# Least-Squares Based Adaptive Source Localization with Biomedical Applications

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**

In this thesis, we study certain aspects of signal source/target localization by sensory agents and their biomedical applications. We first focus on a generic distance measurement based problem: Estimation of the location of a signal source by a sensory agent equiped with a distance measurement unit or a team of such a sensory agent. This problem was addressed in some recent studies using a gradient based adaptive algorithm. In this study, we design a least-squares based adaptive algorithm with forgetting factor for the same task. Besides its mathematical background, we perform some simulations for both stationary and drifting target cases. The least-squares based algorithm we propose bears the same asymptotic stability and convergence properties as the gradient algorithm previously studied. It is further demonstrated via simulation studies that the proposed least-squares algorithm converges significantly faster to the resultant location estimates than the gradient algorithm for high values of the forgetting factor, and significantly reduces the noise effects for small values of the forgetting factor.

We also focus on the problem of localizing a medical device/implant in human body by a mobile sensor unit (MSU) using distance measurements. As the particular distance measurement method, time of flight (TOF) based approach involving ultra wide-band signals is used, noting the important effects of the medium characteristics on this measurement method. Since human body consists of different organs and tissues, each with a different signal permittivity coefficient and hence a different signal propagation speed, one cannot assume a constant signal propagation speed environment for the aforementioned medical localization problem. Furthermore, the propagation speed is unknown. Considering all the above factors and utilizing a TOF based distance measurement mechanism, we use the proposed adaptive least-square algorithm to estimate the 3-D location of a medical device/implant in the human body. In the design of the adaptive algorithm, we first derive a linear parametric model with the unknown 3-D coordinates of the device/implant and the current signal propagation speed of the medium as its parameters. Then, based on this parametric model, we design the proposed adaptive algorithm, which uses the measured 3-D position of the MSU and the measured TOF as regressor signals. After providing a formal analysis of convergence properties of the proposed localization algorithm, we implement numerical tests to analyze the properties of the localization algorithm, considering two types of scenarios: (1) A priori information regarding the region, e.g quadrant (among upper-left, upper-right, lower-left, lower-right of the human body), of the implant location is available and (2) such a priori information is not available. In (1), assuming knowledge of fixed average relative permittivity for each region, we established that the proposed algorithm converges to an estimate with zero estimation error. Moreover, different white Gaussian noises are added to emulate the TOF measurement disturbances, and it is observed that the proposed algorithm is robust to such noises/disturbances. In (2), although perfect estimation is not achieved, the estimation error is at a low admissible level. In addition, for both cases (1) and (2), forgetting factor effects have been investigated and results show that use of small forgetting factor values reduces noise effects significantly, while use of high forgetting factor values speeds up convergence of the estimation.

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To my wife, Zehra, I owe many thanks for love, continued understanding and patience to deal with my busy days as a graduate student. I would also like to thank my family for their love and support, their unconditional encouragement and belief during these years.

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*To my wife*

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# Chapter 1

# Introduction

## 1.1 Sensory Systems and Wireless Sensor Networks

With the recent advances in wireless communications and electronics, which have allowed the improvement of low-cost, low-power and multi-functional small size communication devices, using these devices as sensor nodes, wireless sensor networks (WSN) have been developed. WSN can be described as a collection of spatially scattered autonomous sensor nodes organized to cooperatively collect data. In a WSN, hundreds or even thousands of small self-powered sensor nodes are distributed in an area in order to perform some specific tasks such as sensing sound, pressure, radiation, temperature or any other environmental factors. WSNs not only provide real time monitoring, but they also facilitate control of physical environment from remote location. Each sensor node has its own processing capability (CPUs or DSP chips, micro-controllers), radio frequency (RF) transceiver (usually with a single omni-directional antenna), power source, memory, various sensors and actuators. These sensor nodes collect the data and transmit the data to their neighboring sensor nodes and then pass to specified destinations where the data are processed. Although the sensor nodes individually have limited capabilities, their cooperation to execute a specific task produces an improved view of the physical world [1].

Research in the field of WSN can be divided into three main levels; component level, system level and application level [2]. The component level research is mainly concerned with the enhancement of sensing, communication and computation capabilities of an individual sensor device. Research at the system level focus on WSN network mechanism and collaboration of sensor nodes in an energy efficient and scalable manner. Research at the application level deals with processing of the data obtained by sensors based on the application objective. Sensor networks is useful in a range of application fields, which require constant monitoring and detection, including environmental, medical, military, transportation, and homeland defense. Moreover, as implemented in this thesis, various enabling technologies such as tracking and localization have been developed with WSNs.

More recently, WSNs have been attributed widely to new applications facilitated by large-scale networks with very small devices, which acquire information from the physical environment in real time. Development of micro-electro-mechanical system (MEMS) and recent advance in wireless communication technology have made some visioned applications in WSN feasible. During the last decade, some universities and research institutions have developed some prototypes of sensor nodes, for instance Motes [3, 4] at UC Berkeley and Intel research laboratory, uAMPS [5] at MIT and GNOMES [6] at Rice University, with the functions of localization, detection, tracking and targeting [7]. WSN is an important and exciting new technology with a great potential for improving many current applications in military, environmental, health and home applications [7].

WSNs used in the military field should provide some services such as separation of friendly and opposition forces, battlefield surveillance, targeting, nuclear, biological and chemical attack detection, battle damage assessment with the requirement of instant response time, self-organization, fault tolerance security, longevity and stealthiness. Since most of the basic knowledge of WSNs depend on the defense application at the beginning, for example distributed sensor networks (DSN) and sensor information technology (SenIT), WSNs are implemented very successfully in the military fields. WSNs have a variety of applications in military, examples include target field imaging, intrusion detection and security surveillance. WSNs have also been widely used in environmental applications such as habitat monitoring, fire, earthquakes and floods detection, agriculture research and traffic control. Since there is no strict constraints to the environmental applications, the expected consistency in WSNs applied in environmental areas is not that very high as in military applications. The system of Automated Local Evaluation in Real-Time (ALERT) improved by the American National Weather Service can be given as an example of real world application of environmental monitoring [8]. The system ALERT is fitted with meteorological and hydrological sensing device so as to measure water level, temperature and wind. Moreover, the system ALERT has its own automatic warning model in order to alert central station, when the processed data value is above acceptable rate [8]. Because web based query is available, weather information can be reached in a real time through the ALERT environmental monitoring system.

In recent years a significant development of WSNs in health care has emerged with many exciting applications ranging from real time, continuous patient monitoring, glucose level determination, even to cancer detection. WSNs for body centric applications consist of many tiny sensor nodes, which can be carried by their users in a pocket or otherwise attached to their body [9]. These sensor nodes communicate with an external computer system via wireless interface. Many body centric sensor nodes are organized to an application specific solution to provide remote monitoring of patient and their vital parameters or diagnose and treat disease. For instance, wireless vital sign monitoring system (VitalDust) [10] developed by UC Berkeley enables rapid, continuous survey of patient and in case of emergency situation. VitalDust automatically transfers all vital information to the closest hospital. Another example is recently developed Lens-less Ultra-wide-field Cell monitoring Array platform based on shadowing imaging, LUCAS at UCLA [11]. This system is integrated into regular wireless cell phone and lead to improved wireless diagnose for HIV, malaria and other global medical problems, which can be diagnosed from blood sample. LUCAS provides its users blood test without going any health center, by sending all information taken from mobile phone to the closest hospital in order to be interpreted [12]. In case of emergency, patient can be worn and asked to come health clinic. Through this way, LUCAS brings the hospital to the patient.

Along with the applications in many fields, it is not difficult to say that there are many applications already designed with WSNs to make life easier at home such as "Smart Environment: Residential Laboratory" and "Smart Kindergarten" [13]. When talking about the concept "intelligent home", it can be considered that there are well organized home appliances or furniture collaborating each other through sensor nodes and computer interface to detect users desires [13]. To illustrate, there can be air condition at home adjusts home temperature by itself or the light on the table is automatically on as well.

## 1.2 Sensors and Sensory Network Localization

Localization has been one of the main problem in many research fields such as, WSN, autonomous robot and vehicle navigation, telecommunication, radar, sonar, as well as body centric wireless communication. In many military WSN applications, for instance targeting unfriendly forces or equipments, detecting nuclear, biological or chemical attacks and sources, the measured data are meaningless without a certain information of the position from where the data are acquired. For this reason, it is almost always must to determine the location of a specific sensor so that the appropriate actions can be proceed in case of emergencies. In addition, in the network layer, there are some communication protocols and algorithms, which are required to determine sensors location in order that propagate information through multi-hop sensor networks.

For the outdoor localization, GPS (Global Positioning System) units can easily obtain location information of intended subject. On the other hand, attaching GPS units to every single sensor is both costly and infeasible, because of the power constrain. For the indoor localization, GPS does not work well due to lack of clear line of sight to the satellites [14]. Moreover, although there are some applications require stationary sensor node, for the most WSN applications, the nodes are mobile and entire network is dynamic. Because of the all reasons mentioned, some methods are needed to estimate sensor location for stationary and mobile or indoor and outdoor applications without GPS units.

Localization can roughly be divided into two process categories; the first process is to estimate sensor relations between other sensors with respect to angel, range or distance and the second process is to use information gathered from the first process by some algorithms and estimation to determine location of sensor. For the first process of localization, there are some ranging methods used in literature such as, ultrasonic, sonic and light, but most of them are all limited from widespread usage. The most used method to estimate relation (angle, range, distance) between sensors is RF ranging method, since it does not require additional device as acoustic systems do, overcomes obstacles well when compared to others and does not have limited range as ultrasonic and sonic systems have [15]. Usage of the ranging methods depend on applications that determine requirements on accuracy, latency, and infrastructure complexity of a ranging system. All ranging methods are prone to be polluted with noise, which restricts ranging accuracy by combining with multi-path channel effects, clock synchronization and sampling artifacts [1]. When inter-sensor measurement data is considered, it is possible to classify localization algorithms into two categories; centralized algorithms and distributed algorithms. In centralized algorithms, all estimated inter-sensor information are combined in one central processes unit where non-anchor sensor location is estimated. Multidimensional scaling algorithm (MDS), linear programming algorithm and stochastic optimization algorithm can be given as an example of centralized algorithms [1]. On the other hand, in distributed algorithms, each node estimates its own position by using inter-sensor measurement and its neighbor position. Moreover, a sensor can find its neighbor location by using its own position information (via GPS) and inter-sensor measurement with distributed algorithms [16]. DV-hop and DV-distance algorithms can be given as an example of distributed algorithms [1]. These two kinds of algorithms can be compared with respect to location estimation accuracy, implementation, computational complexity and energy consumption. First of all, distributed localization algorithms are generally more computationally efficient and easier to use in large-scale networks than centralized algorithms [17]. Secondly, centralized algorithms give better results than distributed algorithms in point of accuracy [17]. Moreover, distributed algorithms are more difficult to design because of the difficulty of combining global and local systems [16]. In terms of energy consumption, performance of the algorithm is based on the application kind. While for the large-scale networks, centralized algorithms are more efficient than distributed algorithms, for small-scale networks, distributed algorithms are likely to provide more energy efficient results [17]. Furthermore, localization algorithms can be divided into two categories in terms of mathematical relationship between source and measurement; linear algorithms and non-linear algorithms. Generally, non-linear methodology does not guarantee global convergence because their optimizations cost functions are multi-modal.

However, when noise information is not available, non-linear is simpler and is a practical choice. Non-linear least square algorithm (NLS) and maximum likelihood algorithm (ML) can be given an example of the non-linear localization algorithms. When considering accuracy and complexity, it can be said that ML is more accurate and complex than NLS [18]. Regarding the linear algorithms, the basic idea of the linear localization algorithms is to convert the non-linear expressions of non-linear algorithms equations and measurement information. Linear localization algorithms always guarantee global convergence because their optimization cost functions are unimodal. Linear least square algorithm (LLS) and weighted linear least square algorithm (WLLS) can be given an example of the linear localization algorithms. When regarding accuracy and complexity, WLLS is more accurate and complex than LSS [19]. However, while noise static is not needed for LSS, it is needed for WLLS [20].

## 1.3 Contributions and Thesis Outline

In this thesis, firstly, analytical solution of the localization problem is proposed by deriving a linear parametric model of the unknown sensor-source in three dimensions. Then, based on this parametric model, new localization algorithm, which is least-square based adaptive source localization algorithm, is designed. After analytical studies, we perform some simulations so as to evaluate the proposed algorithm performance. With the simulation results, it is shown that the proposed algorithm outperforms gradient descent localization algorithm studied previous works. It is also shown that the forgetting factor has a considerable impact on both convergence time and noise compensation.

Secondly, as an application of the adaptive least-squares algorithm, we focus on implant localization in human body. Simulations are performed for two different scenarios: priori information related with implant location is available and such a priori information is not available. Simulation results show that the proposed algorithm estimates implant location with almost zero mean estimation error for first scenario even under noisy measurements. For second scenario, even though the proposed algorithm do not obtain perfect estimation results, the estimation error is at low acceptable level.

The basic WSN applications and sensor localization concept are described in the first chapter. The rest of this thesis is divided into four chapters. In Chapter 2, we introduce theoretical study of the localization methods, measurement techniques and presenting a state of the art of the different technical solutions and algorithms. Some challenges with localization algorithms are also discussed in related works part. In Chapter 3, we elaborate new localization algorithm, least-square based adaptive source localization algorithm, with its theoretical study and present the performance of the approach in different conditions and compare its efficiency to Gradient algorithm. Our proposed localization algorithm is demonstrated to be able to achieve better performance comparing to Gradient method. We will then study medical implant localization in human body as an application of the proposed algorithm in Chapter 4. In Chapter 5, we first summarize the studies in the thesis, then finally, we discuss some directions for future work.

# Chapter 2

# Background and Related Works

## 2.1 Measurement Techniques Used in Wireless Sensory Localization

WSN localization depends on measurements which define inter-sensor relation in network. There are many factors that affect selection of the measurement techniques, for instance number of sensor node in WSN, geometric shape of the network area ,distribution of the sensor, and network architecture [1]. Moreover, type of measurement affects algorithm type used for specific localization application. When typical WSN is considered, a generic formula can be written using relation between available measurements and coordinates of sensor;

$$Y = h(X) + e$$

where $Y$ indicates the vector of all measurements, $X$ has true coordinate vectors of localized sensor and $\mathbf{e}$ is the vector of measurement error [1]. If we can acquire distribution of measurements errors, $f_e$, We can estimate sensor location with maximum likelihood approach by minimizing an optimization criteria,

$$\hat{X} = argmin(log f_e(Y - h(\hat{X})))$$

As a cost function related to formula above, Fisher Information Matrix,

$$J(X) = E(\nabla_x^T log f_e(Y - h(X))\nabla_x log f_e(Y - h(X)))$$

Where $\nabla_x log f_e(Y - h(X))$ is partial derivative of $log f_e(Y - h(X)$ in accordance with $X$ evaluated at $X$. Another technique to evaluate the location accuracy is the Cramer-Rao bound;

$$Cov(\hat{X}) = E(X - \hat{X})(X - \hat{X})^T \geq J^{-1}(X)$$

Through the formula written above, any unbiased estimate of $X$ can be found. When right hand side of the above formula is considered, it gives an idea how used sensor node configuration is appropriate for localization of an unknown object. The lower bound in the formula also enables sensor placement according to desired accuracy, with the given sensitivity of the sensors. On the other hand, It should not be forgotten that this lower bound depends on many assumptions and susceptible any changes in conditions.

Moreover, in order to evaluate sensor node performance, the position root mean square error (RMSE) can be better criteria, since it contains estimation error sources covariance and bias error.

$$RMSE = \sqrt{E[(X^0 - \hat{X})^2 + (Y^0 - \hat{Y})^2]} \geq \sqrt{trCov(\hat{p})}$$

Where $p$ indicates the true position. According to the equation above, when we specify RMSE conditions, number of sensor node in the network can be increased until equation shows that the information obtained from sensor nodes is enough.

All measurement models in WSN are vulnerable to noise and type of measurement, algorithm and network architecture affects accuracy level. In the following sections, we will discuss available techniques for measurements.

### 2.1.1 Received Signal Strength Indication (RSSI)

Received signal strength (RSS) measurement is generally modeled as a function of distance between receiver and transceiver. Most wireless device have a function to measure the received signal strength. The relation between received signal strength and distance is inverse linear, which means that power dissipates exponentially from the source as the distance increases between emitter and receiver [16] [21]. RSS measures the power of the signal at the receiver. The power model based on the formula as shown below;

$$P_r(d)[dBm] = P_0(d_0)[dBm] - 10n_p log_{10}(\frac{d}{d_0}) + X_\sigma \tag{2.1.1}$$

Where

- $P_r(d)[dBm]$ is a reference power in dB milliwatts at a reference distance $d_0$ from the transceiver
- $n_p$ is the path loss exponent
- $X_\sigma$ is a zero mean Gaussian distributed random variable with standard deviation $\sigma$

Based on the equation (2.1.1), the propagation loss can be calculated with the transmitted power at the receiver and loss, which decreases with distance, can be translated into distance estimate. In the equation (2.1.1), $X_\sigma$ term stands for the random effect caused by shadowing. Both $n_p$ and $\sigma$ are based on environmental conditions [1]. Moreover, Gaussian model can be used to evaluate accurately lost exponent $n_p$ and for both cases far field region and near field region of the transmitter, lost exponent model need to be considered differently [1].

Although RSS based measurement seems easy to be used for localization, there are some obstacles making RSS measurement difficult. If RSS based measurement is to be attempted, a designer must be able to deal with some nonlinearities and imperfect knowledge originated from propagation and devices used in the process. As an propagation effects, we can count multi-path fading, shadowing and antenna effects. When indoor localization is considered, in order to make efficient measurement with RSS, there must be a line of sight path between emitter and receiver, which provides dominant line of sight link (DLOS). However, most indoor areas have LOS path shadowed by walls and objects. This shadow effect decreases RSS effect at the receiver and multi-path power from many different directions suppresses RSS power. Moreover, antennas used for receivers and transceivers affects RSS measurement. In the medium, there can be some objects, which would block RF signal and attenuate it. Also, some researches have revealed that antenna orientation is important issue so as to obtain efficient measurement.

As shown in Figure 2.1, RSS based measurement requires redesign of emitters and receivers in order to convert transmitted power into location information by estimating path loss effect. Path loss estimation requires to have transmitter parameter, and transmitter may need to have feedback to control its transmitter power.

### 2.1.2 Time of Arrival

Time of arrival (TOA) method estimates the distance based on the signal propagation time between transceiver and receiver nodes. Once speed of the signal and transceiver location are known, receiver location can be found using measured time of arrival. As a propagation

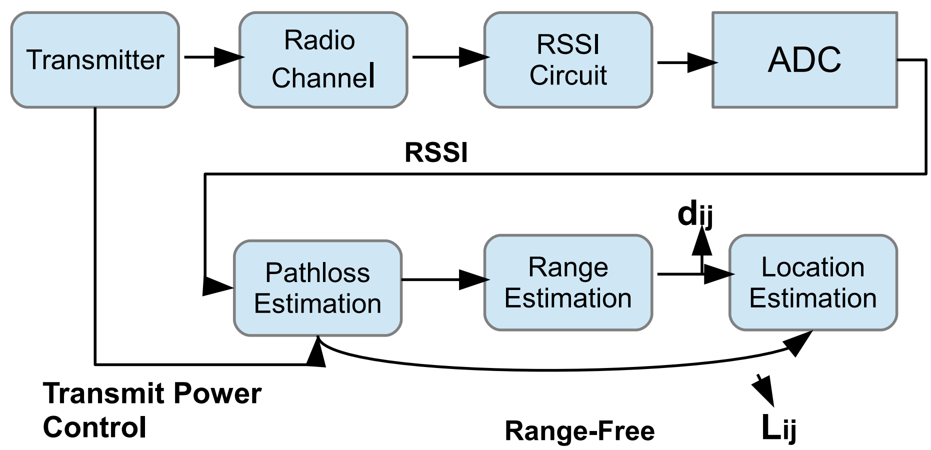



Figure 2.1: RSS-based positioning system architecture.

signal, different types of signal can be used such as RF, ultrasound or acoustic. In this measurement method, it is considered that line of sight signal is available beforehand. The measured signal is contaminated by noise and multi-path channel effects. In order to obtain accurate estimation, multi-path channel and noise effect should be modeled well [22] [23]. Equations (2.1.2) and (2.1.3) represents modeled multi-path wireless channel and received signal in a multi-path channel respectively.

$$h(t) = \sum_{m=1}^{M} \alpha_m \delta(t - \tau_m) \tag{2.1.2}$$

Where, M is the number of multi-path components, $\alpha_m$ and $\tau_m$ represent complex attenuation and propagation delay respectively. Since sensor nodes in WSN can be mobile, $\alpha_m$ and $\tau_m$ are time based random variables.

$$x(t) = \sum_{m=1}^{M} \alpha_m s(t - \tau_m) + v(t) \tag{2.1.3}$$

Where $s(t)$ is a known transmitted signal and $v(t)$ represents noise. As seen in the Figure 2.2, for two dimensions at least three base stations (BS) and for three dimensions at least four base stations are needed to measure TOA of the transmission from each mobile station(MS). The intersection of the circles gives the location of MS. Due to measurement errors, the circles does not create single intersection point and the intersection is formed as a region.

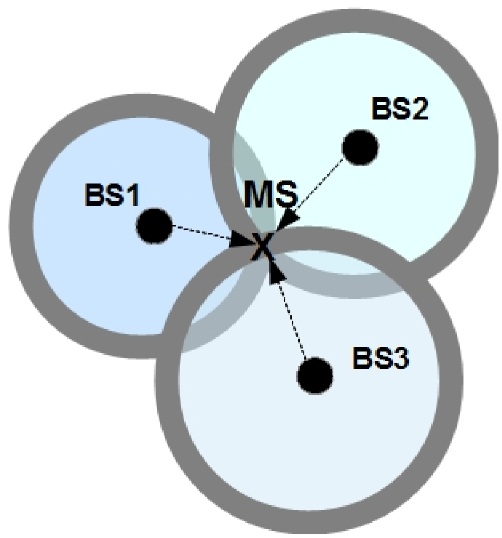



Figure 2.2: Graphical demonstration of TOA based positioning system.

### 2.1.3 Time Difference of Arrival

Time difference of arrival (TDOA) measures the difference in arrival time from the transmitter to the receivers. Time difference is directly proportional with the distance between transmitter and receiver. In two dimension, if we represent receivers coordinates with $Y_i$ and $Y_j$ and transmitter coordinate with $X_t$, the equation (2.1.4) gives measured TDOA [1].

$$\Delta t_{ij} = t_i - t_j = \frac{1}{c}(\|Y_t - Yi\| - \|Y_t - Y_j\|) \tag{2.1.4}$$

Where, $t_i$ and $t_j$ are the arrival times of the signal at receivers $i$ and $j$ respectively and $c$ represents signal propagation velocity. If we consider receivers locations known beforehand

and their clocks are well synchronized, equation (2.1.4) gives a part of hyperbole on which transmitter must be on [1]. The intersection of these part of hyperboles indicates transmitter location. When the system consisting of N receivers is considered, there are N-1 linear TDOA measurements. In order to estimate transmitter's location, we have to have at least three receivers for two dimensions or at least four receivers for three dimensions. Receivers must be placed non-collinearly. Figure 2.3 is the graphical illustration of two dimensional TDOA measurement.

TDOA measurements accuracy depends on synchronization of clock time at the receivers and multi-path effects. In wireless environments, since there are many scatterers such as walls, hills and buildings, multi-path is the major effect of the measurement errors. In order to improve accuracy with TDOA, the distance between receivers can be increased so that difference between time of arrival increases.

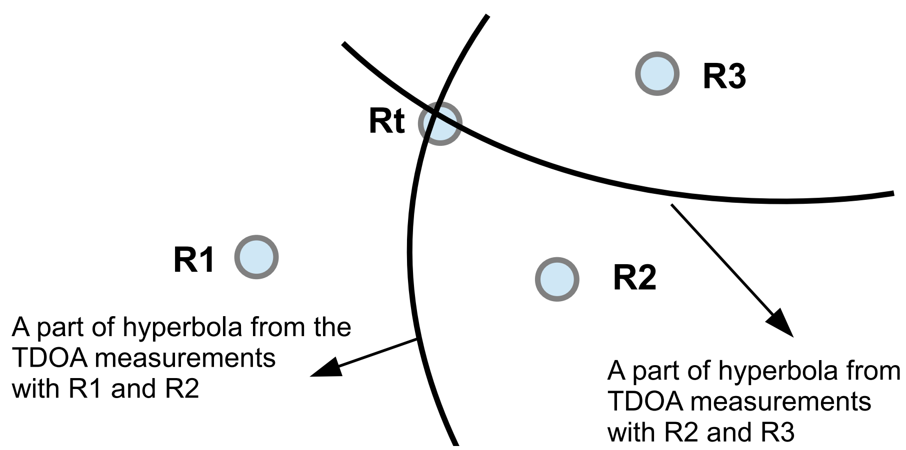



Figure 2.3: Graphical demonstration of TOA based positioning system.

### 2.1.4 Angle of Arrival

Angle of arrival (AOA) measurement provides location information by supporting other measurement methods discussed before. AOA estimates the direction between neighboring sensors rather than distance. AOA system estimates the angle at which signals are received and uses simple geometric relations to measure the relative locations of transmitter and receiver. In order to use AOA measurement technique, antenna array is required. Figure 2.4 illustrates geometrical architecture of AOA with an antenna array. The neighboring antennas are distributed by a fixed distance $d$. Transmitter distance to the $k^{th}$ antenna can be given by

$$R_k \sim R_0 - kdcos\alpha \tag{2.1.5}$$

where $\alpha$ is the direction of the transmitter viewed from the antenna array and $R_0$ represents the distance between transmitter and $0^{th}$ antenna [1]. If the wavelength is $\lambda$ for the transmitter signal, the phase difference between neighboring antennas can be written as $2\pi\frac{dcos\alpha}{\lambda}$ [1]. Thus, the measurement of phase difference gives AOA of transmitter according to antenna array. However, as discussed for other measurement techniques, the accuracy of AOA measurements is limited by the some effects such as, multi-path, shadowing, and the directivity of the antenna. Moreover, there are some others disadvantages of using AOA measurement. First of all, using complex antenna array is expensive and secondly, AOA measurement technique can not support the systems with a large number of sensor node.

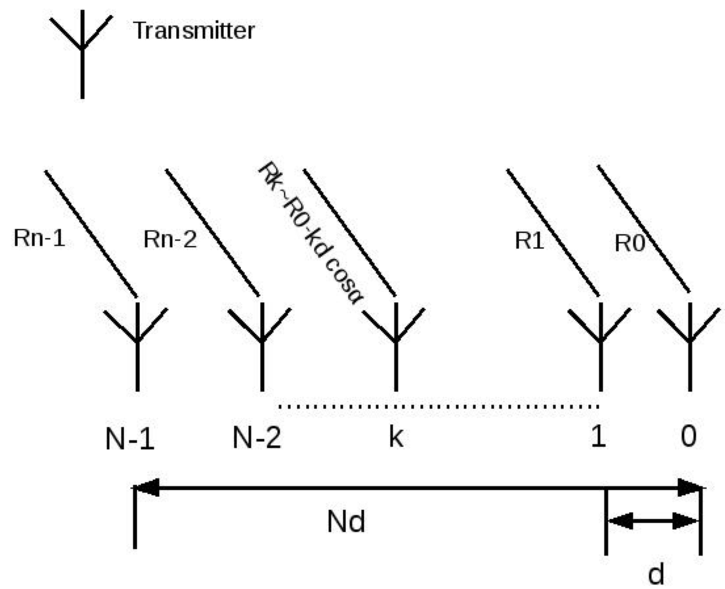



Figure 2.4: Demonstration of AOA measurement using an antenna array.

## 2.2 Geometric Methods in Localization

### 2.2.1 Triangulation

Triangulation is one of geometric technique that benefits from the angle of arrival to obtain location information of sensors. According to the this technique, for two dimensions, unknown sensor location as the third sensor can be found by using one known side and two known angles with the help of the trigonometry laws of sines and cosines. Triangulation uses radio waves to triangulate unknown sensor location in most applications [24]. Figure 2.5 shows computation of triangulation and the location calculation of A is given by the equation (2.2.1).

$$U(s_1, s_2, A) = \frac{d(s_1, A) \times d(s_2, A)}{\sin \beta} \tag{2.2.1}$$

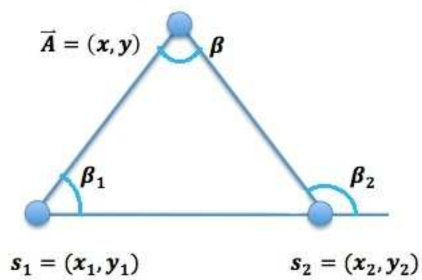



Figure 2.5: Estimation the position of the target A by given $s_1$ and $s_2$

### 2.2.2 Trilateration

Trilateration is another geometric technique that uses distance information between three known sensors and one unknown sensor to estimate the unknown sensor location in case of two dimensions. The location of unknown sensor is determined by measurement of distance, using the geometry of sphere or triangles that are comprised by intersection of three circles. The best example for practical usage of trilateration is global positioning system (GPS). Least squares, nonlinear least squares and circle intersection with clustering are common methods in literature in order to solve trilateration problems [25].

### 2.2.3 Multilateration

Multilateration works almost same idea with trilateration to estimate more precisely unknown sensor location based on its distance measurements to multiple known sensor nodes. The most important difference between trilateration and multilateration is that multilateration uses more known sensors so as to increase localization accuracy.

## 2.3 Related Works

There have been a many efforts to investigate sensor-source localization problems by WSN research community until now. When considering all these studies, they all are employed to achieve localization accuracy or reduce estimation error by using different distance estimation methods or algorithms. Since there is a trade-off between accuracy and cost or estimation error and system complexity for most applications, algorithms and estimation methods have been chosen according to the application types. As an example of localization algorithm used in literature, [26] proposes maximum likelihood estimation algorithm to find robot location, and distributed Kalman filter is used to deal with cooperative localization problem in [27]. Moreover, [28] relies on the statistical algorithm to localize mobile robot location. Another type of localization algorithms are established with large number of sensor nodes with known positions, which are called anchor nodes. Even though this method is effective for monitoring large scale fields, they are expensive to set up and maintain [29]. [30] proposes sensor localization with anchor nodes. Regarding distance estimation methods for localization, they are also application oriented. To illustrate, the received signal strength indicator (RSSI) technique has been commonly used thanks to its simplicity, although it achieves low accuracy [31]. Moreover, many studies utilize time of arrival (TOA), time difference of arrival (TDOA) or angle of arrival (AOA) as an distance estimation method, because they minimize distance estimation error. However, they are expensive to use, since the sensors used in the network need to have powerful processes systems or antenna array. TOA, TDOA and AOA techniques are employed in [32], [33] and [34] respectively. Some geometrical localization techniques such as multilateration and triangulation are also used with integration of some appropriate algorithms to localize sensors and sources. Since geometrical localization techniques are environment dependent, the algorithm performance with multilateration or trilateration changes with sensor network and terrain structures. [16] uses geometrical localization techniques with iterative estimation to develop localization accuracy.

After mentioned about general frame of localization studies briefly, since the thesis content is directly related with least-squares (LS) estimation, we can continue with localization studies with LS approaches in literature. For localization problems, LS estimation and its variations have been commonly used to obtain unknown sensor-source location. The basic type of LS algorithm used for localization is linear least-squares localization approach. Linear LS algorithm is used because of its low complexity, despite the fact that it is sub-optimal in general. [35] studies linear LS considering its theoretical side and it shows some simulation results in which localization error is connected with reference base-station movement. Furthermore, correlation between linear LS and RSSI is investigated in [36], [37]. When the parameters cannot be fit to linear LS, nonlinear LS estimation can be used to estimate location of unknown sensor-source. In some studies nonlinear LS estimation achieves good results compare to linear LS. [38] shows that nonlinear LS estimation outperforms linear LS and distributed LS estimations with respect to energy saving in WSN. In [39], distributed LS algorithm is introduced with the purpose of reducing energy consumption. Also, according to the [40], localization error is reduced less than 1% by separating LS calculation into distributed sub-calculations. As an non-iterative LS algorithm, weighted LS (WLS) algorithm is proposed in [19]. It is shown that WLS has almost Cramer-Rao lower bound performance when the estimation noise is small. Afterwards, researchers developed WLS algorithm as an sequential WLS algorithm in [41]. The study results shows that sequential WSL algorithm is better than WSL for both line-of-sight and non-line-of-sight environment. As used in this thesis, recursive LS algorithm can be used to solve localization problems. For instance, in [42], recursive total LS algorithm is used to find robot position. The authors states that recursive total LS algorithm gives much faster convergence time with regard to Kalman and extended Kalman filters estimations in [43]. Moreover, [44] studies LS kernel method in order to obtain locations of mobile nodes.

In [45], the authors propose continuous time linear adaptive localization algorithm by using gradient descent estimation under the persistent excitation conditions. In the study, a moving sensory agent estimates unknown signal source/target location with the information of its instant position, and distance between unknown signal source/target and itself for both stationary and drifting target cases. The paper evaluates the proposed adaptive localization algorithm performance with respect to convergence speed. [45] has been used for this thesis studies as a reference work.

# Chapter 3

# Least-Squares Based Adaptive Source Localization

## 3.1 Introduction

Location estimation of a signal source or target by a sensory agent or team of such agents has become an important aspect in many application areas recently. For instance, in a wireless sensor network, the base station may have to find an unknown sensor node location in order to adjust the most efficient power level in order to ensure appropriate network coverage [45].

In this thesis, we focus on distance measurement based localization. There are two main approaches for measuring the distance between an agent and the target. The first one is passive measurement. In this case, the signal intensity at the source and the agent locations are used, together with characteristics of the propagation medium, to estimate the distance. On the other hand, in active distance measurements an agent transmits signals in order to estimates the distance by using the time that is measured for the signal reflected off the source to come back [45], [46].

Generally , there are two approaches to characterize this research in this area. The first approach needs clusters of immobile agents that work together to localize a given source. Localizing the source in two dimensions needs at least three separate non-collinearly located agents and their distances from the source. Sometimes, a priori information may be available to resolve that ambiguity. If not, a third agent is required. In three dimensions, there must be at least four agents that are not arranged in an order on the same two dimensional plane [45]. In the second approach, a single mobile agent can be used to estimate the distance between the source and agent by changing the single mobile agent's position.

For this study, second approach is going to be used. According to the this approach, three distance measurements are needed by using only one agent in order to achieve signal source localization. After taking the first distance measurement, move the agent and take the second distance measurement, and then move it again take another distance measurement, but the third measurement must not be collinear considering the first two measurements. In the case of three dimensions, a fourth measurement is required [45]. Nevertheless, there are two main cases which are complicating the estimation of signal source localization. First of all, measurements can be contaminated by noise and this situation can drive system unstable condition. Secondly, the signal source can change its position while agent is moving its new position. To eliminate the these disadvantages, a continuous time algorithm is going to be used that estimates the signal source location by known agent movement in three dimensions [45].

This chapter focuses on the problem of localizing a signal source by a mobile sensory agent using distance measurements. This problem was tackled in [45] using a gradient based adaptive algorithm. In this study, we design a least-squares based adaptive algorithm with forgetting factor for the same task.

## 3.2 Problem Definition

In this section, we consider the following localization problem:

**Problem 3.2.1** *[47] Given a mobile agent $A$ with position $y : \Re \to \Re^n$ as a function of time $t$, and a target $T$ located at an unknown position $x \in \Re^n$, $n \in \{2, 3\}$, devise an adaptive law to generate the estimate $\hat{x}(t)$ of $x$ such that*

$$\lim_{t\to\infty} \|\hat{x}(t) - x\| = 0, \tag{3.2.1}$$

*using only the distance measurement,*

$$D(t) = \|y(t) - x\| \tag{3.2.2}$$

*and the agent's own position $y(t)$.*

A gradient adaptive law has been developed in [45,47] for Problem 3.2.1. Furthermore, in [47] and [48], this adaptive law is integrated with tracking control laws that are designed using constructive Lyapunov approaches to develop adaptive control schemes for, respectively, capturing and circumnavigating the target $T$. Noting that the problem definition in Problem 3.2.1 is given for the ideal case where the target $T$ is stationary and the distance measurement in (3.2.2) is noiseless, stability and convergence for moving (drifting) targets are formally analytically established and the noisy distance measurement cases are studied via numerical simulations as well in [45].

In this study, we revisit Problem 3.2.1 using a least-squares (LS) based approach in place of the gradient approach. The focus of this study is mathematical systems design and analysis for solving Problem 3.2.1 without considering the details of the real life implementation and application. From the applications aspect, solving Problem 3.2.1 is observed to have potential real-life applications in a number of areas including various localization and optimization tasks for mobile sensor networks [1], localization of emergency calls and rescue signal sources, localization of biological and chemical threats [1], localization of printers and other units in pervasive computing [1]. A brief discussion of the implementation and application aspects can be found in [46].

## 3.3 Assumptions and Parametrization

In our approach to Problem 1.1, similarly to [45], [47], we assume the following:

**Assumption 3.3.1** *In problem 3.2.1, $y(t)$, $\dot{y}(t)$, and $\ddot{y}(t)$ are bounded and differentiable, satisfying*

$$\|y(t)\| \leq M_1, \qquad \|\dot{y}(t)\| \leq M_2 \quad \|\ddot{y}(t)\| \leq M_3$$

*for all $t \geq 0$ and some positive $M_1, M_2, M_3$.*

In our localization algorithm design, we use the linear parametric model for the measurement (3.2.2):

$$\bar{z}(t) = x^\top \bar{\phi}(t) \tag{3.3.1}$$

where

$$\bar{z} = \frac{1}{2}\frac{d}{dt}\left(\|y(t)\|^2 - D^2\right), \qquad \bar{\phi} = \dot{y}.$$

As in [45, 47], the unknown position vector $x$ is assumed to be constant for localization algorithm design purposes; and the cases where this assumption is violated will be formally analyzed in Section 3.5.2 and will be tested via simulations in Section 3.6. The implementation of a localization algorithm based on (3.3.1) would require generating the derivative of $D(t)$, rendering it impractical. Instead, we use the following filtered version of the parametric model (3.3.1) derived in [45, 47]:

$$\begin{aligned} z(\cdot) &\equiv x^\top \phi(\cdot), \\ z(t) &= \dot{\zeta}_1(t) = -\alpha\zeta_1(t) + \frac{1}{2}\left(y^\top(t)y(t) - D^2(t)\right), \\ \phi(t) &= \dot{\zeta}_2(t) = -\alpha\zeta_2(t) + y(t), \end{aligned} \tag{3.3.2}$$

where the notation $f_1(\cdot) \equiv f_2(\cdot)$ for two functions $f_1, f_2$ indicates that there exist $\lambda, M > 0$ such that for all $t \geq 0$, $\|f_1(t) - f_2(t)\| \leq Me^{-\lambda t}$; $\alpha > 0$, $\zeta_1(0)$ is an arbitrary scalar, and $\zeta_2(0)$ is an arbitrary vector.

## 3.4 The Localization Algorithm

The localization algorithm proposed and analyzed in [45, 47], for the problem formulation in Problem 3.2.1 and parametrization (3.3.2), can be expressed as

$$\begin{aligned} \dot{\hat{x}}(t) &= \gamma\left(z(t) - \hat{z}(t)\right)\phi(t), \\ \hat{z}(t) &= \hat{x}^\top(t)\phi(t), \end{aligned} \tag{3.4.1}$$

where $\gamma > 0$ is the adaptive gain and $\hat{x}(0)$ is the initial estimate. The algorithm (3.4.1) minimizes the instantaneous cost function [49, 50]

$$J(\hat{x}(t)) = \frac{1}{2}\left(z(t) - \hat{z}(t)\right)^2 = \frac{1}{2}\left(z(t) - \hat{x}^T(t)\phi(t)\right)^2. \tag{3.4.2}$$

In this paper, in place of (3.4.1), we propose a recursive LS algorithm with forgetting factor to produce the estimate $\hat{x}(t)$ in a way that minimizes the integral cost function

$$J(\hat{x}(t)) = \frac{1}{2}\int_0^t e^{-\beta(t-\tau)}\left(z(\tau) - \hat{x}^T(t)\phi(\tau)\right)^2 d\tau + \frac{1}{2}e^{-\beta t}(\hat{x} - \hat{x}_0)^T Q_0(\hat{x} - \hat{x}_0), \qquad (3.4.3)$$

where $Q_0 > 0$ is the design matrix defining the scale of the penalty on deviation from the initial estimate and $\beta > 0$ is the fixed forgetting factor, another design constant. The resultant recursive LS algorithm takes the form

$$\begin{aligned}
\dot{\hat{x}}(t) &= P(t)\left(z(t) - \hat{z}(t)\right)\phi(t),\ \hat{x}(0) = \hat{x}_0 \qquad (3.4.4)\\
\dot{P}(t) &= \beta P(t) - P(t)\phi\phi^T P(t),\ P(0) = P_0 = {Q_0}^{-1}
\end{aligned}$$

## 3.5 Stability and Convergence Properties

### 3.5.1 Stationary Target Case

The stability and convergence properties of the proposed algorithm (3.4.4) are analyzed following a procedure similar to that of [45, 47]. Observing that the same stability and convergence results have been established for the gradient based parameter estimation and LS parameter estimation with forgetting factor in [49, 50] for a broad set of linearly parameterized systems including (3.3.2), the following can be established in parallel to Lemma 2.1 of [47]:

**Lemma 3.5.1** *Consider (3.2.2),(3.3.2),(3.4.4). Assume that $x$ is constant and $y(t)$ obeys Assumption 3.3.1. Define*

$$p(t) = x^\top \phi(t) - z(t) \qquad (3.5.1)$$

*and*

$$\tilde{x}(t) = \hat{x}(t) - x. \tag{3.5.2}$$

*Then there holds*

$$\dot{p}(t) = -\alpha p(t) \tag{3.5.3}$$

*and*

$$\dot{\tilde{x}}(t) = -\gamma\phi(t)\phi^\top(t)\tilde{x}(t) - \gamma\phi(t)p(t). \tag{3.5.4}$$

*Furthermore $\tilde{x}$ converges to zero exponentially if $\phi$ is* persistently exciting *(*p.e.*), viz., if there exist positive $\alpha_1, \alpha_2$ and $T_1$, such that for all $t \geq 0$, there holds*

$$\alpha_1 I \leq \int_t^{t+T_1} \phi(\tau)\phi(\tau)^T d\tau \leq \alpha_2 I. \tag{3.5.5}$$

### 3.5.2 Drifting Target Case

In addition to the nominal cases where the source location $x$ is constant, it is of interest to consider less ideal cases where the target observes a "slow" drift, where the definition of "slow" for this paper is given in the following assumption.

**Assumption 3.5.1** *In Problem 3.2.1, the source trajectory $x(t)$ is differentiable and there exist constants $M_4 > 0$ and $0 < M_5 \ll M_4$ such that for all $t \geq 0$,*

$$\|x(t)\| \leq M_4, \quad \|\dot{x}(t)\| \leq M_5.$$

As in the case of Section 3.5.1, the stability and convergence properties of the proposed algorithm (3.4.4) can be analyzed following a procedure similar to that of (the proof of Theorem 3.1 in) [45]. Again observing that the stability and steady-state convergence characteristics established for the gradient based parameter estimation and LS parameter estimation with forgetting factor are the same [49, 50] for a broad set of linearly parameterized systems including (3.3.2), the following can be established in parallel to Theorem 3.1 of [45]:

**Lemma 3.5.2** *Consider (3.2.2),(3.3.2),(3.4.4). Assume that $y(t)$ and $x$ obey Assumptions 3.3.1 and 3.5.1, respectively; and there exist $\alpha_1, \alpha_2, T_1 > 0$ such that for all $t \geq 0$ (3.5.5) holds. Then, for some constant $K > 0$ depending on $M_1$, $M_2$, $M_3$, $\alpha$, $T_1$, $\alpha_1$, and $\alpha_2$, there holds*

$$\limsup_{t\to\infty} |\hat{x}(t) - x(t)| = KM_5.$$

### 3.5.3 Persistent Excitation

The practical meaning and feasibility of the p.e. condition (3.5.5) is discussed in details in [45, 47]. The same discussions apply here since the p.e. conditions are the same for gradient and LS based parameter identification (and hence localization) algorithms. The following result from [45] is obviously independent of the identification algorithm type used:

**Lemma 3.5.3** *[45] Consider (3.2.2),(3.3.2),(3.4.4). Assume that $y(t)$ obeys Assumption 3.3.1. Then there exist $\alpha_1, T_1 > 0$ such that, for all $t \geq 0$, the lower bound in (3.5.5) holds if and only if there exist $\bar{\alpha}_1, \bar{T}_1 > 0$ such that*

$$\bar{\alpha}_1 I \leq \int_t^{t+\bar{T}_1} \dot{y}(\tau)\dot{y}(\tau)^T d\tau. \tag{3.5.6}$$

As discussed in [45, 47], the condition (3.5.6) in $\Re^2$ requires that $y$ persistently avoids linear trajectories. The same condition in $\Re^3$ requires that $y$ persistently avoids planar trajectories. A further study of relaxation of the conditions (3.5.5) and (3.5.6) is presented in [51].

## 3.6 Simulations

In this section, we provide numerical analysis of the convergence characteristics of the LS based localization algorithm (3.4.4) based on a variety of comparative simulation tests in $\Re^3$. In order to have a fair comparison with the results using the previously proposed gradient based localization algorithm (3.4.1) of [45, 47], we select the design parameters as common as possible, and consider the example scenarios considered in [45, 47]. After obtained all the simulation results with same in previous gradient algorithm based study, we put only a few of them in this study since they are all available in [45]. As an simulation environment we used MATLAB/Simulink tools.

### 3.6.1 Design Parameters

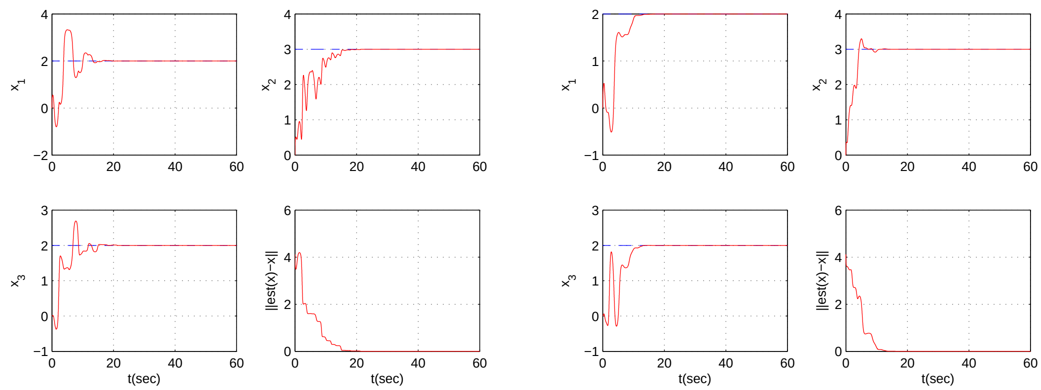
In all the examples, the common design parameters are selected as

$$
\begin{aligned}
\alpha &= 1, \\
\gamma &= 1, \\
P(0) &= P_0 \;=\; \gamma I, \\
\hat{x}(0) &= \phi(0) \;=\; [0,0,0]^T, \\
z(0) &= 0, \\
y(t) &= [2+2\sin t, 2\cos 2t, 2\sin 0.5t]^T.
\end{aligned}
$$

### 3.6.2 Scenarios

In the simulation studies, we consider the following two scenarios:

*Scenario 1:* The target is stationary located at $x = [2,3,2]^T$ (m).




(a) Gradient based localization

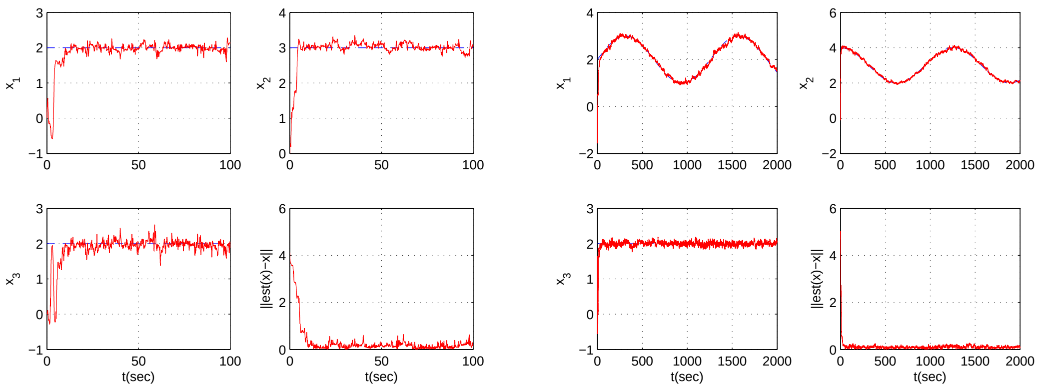
(b) LS based localization, $\beta = 0.9$

Figure 3.1: Gradient and LS based localization algorithms for Scenario 1 without noise.

*Scenario 2:* The target is drifting with position $x(t) = [2 + \sin 0.005t, 3 + \cos 0.005t, 2]^T$ (m).

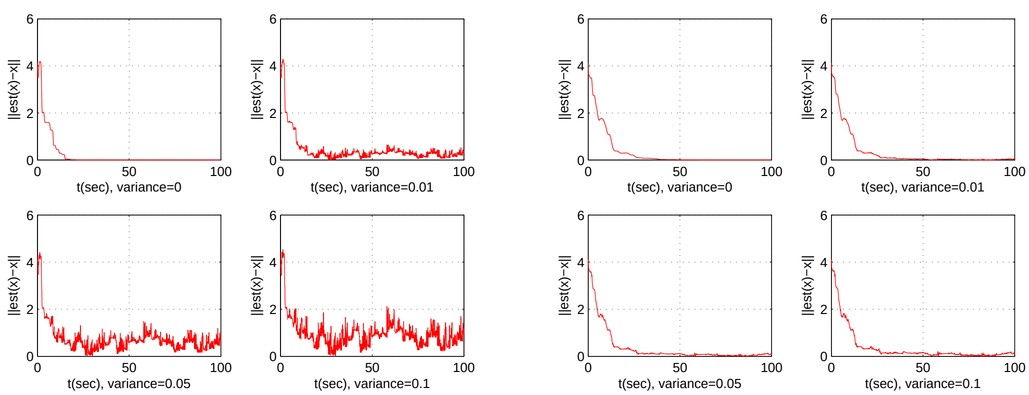
### 3.6.3 A Comparison for Noiseless Distance Measurement Case

For the case where the distance measurements are noiseless, a set of simulation results comparing the transient (convergence speed) performance of the LS based localization algorithm (3.4.4) with the gradient algorithm (3.4.1) of [45, 47] are shown in Figures 3.1. As observed from these figures the convergence settling time $t_s$ for the LS based algorithm (with $\beta = 0.5$) is about half of the gradient algorithm's settling time. Note that the settling time $t_s$ is different for different values of the forgetting factor $\beta$. The effect of $\beta$ on $t_s$ will be further analyzed in Section 3.6.5.



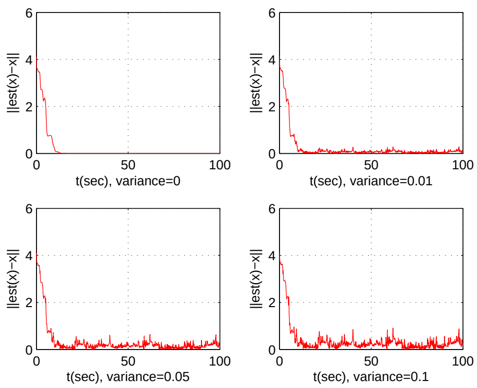

(a) Scenario 1 (b) Scenario 2

Figure 3.2: LS based localization algorithm for Scenario 1 and 2 with measurement noise variance 0.05 ($m^2$), $\beta = 0.5$.

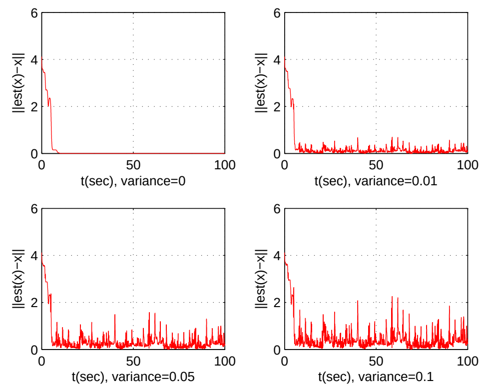



(a) Gradient based localization (b) LS based localization, $\beta = 0.1$

Figure 3.3: Gradient and LS based localization algorithms for Scenario 1 with various measurement noise variances ($m^2$).

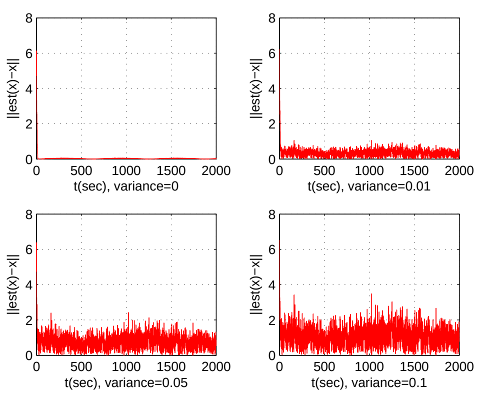



(a) $\beta = 0.5$

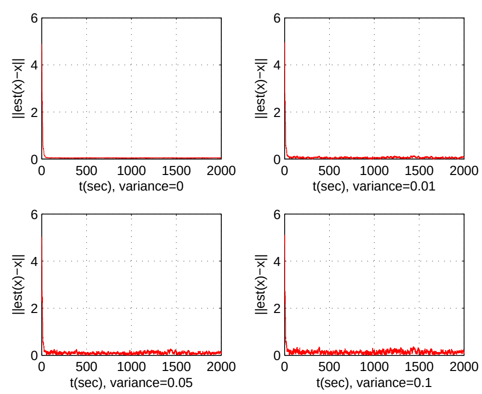



(b) $\beta = 0.9$

Figure 3.4: LS based localization for Scenario 1 with various measurement noise variances $(m^2)$ .

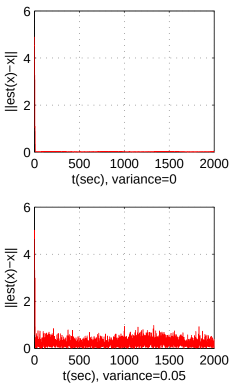



(a) Gradient based localization

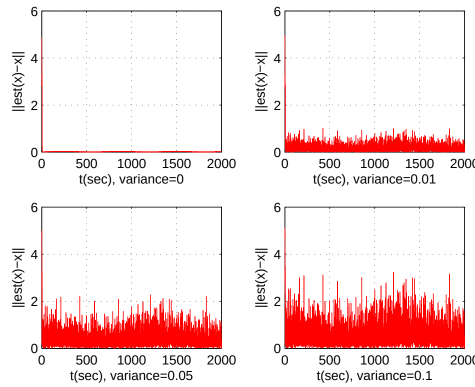



(b) LS based localization, $\beta = 0.1$

Figure 3.5: Gradient and LS based localization algorithms for Scenario 2 with various measurement noise variances $(m^2)$.




(a) $\beta = 0.5$




(b) $\beta = 0.9$

Figure 3.6: LS based localization for Scenario 2 with various measurement noise variances $(m^2)$ .

### 3.6.4 Noisy Distance Measurements

For the case where the distance measurements are noisy, two sample trials using the LS based localization algorithm (3.4.4), one for each of Scenarios 1 and 2, are shown in Figures 3.2. In both of these trials, the noise variance is 0.05 ($\mathrm{m}^2$), a typical value for the distance measurement devices used in localization tasks of type Problem 3.2.1. Comparison of these results with those of [45] demonstrates effectiveness of (3.4.4) in increasing the convergence speed and reducing the measurement noise effect.

Next, we present a set of simulation results comparing the transient (convergence speed) performance of the LS based localization algorithm (3.4.4) with the gradient algorithm (3.4.1) of [45, 47], for both the stationary and drifting source cases with different levels of distance measurement noise. The results for the stationary source case Scenario 1 are shown in Figures 3.3 and 3.4; and those for the drifting target case Scenario 2 are shown in Figures 3.5 and 3.6. The results demonstrate that the LS based algorithm (3.4.4) has two types of advantages, which vary with the selection of $\beta$: For lower values of $\beta$, the measurement noise effects on localization are significantly attenuated. For high values of $\beta$, the localization algorithm converges significantly faster than the gradient algorithm.

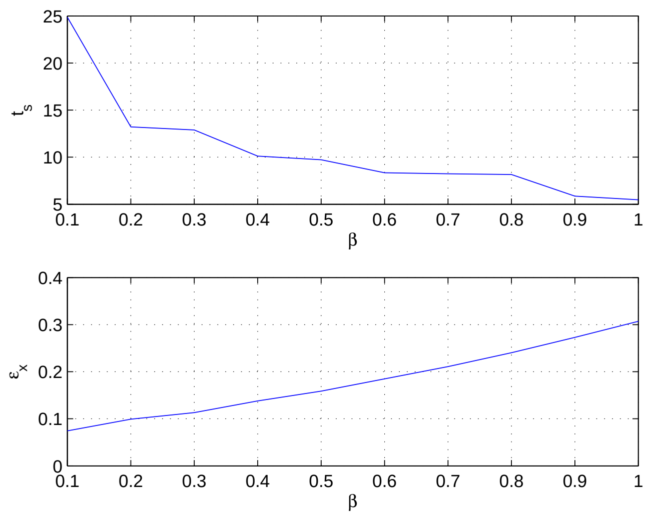



Figure 3.7: Settling time $t_s$ (sec) and localization accuracy $\varepsilon_x$ (m) for different values of the forgetting factor $\beta$.

### 3.6.5 Selection of the Forgetting Factor

Localization accuracy $\varepsilon_x$ and settling time $t_s$ for different values of the forgetting factor $\beta$ are plotted in Figure 3.13, where $t_s$ is defined as the first time instant when the localization error $\|\hat{p}_T - p_T\|$ drops below $\sigma = \sqrt{0.05}$ and $\varepsilon_x$ is taken as the average of $\|\hat{p}_T - p_T\|$ for $t > t_s$, considering a noisy measurement case with noise power $\sigma^2 = 0.05$ m$^2$.

Figure 3.7 illustrates the trade-off between $\varepsilon_x$ and $t_s$, and rules of thumb for selection of $\beta$. For lower $\varepsilon_x$, one needs to choose $\beta$ at low values, close to zero; while to obtain lower

$t_s$, $\beta$ needs to be chosen larger. Depending on design requirements, an optimal $\beta$ can be selected, e.g., $\beta = 0.5$ in ours simulations appears to be an "optimal" choice for Scenarios 1 and 2.

## 3.7 Conclusion

In this chapter, we have studied the problem of localizing a signal source by a mobile sensory agent using distance measurements, which was addressed in [45] using a gradient based adaptive algorithm. Particularly, given a mobile sensory agent knowing its location and the distance between signal source and itself, the algorithm searches the location of signal source in three dimensions. We have designed a least-squares based adaptive localization algorithm for the same task. We have established that the least-square based algorithm we propose bears the same asymptotic stability and convergence properties as the gradient algorithm. Under the persistent of excitation condition, least-square algorithm also accomplished tracking the source movement precisely and has ability slow and bounded for both stationary and mobile cases. It is further demonstrated via simulation studies that the proposed least-square algorithm converges significantly faster to the resultant location estimates than the gradient algorithm, and significantly reduces the noise effects for small values of the forgetting factor. While convergence time changes in direct proportion to the $\beta$ values, noise compensation is inversely correlated with $\beta$.

# Chapter 4

# Least-Squares Based Implant Localization in Human Body

## 4.1 Introduction

Recently, wireless communication devices and protocols have been studied in biomedical field to efficiently administer and deliver a variety of health care services. Advance WSN systems have been used to observe patients physiological signals not only in medical centers or hospital, but also in their homes and workplaces [9]. In addition, with the advance of MEMS technology, wireless sensor networks component sizes reduced and wearable and implementable devices such as smart sensors and peacemakers have been extensively used in health care systems.

The WSN system on human body is called wireless body area sensor network (WBAN). WBAN conveys real world WSN applications to practical use improving quality of life of human by allowing real time, non-invasive medical assistance at low cost. WBAN can monitor the body's condition and to detect any possible problem occurs in the human body by transmitting vital data from one device to another implanted device in a network. As an example of the biomedical implanted devices, wireless capsule endoscopy (WCE) [52] has attracted lots of attention, since it is easy to use and highly efficient comparing to exiting endoscopy systems. WCE has a tiny camera on it and exact location of the capsule (or camera) has to be known by treating physician when each image is taken in order to be interpreted. Moreover, assigning allowable power rate of the transmitter signal and bandwidth range are very important, because human body tissues and organs are vulnerable to be affected by them. In that respect, knowing of each device location in human body can help to optimize transmission power and identify the position of biological information acquired from medical device.

In classical WSNs, there are some destructive effects between transmitter and receivers such as multi-path, shadowing and broadening, arising from medium characteristics. Despite having similar generic structures, WBANs and classical WSNs have significant differences as well. Since human body consists of different organs and tissues, each with a different signal permittivity coefficient and hence a different signal propagation speed, the signal propagation velocity between transmitter and receiver in human body is expressed as a function of the permittivity. In order to characterize the human body as a channel, instant geometrical model of the body has to be known, because the power absorption parameters and path loss exponents change with thickness of the tissue.

With all the considerations mentioned above, in order to use some distance measurement techniques such as received signal strength (RSS) or time of arrival (TOA), there have to be some prior information about the location of the implant. In some studies, researches obtain the configuration of the human body beforehand from magnetic resonance imaging (MRI) or computed tomography (CT) in order to estimate average permittivity [53], [54].

In this study, we focus on the problem of localizing a medical device/implant in human body by a mobile sensor unit (MSU) using distance measurements. As the particular distance measurement method, time of flight (TOF) based approach involving ultra wide-band signals is used, noting the important effects of the medium characteristics on this measurement method. Since human body consists of different organs and tissues, each with a different signal permittivity coefficient and hence a different signal propagation speed as mentioned above, one cannot assume a constant signal propagation speed environment for the aforementioned medical localization problem. Furthermore, the propagation speed is unknown.

Considering all the above factors and utilizing a TOF based distance measurement mechanism, we propose a least-squares (LS) based adaptive algorithm with forgetting factor to estimate the 3-D location of a medical device/implant in the human body. In the design of the adaptive algorithm, we first derive a linear parametric model with the unknown 3-D coordinates of the device/implant and the current signal propagation speed of the medium as its parameters. Then, based on this parametric model, we design the proposed adaptive algorithm, which uses the measured 3-D position of the MSU and the measured TOF as regressor signals.

After discussing convergence properties of the proposed localization algorithm, we perform numerical tests to analyze the properties of the localization algorithm, considering two types of scenarios: (1) A priori information regarding the region, e.g quadrant (among upper-left, upper-right, lower-left, lower-right of the human body), of the implant location is available and (2) such a priori information is not available. In (1), assuming knowledge of fixed average relative permittivity for each region, we established that the proposed algorithm converges to an estimate with zero estimation error. Moreover, different white Gaussian noises are added to emulate the TOF measurement disturbances, and it is observed that the proposed algorithm is robust to such noises/disturbances. In (2), although perfect estimation is not achieved, the estimation error is at a low admissible level. In addition, for both cases (1) and (2), forgetting factor effects have been investigated and results show that use of small forgetting factor values reduces noise effects significantly, while use of high forgetting factor values speeds up convergence of the estimation.

### 4.1.1 Problem Definition

In our study, we propose the adaptive least-square localization algorithm estimating implant position iteratively. According to the model, a moving device takes continuous distance measurements from implant in its non-collinear trajectory. Also, since signal velocity is permittivity dependent, in every step of the algorithm, we estimate permittivity of the body part in which device takes measurement. Distance measurements are calculated with basic velocity-time multiplying correlation. Through this way, the calculated distance is updated with regard to combination of the tissue permittivity. Figure 4.1 illustrates proposed system model.

We focus on problem of localizing an implant in human body by a mobile sensor unit (MSU) using distance measurements. As the particular distance measurement method, time of flight (TOF) based approach involving ultra wide-band signals is used, noting the important effects of the medium characteristics on this measurement method. Since human body consists of different organs and tissues, each with a different signal permittivity coefficient and hence a different signal propagation speed, one cannot assume a constant signal propagation speed environment for the aforementioned medical localization problem. Furthermore, the propagation speed is unknown. Considering all the above factors and utilizing a TOF based distance measurement mechanism, we propose a least-squares based adaptive algorithm with forgetting factor to estimate the 3-D location of an implant in the human body. In the design of the adaptive algorithm, we first derive a linear parametric model with the unknown 3-D coordinates of the implant and the current signal propagation speed of the medium as its parameters. Then, based on this parametric model, we design the proposed adaptive algorithm, which uses the measured 3-D position of the MSU and the measured TOF as regressor signals.

After providing a formal analysis of convergence properties of the proposed localization algorithm, we perform numerical tests to analyze the properties of the localization algorithm, considering two types of scenarios: (1) A priori information regarding the region, e.g quadrant (among upper-left, upper-right, lower-left, lower-right of the human body), of the implant location is available and (2) such a priori information is not available. In (1), assuming knowledge of fixed average relative permittivity for each region, we established that the proposed algorithm converges to an estimate with zero estimation error. Moreover, different white Gaussian noises are added to emulate the TOF measurement disturbances, and it is observed that the proposed algorithm is robust to such noises/disturbances. In (2), although perfect estimation is not achieved, the estimation error is at a low admissible level. In addition, for both cases (1) and (2), forgetting factor effects have been investigated and results show that use of small forgetting factor values reduces noise effects significantly, while use of high forgetting factor values speeds up convergence of the estimation.

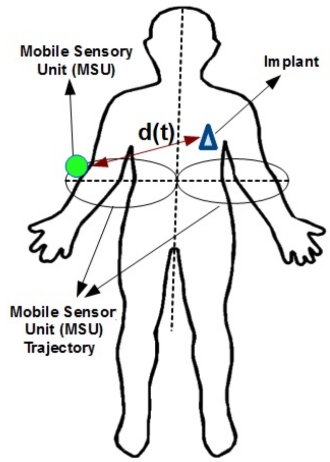



Figure 4.1: On-body implant localization with moving agent.

## 4.2 Problem Formulation and System Model

Consider a sensory tool transmitting a signal and estimating the distance between an implant and itself using the time it takes for the signal to be reflected by the implant and return to the sensory tool. Next, we elaborate main components of the localization problem setting using this sensory tool.

### 4.2.1 Measurement Technique and Mobile Sensory Unit (MSU)

We consider use of a mobile sensory unit (MSU) consisting of two main components; the first component is an accurate indoor positioning system (IPS) that is used to determine the MSU's own location in three dimensions and the second component is a narrow band radio-frequency distance measurement system (RFDMS) for measuring the distance between MSU and the implant utilizing TOF technique [55]. The RFDMS component is equipped with a transceiver, a receiver and a clock with high accuracy. According to the distance estimation scenario with RFDMS, RFDMS sends out a signal and starts the clock. The receiver in RFDMS receives the reflected signal from implant and stops the clock. Dividing the signal travel time $t_D$ by two and obtaining the time it takes to go one way, the distance between MSU and the implant can be found multiplying $t_D/2$ by the signal velocity, whose estimation is described in the next subsection. Regarding medical implant communication services (MICS) standards, RFDMS needs to use frequency band 401-406 MHz with the maximum signal bandwidth of 300 KHz and maximum transmitted power of 25 $\mu W$ [56].

### 4.2.2 Propagation Signal and Its Velocity in the Human Body

In free space, signal velocity is constant. However, since human body comprises different organs and tissues with complex structures and each organ and tissue has different characteristics of the electrical constants, signal velocity can be given by the formula

$$v_{ave} = \frac{c}{\sqrt{\varepsilon_{ave}}} \tag{4.2.1}$$

where $v_{ave}$ represents average velocity of the propagation signal through the propagation path, $\varepsilon_{ave}$ represents the corresponding average relative permitivity of human organs and tissues, and $c$ is the speed of the light in free space.

An important parameter in distance measurement within a human body is relative permittivity of the organs and tissues mentioned above. In this study, similar to [53], we consider the average relative permittivity

$$\varepsilon_{ave} = \sum_{i=1}^{I} (\varepsilon_t(i) p_t(i)) \tag{4.2.2}$$

where $\varepsilon_t(i)$ is relative permittivity of $i^{th}$ organ or tissue and $p_t(i)$ is the percentage of the each organ or tissue on the path of propagation signal, and $I$ is the total number of organs

Table 4.1: The Average Relative Permittivity of the Human Body Tissues [53].

| ***Tissue*** | Muscle | Fat | Blood | Intestine | Lung | Stomach | Bone | Tendon |
|---|---|---|---|---|---|---|---|---|
| $\boldsymbol{\varepsilon_r}$ | 47.83 | 4.08 | 51.59 | 50.67 | 42.56 | 56.99 | 17.09 | 37.61 |

and tissues. Table 4.1 shows some of the organ and tissue relative permittivities in human body. The specific values in Table 4.1 can be obtained from MRI or CT beforehand.

### 4.2.3 Time of Flight and Distance Measurement

Considering the signal velocity formula (4.2.1), and the signal propagation time between moving agent and implant, the distance

$$d(t) = \|p_s(t) - p_T\| \tag{4.2.3}$$

between moving agent and implant, where $p_s(t)$ is the location of moving agent at time $t$ and $p_T$ is the location of implant. Using the TOF measurement $t_D$, the distance $d$ can be estimated as

$$\hat{d}(t) = \frac{\hat{v}_{ave} t_D}{2} \tag{4.2.4}$$

where $\hat{v}_{ave}$ is the estimate of the average propagation velocity $v_{ave}$.

### 4.2.4 System Parametrization

In the localization algorithm, we lump all the unknown parameters in a vector $\theta^* = [p_T^T, \frac{(v_{ave})^2}{4}]^T$ and express (4.2.3), (4.2.4) in the following static parametric model (SPM) [1] form:

$$z = \theta^{\star T} \phi \tag{4.2.5}$$

where $z$ and $\phi$ are derived as follows. From (4.2.3), (4.2.4), we have

$$d(t)^2 = (p_s - p_T)^T(p_s - p_T) = \frac{(t_D)^2(v_{ave})^2}{4} \tag{4.2.6}$$

taking both side derivatives,

$$2\dot{p}_s^T p_s - \dot{p}_s^T p_T = \frac{(v_{ave})^2}{4}\frac{d}{dt}(t_D)^2. \tag{4.2.7}$$

Defining $P_s = \|p_s\|^2$ and $T_D = t_D^2$, we rewrite (4.2.7) as;

$$\dot{P}_s = \frac{(v_{ave})^2}{4}\dot{T}_D + p_T^T\dot{p}_s \tag{4.2.8}$$

$$\dot{P}_s = [p_T^T, \frac{(v_{ave})^2}{4}][\dot{p}_s, \dot{T}_D]^T \tag{4.2.9}$$

Finally filtered version of the equation is given by

$$\frac{s}{s+\alpha}[P_s] = \theta^{*T}[\frac{s}{s+\alpha}p_s, \frac{s}{s+\alpha}T_D]^T, \tag{4.2.10}$$

i.e., (4.2.5) with $z = \frac{s}{s+\alpha}[P_s]$ and $\phi = [\frac{s}{s+\alpha}p_s, \frac{s}{s+\alpha}T_D]^T$.

## 4.3 The Localization Algorithm

In [57], a recursive LS algorithm with forgetting factor for position estimation using distance measurements was proposed and analyzed, as an improvement of the algorithms proposed in [45], [46], [47] based on parametrization and parameter identification techniques in [49], [50]. Regarding LS algorithm in [57], we rewrite LS algorithm with the parametrization in Section 4.2.4

$$\begin{aligned} \dot{\hat{\theta}}(t) &= P(t)\,(z(t) - \hat{z}(t))\,\phi(t),\ \hat{\theta}(0) = \hat{\theta}_0 \\ \dot{P}(t) &= \beta P(t) - P(t)\phi\phi^T P(t),\ P(0) = P_0 = {Q_0}^{-1} \end{aligned} \tag{4.3.1}$$

where $P > 0$ is the adaptive gain and $\hat{\theta}(0)$ is the initial estimate. As noticed from system parametrization equations, $\theta^*$ is the $4 \times 1$ vector consisting of implant location in three dimensions $(p_{Tx}, p_{Ty}, p_{Tz})$ and estimate of the average propagation velocity $(v_{ave})$.

## 4.4 Numerical Simulations

### 4.4.1 Simulation Model

In this section, we provide numerical analysis of the convergence characteristic of the LS based algorithm as proposed in Chapter 3. The performance of the algorithm is shown with variety of simulation tests at $\Re^3$. As a simulation environment, MATLAB/Simulink is used. In this study, we consider two different cases. In the first case, we have a priori information about region of implant in human body, however in second case, we have no any priori information about implant location. Design parameters used in simulations are given below as;

$$\alpha = 1, \qquad \gamma = 1, \qquad P(0) = P_0 = \gamma I, \qquad \hat{\theta}(0) = [0, 0, 0, 0]^T, \qquad z(0) = 0,$$

$$p_s(t) = [50 \sin(0.3\pi(t-2)) + 20 \sin(\pi(0.5t)) + (40 + 15 \sin(\pi(0.7t)))]$$

### 4.4.2 First Scenario

We evaluate the algorithm performance having a priori information about implant location. Considering that the average relative permittivity in the vicinity of the implant is constant, we obtain average signal propagation velocity fixed for that vicinity in human

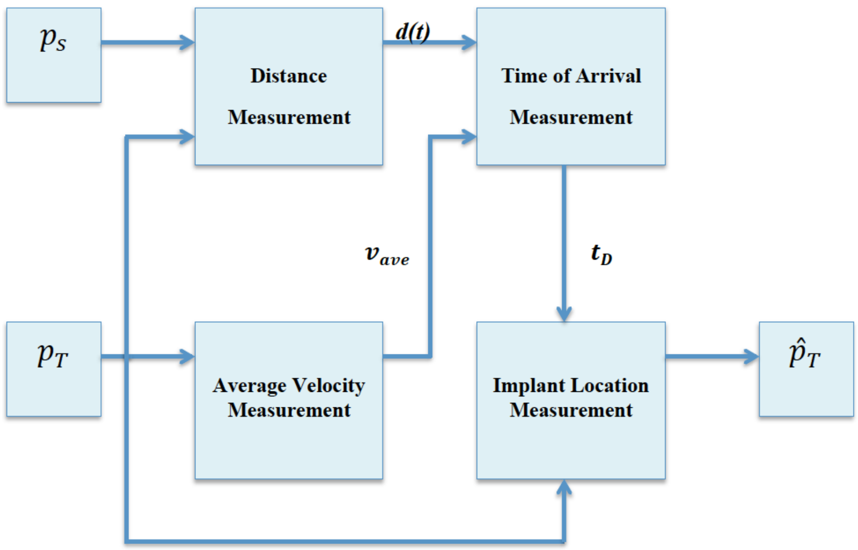


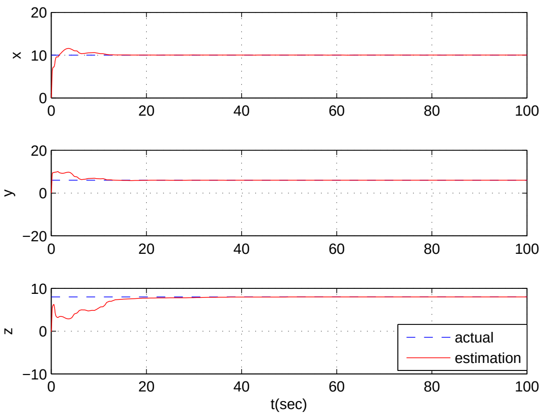

Figure 4.2: Implant localization algorithm block diagram

body. Moreover, we take into account both noiseless and noisy cases in the simulations. Other disturbance effects such as shadowing, multi-path and broadening are not considered.

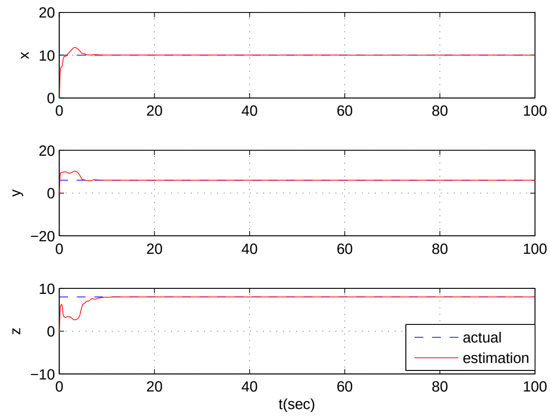
In the scenario, the implant assumed to be located at $p_T = [10, 6, 8]^T$ (cm), where the coordinates are considered for a certain body coordinate frame.

### 4.4.3 Second Scenario

In this scenario, holding all design parameters given before, we assume that there is a priori information regarding the region about implant location. Considering that human body consists of four different regions (upper-left, upper-right, lower-left, lower-right), we take four different average relative permittivities for each region. According to the scenario, the implant can exist in any of these regions. Having no location information about implant, TOF measurements are highly affected by variable signal velocity. For this scenario, we

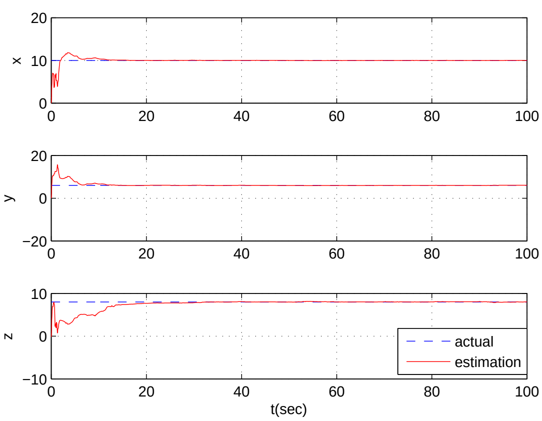



(a) $\beta = 0.1$

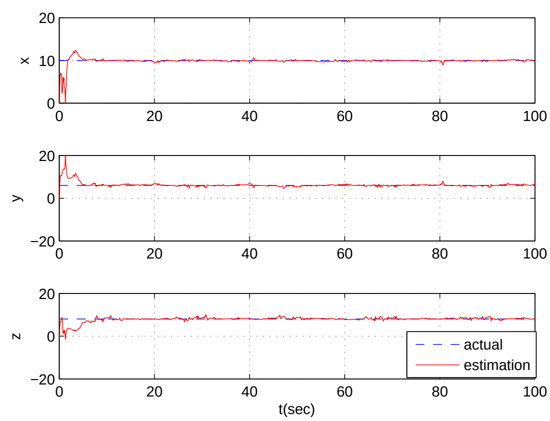



(b) $\beta = 0.9$

Figure 4.3: LS based localization algorithm for first scenario without noise.

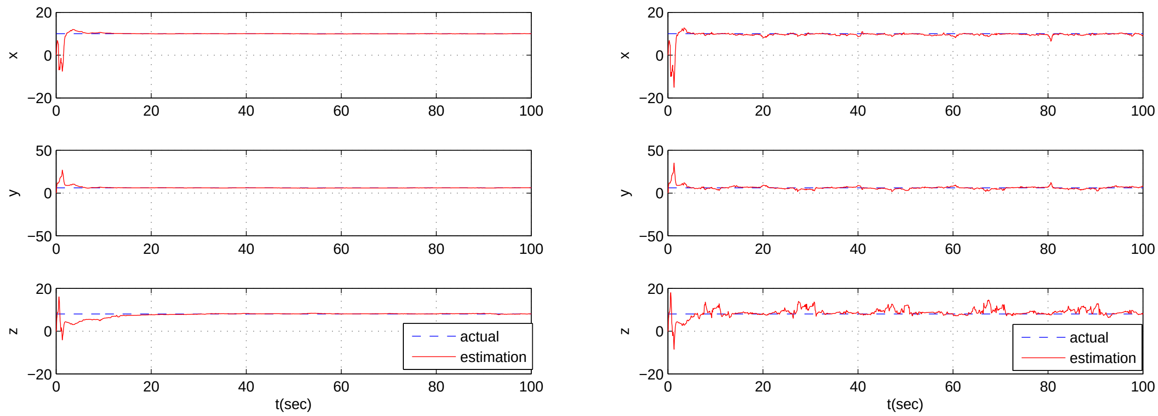



(a) $\beta = 0.1$



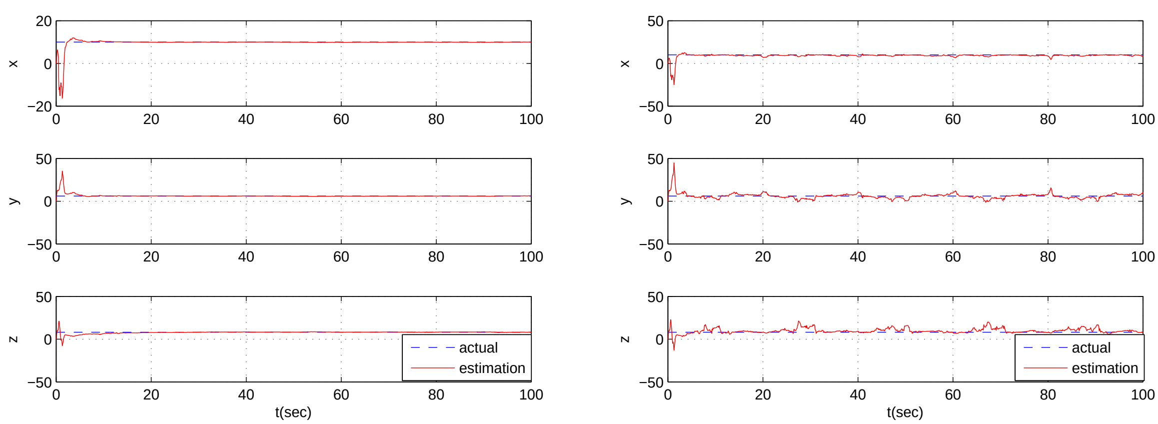

(b) $\beta = 0.9$

Figure 4.4: LS based localization algorithm for first scenario with noise variance $0.01(cm^2.)$



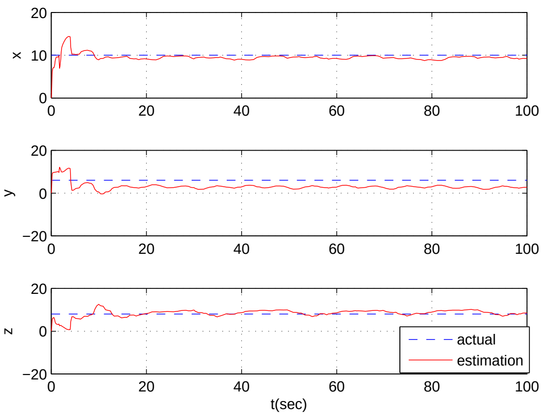

(a) $\beta = 0.1$ (b) $\beta = 0.9$

Figure 4.5: LS based localization algorithm for first scenario with noise variance $0.05(cm^2)$.

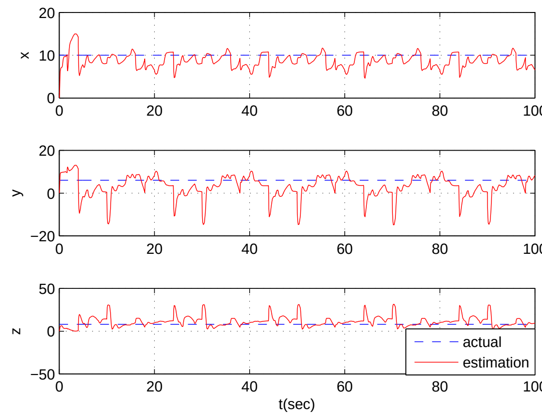



(a) $\beta = 0.1$ (b) $\beta = 0.9$

Figure 4.6: LS based localization algorithm for first scenario with noise variance $0.1(cm^2)$.

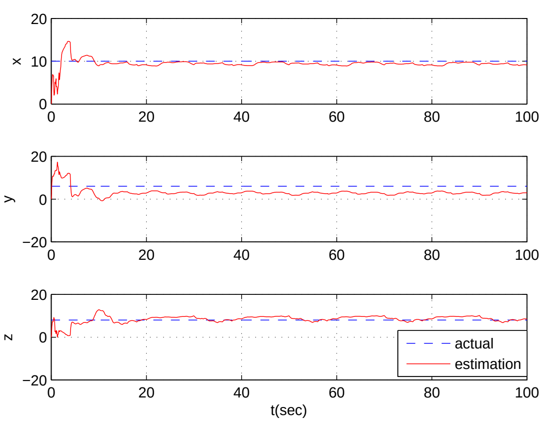



(a) $\beta = 0.1$

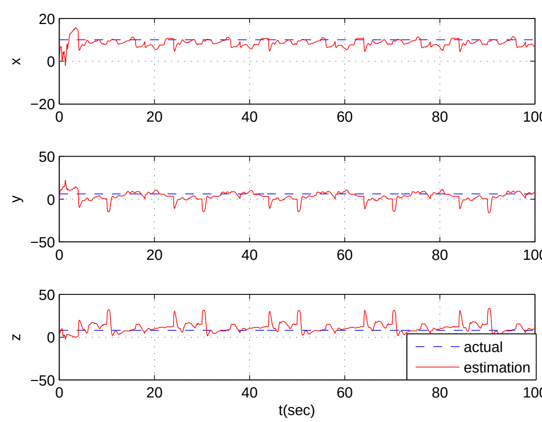



(b) $\beta = 0.9$

Figure 4.7: LS based localization algorithm for second scenario without noise.

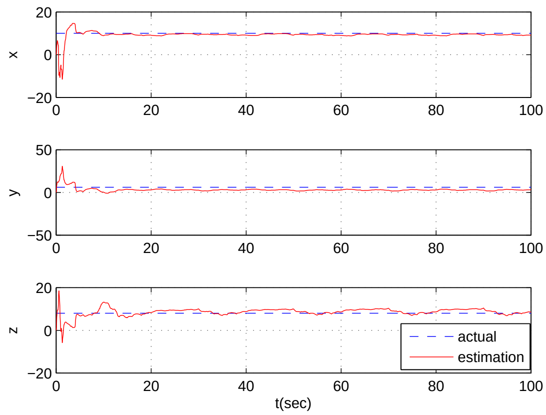



(a) $\beta = 0.1$

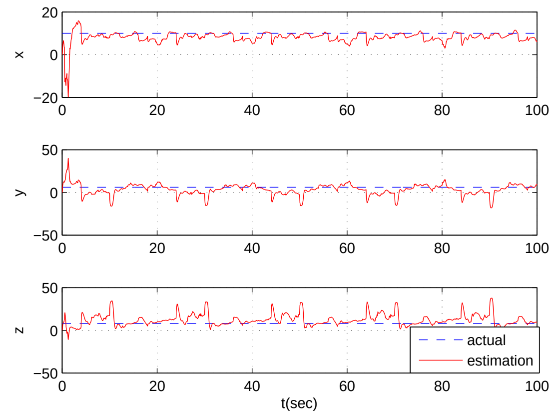



(b) $\beta = 0.9$

Figure 4.8: LS based localization algorithm for second scenario with noise variance $0.01(cm^2)$.

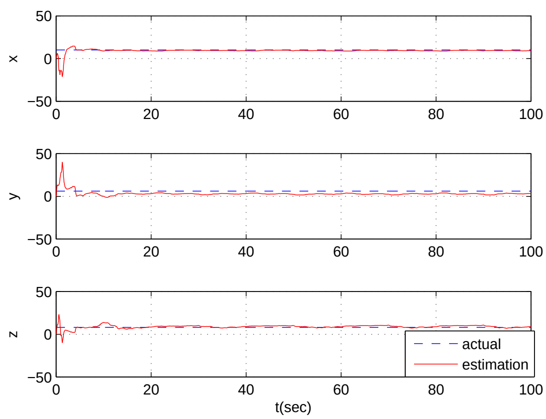



(a) $\beta = 0.1$

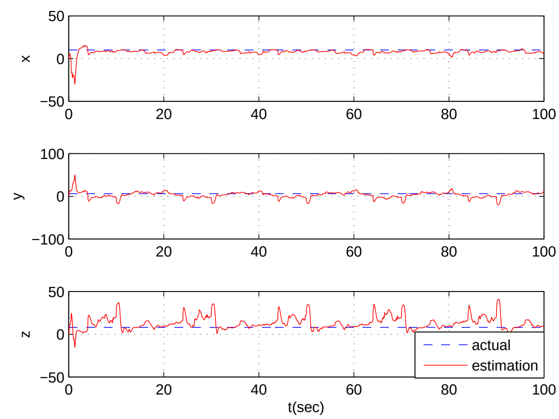



(b) $\beta = 0.9$

Figure 4.9: LS based localization algorithm for second scenario with noise variance $0.05(cm^2)$.




(a) $\beta = 0.1$




(b) $\beta = 0.9$

Figure 4.10: LS based localization algorithm for second scenario with noise variance $0.1(cm^2)$.

also evaluated the performance of the proposed algorithm for various measurement noise variances.

## 4.5 Discussion on the Simulation Results

For the case where a priori information regarding the region of the implant location is available , a set of simulation results are shown in Figures 4.3 to 4.6. As seen from these figures, the implant location estimation converges to its actual value $\theta$ exponentially fast and with zero estimation error. Figures 4.4 to 4.6 reveal role of forgetting factor $\beta$ on algorithm performance for different distance measurement noises. According to the results, the algorithm significantly reduces the effect of noise for small $\beta$ values. For lower convergence time, one needs to choose $\beta$ at high values, close to one.

For the case where there is no a priori information regarding the region of the implant, four simulation results for noisy and noiseless measurement cases with different $\beta$ values are shown in Figures 4.7 to 4.10. As observed from these figures, although perfect estimation is not achieved, the estimation error is at a low acceptable level.

## 4.6 Conclusion

In the study, we examine the performance of the proposed adaptive localization algorithm on implant localization problem. The algorithm performance is evaluated for two different cases. For the first case, human body is considered as a static channel model. Thus, we take fixed average relative permittivity in order to find propagation velocity between moving sensory agent and implant. For the second case, we consider that there is no any priori information about implant location in human body. Therefore, TOF measurements contain some admissible errors, because of the organ variations and changeable body geometry. Simulation results show that the proposed algorithm is effective and efficient on implant localization problem.

# Chapter 5

# Conclusion and Future Work

### 5.0.1 Summary

Wireless sensor networks have been employed widely for many applications with the help of recently developed micro-electro-mechanical systems (MEMS) and newly proposed efficient algorithms. As an example of applications performed by wireless sensor network, tracking, sensing and localizing can be given. Sensor-source localization is fundamental and significant since all other applications directly or indirectly depends on it. To illustrate, location information is precondition for navigation in which object positioning, tracking and targeting are main tasks. On the other hand, WSN systems need some robust and efficient algorithms for localization to facilitate power administration and achieve self localization. Considering capsule endoscopy system, researchers expect the system to localize capsule position and govern itself with some algorithms in order to fulfill non-invasive gastro-intestinal tracking. Regarding all above reasons, localizing and tracking of the objects are crucial issues to be solved in order to obtain high performance from sensory systems.

In this thesis, new localization algorithm, namely: Least-squares based adaptive source localization algorithm, is proposed and evaluated in a simulation-based experiment. Moreover, as an application study of aforementioned algorithm, new linear parametric model are derived and some simulations are achieved so as to localize device/implant in human body. Based on the results presented in the previous chapters, the following conclusion regarding simulation results are acquired.

The proposed least-squares based adaptive algorithm is compared with gradient based algorithm performance for both noisy and noiseless cases. According to the simulation results, the proposed algorithm outperformed gradient based algorithm. Least-squares based algorithm performance is evaluated for both stationary and mobile target cases. The algorithm satisfies the persistent of excitation condition for both cases. The proposed algorithm bears the same asymptotic stability and convergence properties as gradient based algorithm previously studied. Moreover, it is shown that the proposed algorithm converges significantly faster to the resultant location estimates than gradient algorithm for high values of the forgetting factor. Simulation results demonstrated that noise compensation is directly proportional with forgetting factor values. For small forgetting factor values, the the proposed algorithm reduces significantly the noise effects. we also focus on problem of localizing an implant in human body by a mobile sensory unit with proposed least-squares algorithm. As the particular distance measurement method, TOF based approach involving ultra wide-band signals is used. According to the simulation results, the algorithm achieves good results with respect to convergence time. Since human body contains many organs and tissues with different permittivitis, we consider their electrical properties differently in order to model human body as a signal propagation medium channel. In simulation studies, different white Gaussian noises are added to emulate the TOF measurement disturbances, and it is observed that the proposed algorithm is robust to such noises/disturbances. Simulations are performed for two different scenarios; a)assuming knowledge of fixed average relative permittivity for each region, we established that the proposed algorithm converges to an estimate with zero estimation error and b)without any priori information about implant location, although perfect estimation is not achieved, the estimation error is at a low admissible level. Same forgetting factor-noise compensation and convergence time relation is valid for this problem explained for the signal source localization problem.

### 5.0.2 Future Work

There are still some open issues to be addressed related with our studies. In this thesis, we use the proposed least-squares algorithm for two different cases; stationary target case and drifting target case. However, we envision adaptive estimation method on a parametrized orbit and algorithm for tracking moving target in a three dimensions as a future direction of the research.

Since the advantages of the implant localization can be many, some future research directions can be addressed in order to use it in a real life. Firstly, although we demonstrated human body modeling as a communication channel by using organ and tissues permittivities, large scaled channel characterization of human body with the consideration of broadening, refraction and multi-path effects is useful line of future research. Secondly, because of complex structure of human body and tissues, estimation of the propagation velocity inside human body without priori information is important research task. We additionally consider to design and fabricate mobile sensory unit (MSU) in order to localize implant in human body in the future.

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