environmental coefficient.
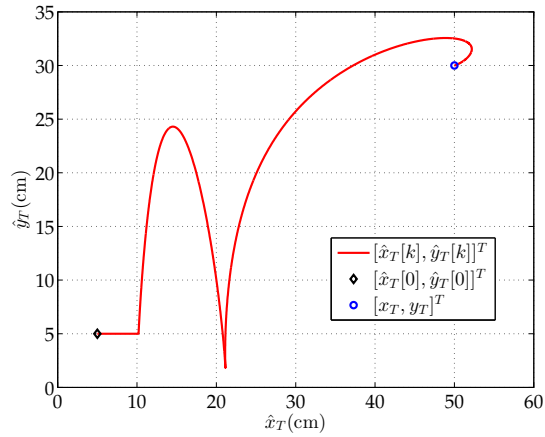
Figure 3.10: Lateral coordinate estimates $(\hat{x}_T[k], \hat{y}_T[k])$ for stationary WBC case localization with a given environmental coefficient.

3.4 Chapter Summary

This study has addressed the problem of WBC localization with unknown path loss coefficient and permittivity by considering a discrete time framework for stationary and drifting WBC cases. First, based on geometric relationship and measurements, an estimation technique for path loss coefficient and permittivity of the medium has been presented. An adaptive discrete RLS algorithm for estimation of the position has been derived. Simulation results demonstrated fast convergence and superior localization accuracy for both stationary and drifting WBC cases. The proposed localization scheme not only provides fast and non-complex solution, but also is cost effective, not requiring any additional dynamic algorithm or priori information for determining environmental coefficients. Future work will cover some experimental studies for the proposed technique.

Chapter 4

Adaptive Tracking Control of the Capsule

In the literature, there are many WBC localization and tracking algorithms and methods [22]. Most of the researchers consider magnetic sensing based methods to enable pursuit and control the movement of the WBC using a permanent magnet inside the capsule. However, there is nothing available in the literature to control the movement of the WBC only depending on electromagnetic wave based measurements. Hence, this chapter deals with adaptive tracking control of WBC depending on TOF based measurements and location estimate by considering a similar approach with the study in [52].

4.1   Problem Definition

Consider the same scenario in Section (3.1) and similar cartesian robot environment in Fig.3.1. Here, C is a WBC robot in an unknown position $p_T(t)$ at time $t = tk$, where

$tk = t0 + kT, k = 1, 2, ..., T$. Also, $p_i[k]$ is sensor position in (3.1) with the same design constants. The objective is to apply a tracking control law based on estimate $\hat{p}_T[k]$ of the unknown WBC position to achieve

$$\lim_{k \to \infty} \|\hat{p}_T[k] - p_T\| = 0 \tag{4.1}$$

using only the geometric relationships between the sensor and WBC locations and the measurements of the distances Fig. 3.1.

$$d_i[k] = \|p_i[k] - p_T[k]\| \tag{4.2}$$

$i = 1, 2, 3$. The representation of the proposed motion law is demonstrated in Fig.4.1. In our adaptive tracking motion law design, we assume that there is no any measurement noise in our system.

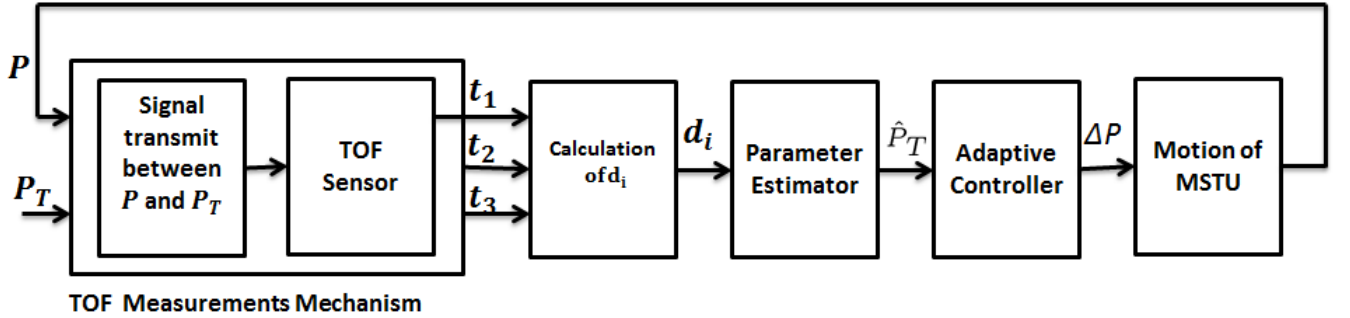Figure 4.1: Block diagram of tracking control of WBC

According to Fig.4.1, the transmitter placed in the WBC emits a signal and the signal received by the receiver placed in the MSTU frame, as seen in Fig. 3.1. Here, from TOF or RSS based sensors, we can easily measure signal traveling time or received and transmitted signal strength. Based on these measurements and the proposed environmental coefficient

estimate, the distance d_i is obtained, introduced in Chapter 3. Later, we apply a parameter estimator to find estimate location of the capsule as shown in Section 3.2. Then, utilizing the location estimate, a motion control law represented in (4.3) is introduced in discrete time case. The motion control law, that helps to move the MSTU, p towards estimate position $\hat{p}_T$, and the location estimate generated by the localization algorithm in Section 3.2. The proposed motion control law is introduced in Section 4.2. Also, performance of the proposed tracking control law is demonstrated in Section 4.3. Chapter summary and future works are given in Section 4.4.

4.2 Proposed Motion Control Law

In previous chapter, capsule localization problem is presented as a parameter identification problem. In this section, a motion control law is applied using an adaptive controller based on the location estimate of the capsule. Here, the MSTU has an ability to track movement of the capsule outside of the human body based on localization information with a similar approach in [52]. In order to see capsule movement in x-y plane, we apply a discrete motion control law to be in the form

$$u[k] = p[k] - p[k-1] = (\hat{p}_T[k] - \hat{p}_T[k-1]) - \Delta t \beta (p[k] - \hat{p}_T[k]) \tag{4.3}$$
$$+ (\sigma[k] - \sigma[k-1]) f(D)$$

Here, $\beta > 0$ is a design constant and

$$\sigma[k] = A_d[k] \sigma[k-1] \tag{4.4}$$
$$A_d[k] = (I - \Delta t A[k])^{-1}$$
$$f(D) = 1 - e^{-D}$$
$$D = \sqrt{p_T^2 - p^2}$$

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In this approach, (4.4), $\hat{p}_T[k] - \hat{p}_T[k-1]$) and $\Delta t \beta (p[k] - \hat{p}_T[k])$ have the role of driving p to p_T achieving the control objective. Also, third term in the law, $(\sigma[k] - \sigma[k-1])f(D)$, ensures that $p[k]$ is a signal with a degree of excitation that declines with D. When the sensor is far away from the capsule, $p[k]$ has large degree of excitation. Otherwise, the degree of excitation decreases correspondingly. Also, it is considered in [52] that $f : R^+ \longrightarrow R^+$ (R^+ standing for $[0, \infty)$) and $A(.) : R^+ \longrightarrow R^{n \times n}$ and design constant β are to be selected such that they obey some assumptions.

4.3   Simulation Case Study

In this scenario, we assume all design parameters same as given before and consider the target point is moving with a constant speed, V_t. In this case;

$$x_T(t) = 10\sin(0.01t) + 50)$$
$$y_T(t) = 10\sin(0.01t) + 30)$$
$$\sigma[k-1] = [0.1sin(0.1t), 0.1cos(0.1t)]^T$$
$$\sigma(0) = [0.6, 0.6]^T$$
$$\beta = 3$$

The simulation results for drifting target with adaptive motion law case are shown following: In Fig. 4.2, we can easily see that the $p[k]$ values converge to $\hat{p}_T[k]$,an so, $pT[k]$ values in x-y frame. In other word, MSTU is tracking the capsule with zero estimation error and lateral trajectory of the estimate target is exactly same as with lateral trajectory of the MSTU. The simulation results demonstrate that the tracking task of the WBC is achieved.
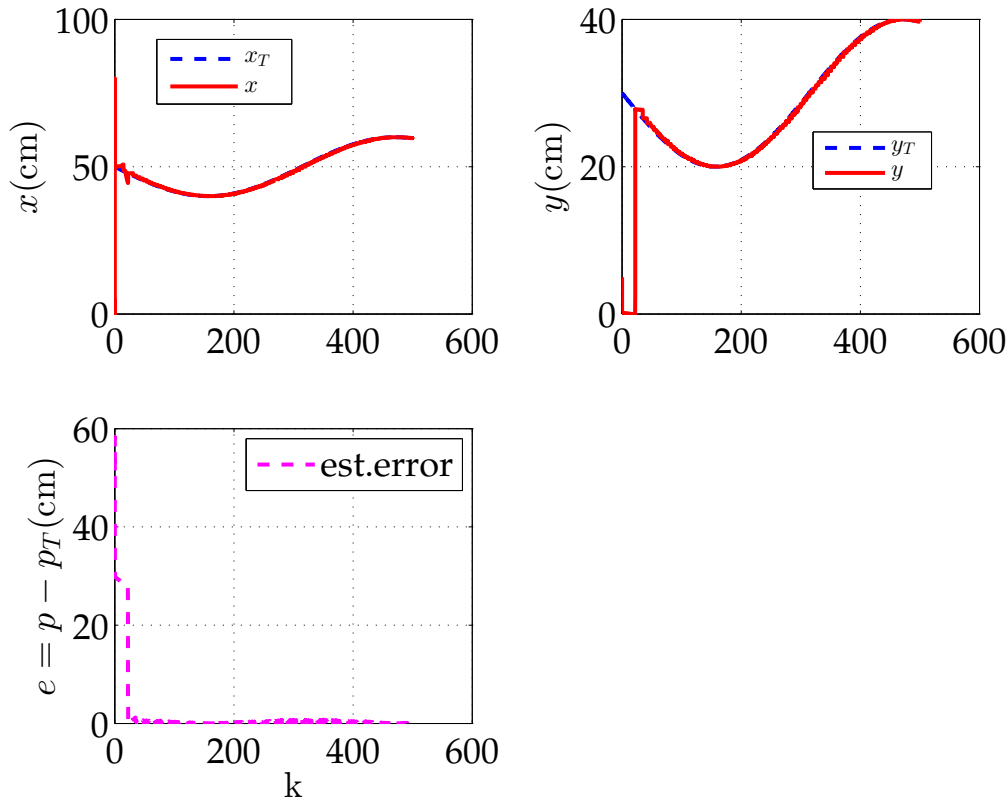
Figure 4.2: Tracking Path of the Target.

4.4   Chapter Summary

In this chapter, a motion control law of a MSTU have been introduced so that the MSTU track and capture the WBC based on location estimate from the previous chapter. Motion control law forces the sensor unit toward estimated positions. Simulation results demonstrate that tracking control of WBC by MSTU is achieved.

Figure 4.3: Lateral coordinate estimates $(\hat{x}_T[k], \hat{y}_T[k])$ for drifting target case

Figure 4.4: Lateral trajectory $(x[k], y[k])$ of the sensor S.

Chapter 5

Magnetic-Field Strength Based Capsule Localization

Although, wireless capsule endoscopy (WCE) has more acceptable reputation among researchers and physicians, the doctors cannot control the capsule motion, or its orientation and so they can miss some signifi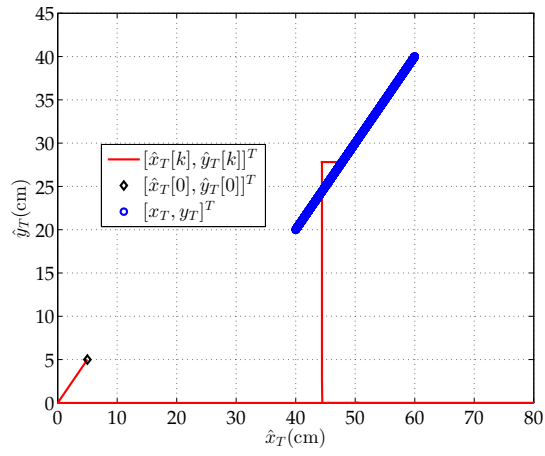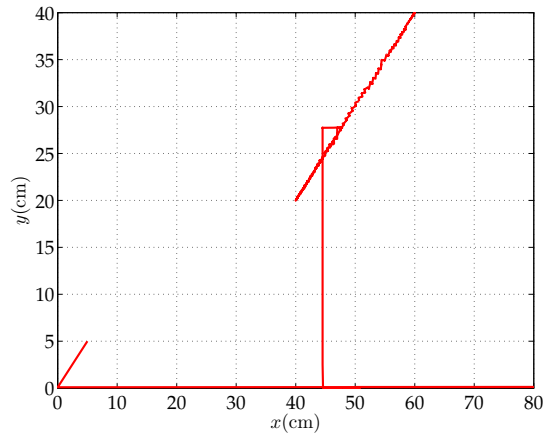cant spots. To address these problems, some research consider use of a small permanent magnet inside the passive capsule, which make possible to external control by an externally applied magnetic field. In addition, magnetic strength based technique itself for position estimate has its own advantage such as magnetic levitation, robotic magnetic steering, helical propulsion by a rotational magnetic field and remote magnetic manipulation [27–29].

More so, WCE with active locomotion helps the endoscopist to guide and steer the capsule. This feature shows same reliability with traditional flexible endoscopy, but with much less pain for the patient. Accordingly, many researchers focus on developing active locomotion devices and platforms [30]. In other words, for future wireless biomedical

capsule robot (WBCR), which combines multitasks of the endoscopy, microsurgery, biopsy and drug delivery, magnetic based techniques will be essential.

In this chapter, we focus on position estimate of a WBCR depending on mathematical model of magnets magnetic field which has been presented in [29]. First, a localization algorithm will be applied in discrete time WBCR position estimate in 2D, that is helpful for establishing a motion tracking algorithm with minimum error. Here, a discrete time adaptive recursive least square algorithm is applied to obtain the position of the WBCR in the GI track. In this approach, we assume using a cartesian robot equipped with a magnetic sensor frame at the end effector. This robotic platform, schematically represented in Fig. 5.1. This paper is organized as follows: Section 5.1 briefly introduces problem definition and proposed design. In Section 5.2, an adaptive RSL localization algorithm with forgetting factor are presented. Section 5.3 demonstrates simulations and results of the proposed method. Conclusion is shown in Section 5.4 [60].

5.1 Problem Definition and Proposed Design

A is a magnet inside a WBCR at an unknown position $p_T[k] = [a, b]^T := p_T(t_k)$ and B_l is magnetic field of the A. Assume that orientation $H_0[k] = [m, n, p]^T$ and z coordinate of the WBCR c are known. Also, $P_l[k] = [x_l - a, y_l - b, z_l - c]^T$ is spatial point of each sensor outside of the human body Fig. 5.2. The objective is to develop an adaptive estimation and a tracking algorithms to visualize movement of the WBCR in 2D by considering related measurements and mathematical model of the magnet's magnetic field from [29]. The law is;

$$B_l = \frac{\mu_T \mu_0 M_T}{4\pi} \left[\frac{3(H_0.P_l)P_l}{R_l^5} - \frac{H_0}{R_i^3} \right] \tag{5.1}$$

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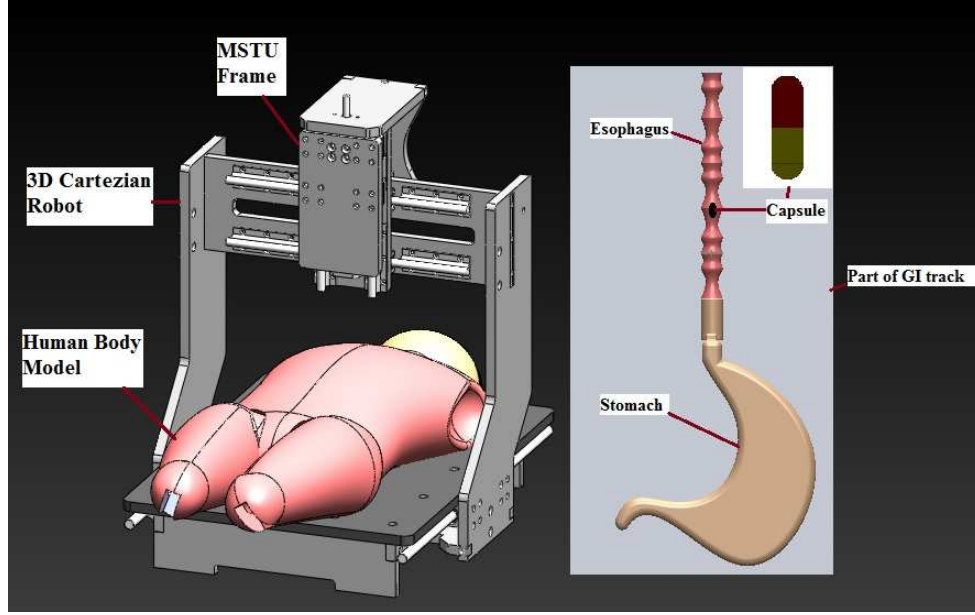
Figure 5.1: 3D endoscopic capsule robotic platform

Here, μ_T is relative permeability of the medium($\mu_{Tbody} = 40$). μ_0 and M_T are air magnetic permeability and magnetic intensity of the magnet respectively. μ_0=4πx10$^-$7 T.m/A

$$M_T = \pi\sigma^2 L M_0 \tag{5.2}$$

σ, L and M_0 represent radious of the magnet, length of the magnet and magnetization strength in return. For Nd-Fe-B magnet; M_0=1,032x10^6 A/m, $L = 70mm$ and $\sigma = 30mm$.

Also, since flux intensity is invariant to the rotation of the circular magnet along its central axis, the magnets orientation H_0 is in two dimensions, in other words, the length of the vector $[m, n, p]^T$ can be any fixed value. Therefore the following constraint for $[m, n, p]^T$ is added :

$$m^2 + n^2 + p^2 = 1 \tag{5.3}$$

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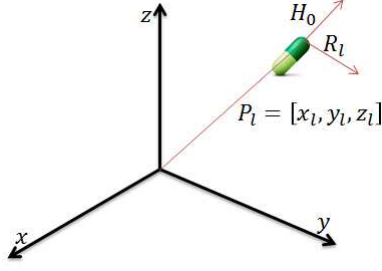
Figure 5.2: Coordinate Frame of a Magnet for WBCR Localization

$$(B_l \times P_l)H_0 = 0 \tag{5.4}$$

rearranged above equation in [29] and tried to write in SPM form;

$$a(B_{ly}p - B_{lz}n) + b(B_{lz}m - B_{lx}p) = -B_{lx}(cn - nz_l + py_l)$$

$$+B_{ly}(cm - mz_l + px_l) + B_{lz}(my_l - nx_l) \tag{5.5}$$

where l=$1,2,3$, $B_{l(x,y,z)}$, and (x_l, y_l, z_l) are the number of the sensors outside of the patient body, magnetic field of the magnet and position of the sensors respectively.

5.2 Adaptive Source Localization Algorithm

In this section, a RLS with forgetting factor is applied to estimate $\hat{p}_T$. Also, stationary and drifting capsule cases are considered based on the RLS algorithm. The localization algorithm is based on a linear parametric model derived in the sequel. From (5.5) and

(5.1), we have the following SPM form that is

$$z_l[k] = \theta_l^T \phi_i[k], \tag{5.6}$$

$$\phi_l[k] = [(B_{ly}p - B_{lz}n), (B_{lz}m - B_{lx}p)]^T,$$

$$z_l[k] = -B_{lx}(cn - nz_l + py_l) + B_{ly}(cm - mz_l + px_l)$$

$$+ B_{lz}(my_l - nx_l),$$

$$\theta_l[k] = [a, b]^T$$

where l is the number of the sensors. Based on the SPM (5.7), various estimators can be designed to produce the estimate $\hat{\theta}_T$ of θ_T. Next, we design an RLS based on-line estimator based on the parametric model (5.7). Following the design procedure in [26], we obtain the following RLS adaptive law:

$$
\begin{aligned}
\hat{\theta}[k] &= \hat{\theta}[k-1] + P[k]\phi[k]\epsilon[k], \\
\epsilon[k] &= z[k] - \hat{\theta}^T[k-1]\phi[k], \\
P[k] &= \frac{1}{\beta}\left(P[k-1] - \frac{P[k-1]\phi[k]\phi[k]^T P[k-1]}{\beta + \phi[k]^T P[k-1]\phi[k]}\right)
\end{aligned}
\tag{5.7}
$$

where $P(0) = P_0$ (and hence $P(k)$, $\forall k > 0$) is an $n \times n$ positive definite matrix, $0 < \beta < 1$ is the forgetting factor coefficient.

5.3   A Simulation Case Study

In this section, we analyze the proposed adaptive localization scheme with combination of the RLS algorithm (5.7). We consider a mobile sensor unit (MSU) localization scenario, where the MSU is equipped with magnetic sensors. The task of the MSU is to estimate

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the position of the p_T of a certain target T. For, this task, the MSU uses the localization algorithm (5.7) and it follows a PE path , a path satisfying ϕ to be PE and modified LS algorithm. Such a PE path follows the path, whose x and y coordinates, as shown in Fig. 5.3:

$$x(t) = 15\sin(0.1t)cm,$$

$$y(t) = 10\cos(0.1t)cm,$$

$$z(t) = 10\sin(0.1t) + 5cm.$$
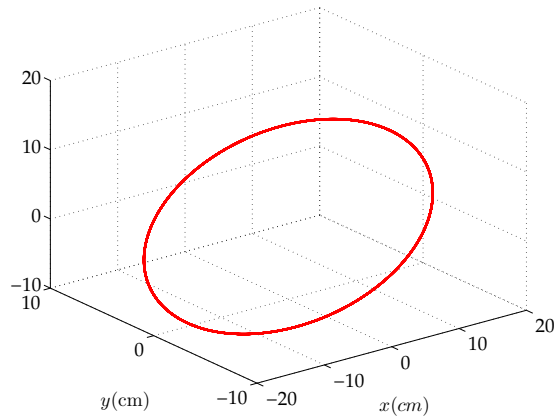

Figure 5.3: Lateral trajectory $(x(t), y(t))$ of the sensor S.

We consider the following design parameters for the algorithm (5.7):

$$\beta = 0.95$$

$$\Gamma[0] = I$$

$$\hat{p}_T(0) = [0, 0]^T cm$$

$$m = \sin 30°$$

$$n = \cos 30° \sin 60°$$

$$p = \cos 30° \cos 60°$$

Stationary and drifting WBC cases are considered in the following subsections.

5.3.1   Stationary Capsule Case

First, the performance of the proposed technique is demonstrated for stationary WBC case in MATLAB/Simulink environment. A stationary WBC located at

$$p_T = [10, 15] cm \tag{5.8}$$

The position estimation results for this case are shown in Fig. 5.4 and Fig. 5.5, $(c = 12)$.

The figures illustrate that the position estimate of the WBC $\hat{p}_T[k]$ rapidly converge to their actual values, leading the estimation error $e[k] = \|\hat{p}_T[k] - p_T\|$ to converge zero.

Fig. 5.4 shows the resulting average localization error (cm) around 5×10^{-4} without any random noises, where the distance between the WBC to the sensor plane is around 20 cm and time step $t_k = k = 0.01$.

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Figure 5.4: Location estimate $\hat{p}_T[k]$ and estimation error $e[k] = \|\hat{p}_T[k] - p_T\|$ for stationary WBC case localization

5.3.2   Drifting Capsule Case

In this case, all design parameters are assumed same as given before and the WBC is moving with a constant speed, V_t. In this case;

$$x_T(t) = 10 - 0.5\cos(0.01t)cm$$

$$y_T(t) = 15 - 0.5\cos(0.01t)cm$$

$$z_T(t) = 12 - 0.5\cos(0.01t)cm$$

$$V_T = [(-0.005\sin(0.01t)), (-0.005\sin(0.01t)),$$

$$(-0.005\sin(0.01t))]^T cm/s$$

$$t_k = k = 0.1$$

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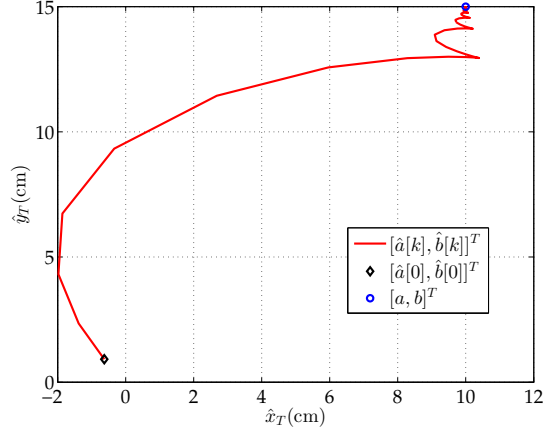
Figure 5.5: Lateral coordinate estimates $(\hat{a}[k], \hat{b}[k])$(cm) for stationary WBC case.

The simulation results for drifting WBC case are shown following:

The average localization error (cm) in Fig. 5.6 is around 0.5 without any random noises, where the distance between the WBC to the sensor plane is around 20 cm.

5.4   Chapter Summary

This study has introduced a non-complex magnetic sensing based WBCR localization method using a discrete adaptive RLS with forgetting factor, which will be be very useful to establish an external control mechanism of an active WBCr. In addition, in the future, we can apply this magnetic localization system to the medical examinations in an experimental setup and analyze security and reliability issues for the proposed method. For those purposes, model of movement of the WBCr inside GI track from some medical data base and have a reliable GI tract path to test such a real system will be essential.
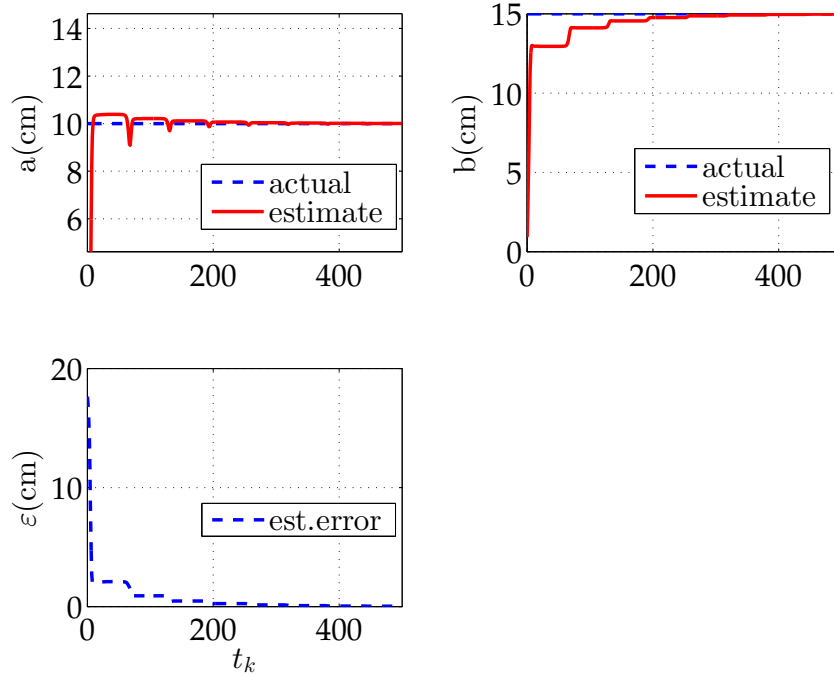
51

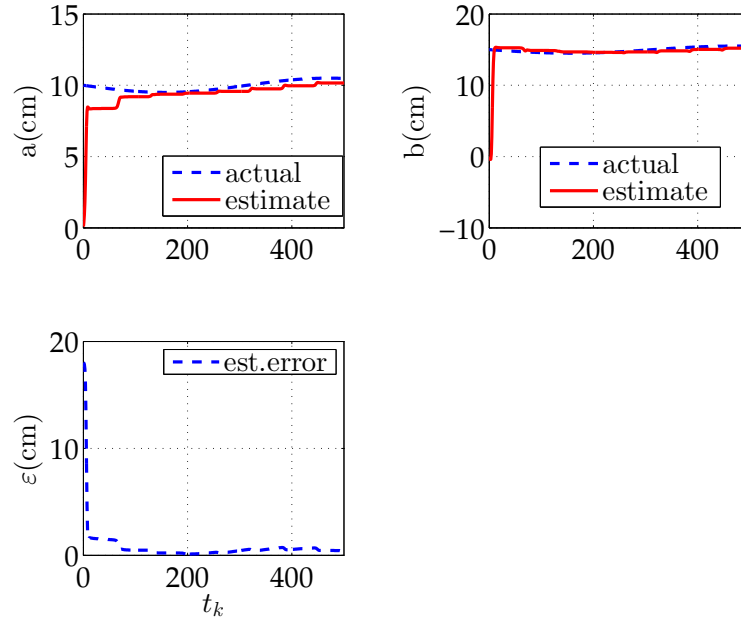Figure 5.6: Location estimate $\hat{p}_T[k]$ and estimation error $e[k] = \|\hat{p}_T[k] - p_T\|$ for drifting WBC case.
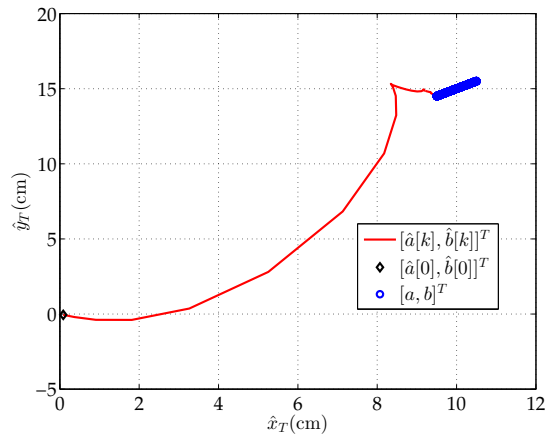
Figure 5.7: Lateral coordinate estimates $(\hat{a}[k], \hat{b}[k])$ for drifting WBC case.

Chapter 6

Conclusion and Future Work

In this thesis, we introduced localization and tracking control of a wireless biomedical capsule robot inside the GI track based on a novel cost and time effective geometric environmental coefficient estimation technique for TOF and RSS based measurements. In order to see the proposed method efficiency, first, we applied a discrete RLS algorithm for position estimate of the capsule based on the proposed coefficient estimation technique, then a discrete motion tracking adaptive law was introduced using position estimate data found in previous step. The simulation results demonstrated the proposed methods sufficiency and accuracy levels. Finally, we developed a magnetic strength based localization algorithm and applied a discrete RLS algorithm for capsule position estimate in 2D as a first step to have a future active WBC robotic environment. Also, for this design, results of our simulations showed good convergency and almost zero localization error.

For the future work, a 3-dimension adaptive tracking control law can be established as well as together with an optimal z value between the MSTU and the WBC. We can also have an experimental set-up to test such an design in real-time and to eliminate noise effect,

we can apply a adaptive kalman filter. WCE with the capability of moving automatically in the digestive tract under an external control will be introduced in the near future. Such an active system requires a sufficiently accurate tracking system. Also, wireless power transmission based on magnetic resonance can be introduced to enable active localization system of the capsule robot by transferring electronic energy.

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