Evaluation of TDOA based Football Player’s Position Tracking Algorithm using Kalman Filter

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This thesis is submitted to the Department of Applied Signal Processing at Blekinge Institute of Technology in partial fulfillment of the requirements for the degree of Master of Sciences in Electrical Engineering with Emphasis on Signal Processing.

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Abstract

Time Difference Of Arrival (TDOA) based position tracking technique is one of the pinnacles of sports tracking technology. Using radio frequency communication, advanced filtering techniques and various computation methods, the position of a moving player in a virtually created sports arena can be identified using MATLAB. It can also be related to player's movement in real-time. For football in particular, this acts as a powerful tool for coaches to enhance team performance. Football clubs can use the player tracking data to boost their own team strengths and gain insight into their competing teams as well. This method helps to improve the success rate of Athletes and clubs by analyzing the results, which helps in crafting their tactical and strategic approach to game play. The algorithm can also be used to enhance the viewing experience of audience in the stadium, as well as broadcast.

In this thesis work, a typical football field scenario is assumed and an array of base stations (BS) are installed along perimeter of the field equidistantly. The player is attached with a radio transmitter which emits radio frequency throughout the assigned game time. Using the concept of TDOA, the position estimates of the player are generated and the transmitter is tracked continuously by the BS. The position estimates are then fed to the Kalman filter, which filters and smoothen the position estimates of the player between the sample points considered. Different paths of the player as straight line, circular, zig-zag paths in the field are animated and the positions of the player are tracked. Based on the error rate of the player’s estimated position, the performance of the Kalman filter is evaluated. The Kalman filter’s performance is analyzed by varying the number of sample points.

Keywords: Gauss Newton method, Player Localization, Radio transmission, Single Point Localization, TDOA, Kalman filter, Wireless Sensor Network
Acknowledgments

On the very outset of this report, we would like to thank our Industrial supervisor Dr. Benny Sällberg and University supervisor Dr. Josef Ström Bartunek for their valuable expert advice throughout the work. Furthermore, we would like to thank our examiner, Dr. Sven Johansson for his useful comments and remarks through the learning process of this master thesis.

We would like to extend our sincere gratitude to our University, Blekinge Institute of Technology for providing us with this opportunity. The Department of Signal Processing has provided the support which made our thesis work complete and productive.

We are thankful to our family members for their everlasting love and support throughout the journey of our studies. Finally, we would like to thank one and all, who might have their contribution in completion of our thesis.

Thank you all.
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<tbody>
<tr>
<td>AEKF</td>
<td>Adaptive Extended Kalman Filter</td>
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<tr>
<td>A-GPS</td>
<td>Assisted-Global Positioning System</td>
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<tr>
<td>BS</td>
<td>Base Station</td>
</tr>
<tr>
<td>CRLB</td>
<td>Cramer-Rao Low Bound</td>
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<tr>
<td>CWLS</td>
<td>Constrained Weighted Least Squares</td>
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<tr>
<td>D-GPS</td>
<td>Differential-Global Positioning System</td>
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<tr>
<td>DMS</td>
<td>Degree Minutes Second</td>
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<tr>
<td>EKF</td>
<td>Extended Kalman Filter</td>
</tr>
<tr>
<td>FDOA</td>
<td>Frequency Difference Of Arrival</td>
</tr>
<tr>
<td>GNSS</td>
<td>Global Navigation Satellite System</td>
</tr>
<tr>
<td>GPS</td>
<td>Global Positioning System</td>
</tr>
<tr>
<td>LPTS</td>
<td>Local Position and Tracking System</td>
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<td>MATLAB</td>
<td>Matrix Laboratory</td>
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<td>MLAT</td>
<td>Multilateration</td>
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<td>MS</td>
<td>Mobile Station</td>
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<td>NLOS</td>
<td>Non-Line Of Sight</td>
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<tr>
<td>PF</td>
<td>Particle Filter</td>
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<tr>
<td>RFID</td>
<td>Radio Frequency Identification</td>
</tr>
<tr>
<td>RSS</td>
<td>Received Signal Strength</td>
</tr>
<tr>
<td>RSSD</td>
<td>Received Signal Strength Differences</td>
</tr>
<tr>
<td>RTLS</td>
<td>Real Time Localization System</td>
</tr>
<tr>
<td>SSP</td>
<td>Sound Speed Profile</td>
</tr>
<tr>
<td>TDOA</td>
<td>Time Difference Of Arrival</td>
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<tr>
<td>TOA</td>
<td>Time Of Arrival</td>
</tr>
<tr>
<td>TOF</td>
<td>Time Of Flight</td>
</tr>
<tr>
<td>UTM</td>
<td>Universal Transverse Mercator</td>
</tr>
<tr>
<td>UKF</td>
<td>Unscented Kalman Filter</td>
</tr>
<tr>
<td>UWB</td>
<td>Ultra Wide-Band</td>
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<tr>
<td>WSN</td>
<td>Wireless Sensor Network</td>
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1.1 Background

Multilateration (MLAT) is increasingly significant and effective location and identification system [1]. It is a technique based on navigation and the measurement of difference in the distance between two BS whose location is known that transmit signals at known times. Measuring the difference in distance between two stations results in a finite number of locations that satisfy the measurement. It is an effective algorithm when the distance between the two nodes or the base stations are known [2]. MLAT is also considered to be a surveillance technique. This technique combines a dependence on target-derived data for identification and altitude with ground based calculation of position. Determined by the responses, MLAT can achieve a higher update rate than a typical rotating radar. To enable monitoring of targets, this technique supports ground conflict detection by providing frequent updates of target positions.

Local Position and Tracking System (LPTS) enables the user to setup an accurate position tracking system where GPS is unavailable or unreliable. It is an effective solution for personnel tracking [3]. This system doesn’t provide global coverage. Instead, it uses a set of BS with limited range to track the transmitter. Indoor robot and user tracking, positioning and navigation were one of the first research areas for such location sensing techniques. Due to its simplicity and low demands to processing power and synchronization as well its high accurate distance measurements under optimal and static conditions. In general, these systems rely on TOF measurements between base stations with known positions and moving tags. Ultrasonic based positioning was first of its kind in measuring the distances but has got several drawbacks. To be specific, reflections and occlusions occur within the selected field of monitoring. Ultrasonic distance measurements essentially require line-of-sight between the communicating devices. In case the transmitter turns away from the receiver or some person/object comes between the two, the signal is faded, or a redirected signal is received. Secondly, due to the speed of sound (about 340 m/s) its highest possible sampling rate is quite low compared to human motions. Moreover, the system must operate in consec-
utive mode, i.e., specific distance measurements must be conducted separately. The accuracy highly decreases with the instantaneous speed and dynamics of the transmitter. The time slot for each distance measurement must be at least 0.031 sec and thus the transmitter could be covering a distance up to 0.31 m in between two consecutive distance measurements. Such an inaccuracy is not viable for most applications in sports.

The Gauss–Newton method is a technique used for solving a set of nonlinear least squares problem to linearise the nonlinear regression function around the current estimate of an unknown parameter by the first-order Taylor series expansion. This obtains a simple quadratic programming function by simplifying the nonlinear minimization problem [4]. Minimizing this resulting quadratic function avoids the further evaluation of the second derivatives of the regression function, which would be needed by. This is the advantage over the Newton’s method, which needed the evaluation of second derivatives.

Kalman filter is an optimal recursive data processing algorithm [5]. One aspect of this optimality is that the Kalman filter integrates all information that can be provided to it. In other way, the Kalman filter processes all available measurements, regardless of their precision, to estimate a current value of the studied object. Concerning recursiveness, the Kalman filter does not need all previous data to be stored and reprocessed every time a new measurement is taken. This is important for the filter’s implementation, which is in fact a data processing algorithm. This filter naturally integrates discrete-time measurements instead of continuous time inputs. The Kalman filter merges all the available measurement data with a prior knowledge about the system and measuring devices, to generate an estimation of the desired variables in such a way the error is minimized statistically. Kalman Filter has numerous applications in technology. A common application is for guidance, navigation, and control of vehicles, particularly aircraft and spacecraft. Furthermore, the kalman filter is a widely applied concept in time series analysis used in fields such as signal processing and econometrics. The Kalman filter is essentially a set of mathematical equations that implement a predictor-corrector type estimator that is optimal in the sense that it minimizes the estimated error covariance—when some presumed conditions are met. Since the time of its introduction, the Kalman filter has been the subject of extensive research and application, particularly in the area of autonomous or assisted navigation. This is likely due in large part to advances in digital computing that made the use of the filter practical, but also to the relative simplicity and robust nature of the filter itself. Rarely do the conditions necessary for optimality actually exist, and yet the filter apparently works well for many applications in spite of this situation [6].
1.2 Motivation

The current Master Thesis is motivated from the position tracking and path recognition of a football player using different algorithms. TDOA based position tracking technique is one of the pinnacles of sports tracking technology. Football clubs can use the player tracking data to boost their own team strengths and gain insight on their competing teams as well and improve the success rate of Athletes. The algorithm can also be used to enhance the viewing experience of audience in the stadium, as well as broadcast. The main aim is to characterize the amount of error in position of the player and evaluate the performance of the algorithm based on the chosen parameters. Based on this study, the sports tracking technology may take adequate measures to ensure the desired tracking model.

1.3 Applications

Tracking the position of a player has many practical applications and advantages listed below.

- Analyzing team’s performance and boost their strength using tracking data [7].

- Anticipating accidents and avoiding injuries [8].

- Individual or personal coaching as well as team’s coaching with different patterns of game play [9].

- Enhance viewer’s experience as well as broadcast [10].

- Judgment at critical stages can be relied on the algorithm [11].

Other Applications

- Implemented to other sports to increase the performance and analysis of play [11].

- Tracking of products stored in a ware house [12].

- Location detection of fire fighters in a building on fire [13].
1.4 Research Questions

In this Master Thesis, many research questions are formulated as listed below,

1. How well is a football player’s position tracked using advanced mathematical methods and techniques accurately?

2. How well is the accuracy of the algorithm in localizing the position of a football player retained?

3. How well is the simulated model related to the practical scenario of football game?

1.5 Proposed Solution

Initially a real football field is virtually created using MATLAB. As considered, the base stations and the player are initiated in the model. Thereby, the TDOA are calculated based on TOA of the player’s position to the base stations. Then the position of the player is tracked using Gauss-Newton method. The obtained position of the player moving in the football field is smoothened using Kalman Filtering Technique by making it closer to the original value. Thus, the position of the player is approximated.

From these position estimates, the path of the football player moving in the football field is recognized and the speed of the player is analyzed basing on the sample points. The Figure 1.1 illustrates the flow-graph of the proposed solution adopted for the simulation.
Chapter 1. Introduction

1.6 Survey of Related Works

In the previous study, the technique of Vehicle Position Estimation has been performed by integrating the information about the vehicle and optimizing by Constrained Weighted Least Squares (CWLS) with TDOA technique. This minimizes the position estimate error of the vehicle. Further Kalman Filtering technique can be used for smoothening purpose [14]. This can be applied to estimate the position of a football player moving in a football field.

In a research to estimate the movement of a non-stationary body like a ship with respect to a non-moving target, an Extended Kalman Filter (EKF) and a Particle Filter (PF) can be utilized as smoothening filters. The performances of
both the filters are compared and inferred that the EKF has relatively smoother performance. In this technique a modelling error with a Gaussian distribution is assumed [15].

A method employed on a Non Line-of-Sight (NLOS) environment to estimate the location of Radio Frequency Identification System (RFID) tag. The better method for position estimation of between Kalman filter and EKF is studied. It is inferred from simulation that EKF is more precise for Real Time Localization Systems (RTLS). In this method, RTLS is based on TDOA and Error compensation technique [5].

In the study of a Geolocation, TDOA along with Received Signal Strength Differences (RSSD) technique are used in the analysis. An Unscented Kalman Filter (UKF) algorithm is used for this geolocation system. It is inferred from the simulation that the use of UKF compensates the instability of RSSD geolocation. The motive of this hybrid method is to gain from the signal power information without deteriorating the accuracy. UKF is seen as an effective approach relative to least squares hybrid method [16].

The techniques of TDOA and Frequency Difference of Arrival (FDOA) are utilized in the tracking of location and velocity at discrete times of a moving target. Kalman Filter has a remarkable performance in the calculation and position estimation. To update the noise covariance at every measurement, an Adaptive Extended Kalman Filter (AEKF) is introduced. This effectively reduces the position tracking error and improves the accuracy of the tracking [17].

In the previous study of solving the problem of localizing and tracking a mobile node underwater can be achieved through multilateration. This is achieved by utilizing the Kalman Filter for multilateration of the node which is tracked in a recursive manner. In this technique the Time of Flight (TOF) between two underwater nodes to their locations for an isogradient Sound Speed Profile (SSP) are related. Further, the Kalman filter approach is used for proper formulation in solving the problem of positioning and tracking [18].

In an investigation on the performance of tracking algorithms in wireless cellular networks where the measurements provided by base stations are based on TDOA. The Non-linear least squares estimation problem cannot be solved by Gauss-Newton method since it cannot converge for particular geometric constellations [19].
1.7 Thesis Organization

Chapter 2 deals with the Theoretical Framework required for the implementation and simulation of the research work. Chapter 3 deals with the proposed method of the algorithms used in the implementation and simulation. Chapter 4 presents the different results obtained from the simulation of the algorithms adopted. Chapter 5 discusses about the conclusions drawn from the results presented. It also presents the extension of current work.
Chapter 2

Theoretical Framework

2.1 Wireless Sensor Networks

During the past two decades, Wireless technology has a very rapid growth in progress. This has opened doors for researchers to salient improvements in technology to conceive adaptable solutions for different kinds of applications. Wireless sensor networks (WSN), Cellular and Ad hoc networks are the examples of recent wireless technology. These technological advancements are also being used in position estimation and tracking systems. WSN has pulled a very large attention of government and non-government organizations for position tracking awareness in several services. There are many source location or position estimation techniques available for commercial usage. Among them, the most significant technique for research on WSN is position estimation for object tracking [20].

WSN communication uses sensors to collect the data, which helps us in monitoring and target tracking. One of the application of WSN is estimating the position of a football player in play field. With the help of these sensors, we can track, estimate and analyze the position of the football player who are primary objects of interest in the field. There are many obstacles like time synchronization, sensitivity, environment, unwanted signals, noise and uncertainties in player’s location that may sometimes contribute to false decision during an important game. Having a clear cut, crystallized data of player’s position is mandatory in high level competitions when professional football players invest their blood and life in a win or lose situations [21].

Additionally, powerful data analysis can help directors and coaches to summarize the statistics regarding each player, calculated predictions can be made and individual’s weakness can be distinguished. When we continuously track/calculate the location of the participant during the game, false decisions can be averted. The primary trouble is mobility, which adds a novel layer of complexity in the appraisal of the player’s position. When the player is moving, the complexity increases in sensing object’s mobility than in stationary because the player may be active time to time. As player in a football field moves randomly accord-
ing to the game play, it is difficult to update the player’s position data timely for data analysis in order to extract a highly accurate result. WSN is a web that consists of sensing elements [22] which have battery power, limited storage and processing power. With the help of these sensor networks, we can spread sensing, wireless communication and computation by extracting the data from detectors. Detectors have two basic categories, they are the hardware and the software. The hardware consists of group of nodes, which are likewise recognized as clusters or tree. A BS acts as a controller to compile data in the clusters [23].

WSN can be applied in position localization technology by dividing the nodes or BS by their identities. The BS are fixed with identified positions, interconnection between these base stations create a network. Every base station in the network acts as a gate way to other clients. The transmitters in the network acts a s beacons of broadcasting their positioning information periodically. This is called proximity based method [24].

Position location approaches in WSN is classified into two categories, range based and range-free methods. The primary conflict lies in the direction of making the distance related information. The orbit-based methods rely on the distance calculation by measuring the radio signals using methods such as TOA, TDOA, RSS. The range free method uses special protocols to do away with the demand for radio signals calculation [25].

2.2 Object Tracking

One of the most important application of wireless networks is target/object tracking. For an example, it is also used in military for intrusion detection and habitat monitoring. Existing research efforts on target tracking can be categorized in to two. In the first category, the problem of accurately calculating the position of an object. In the second category, in-network data processing and data aggregation model for object tracking [26].

A particular target is selected and tracked by the network, which uses the object tracking techniques to continuously report the status of the object in terms of Cartesian coordinates to a sink node or to a central base station. [27].

2.2.1 Position Estimation Techniques

For mobile nodes in moving object detection and tracking, the sensor network uses different position estimation techniques. All these techniques are based on few fundamental things like measurement of angle or time or delay or amplitude.
Depending upon the requirement and situation, the combination of these measurements are considered and position is localized based upon the calculations by analyzing the parameters and data through signal processing. There are many estimation techniques like Bayesian approach, Maximum likelihood estimation, Cramer-Rao Low Bound (CRLB) and other mapping techniques. The problem of position estimation is simplified when the receivers are distributed on a straight line, and many optimum processing techniques for this situation have been proposed [28].

Although other methods [29][30] have also been considered, these algorithms do not take in account the inferences of NLOS propagation on the location estimation. Because NLOS propagation always exist in urban area or other built-up environments so that, actually the signals come at different receivers via NLOS propagation, the influences of the NLOS propagation on the position estimation must be brought into account. But especially where higher accuracy is demanded, the effects caused by NLOS error usually cannot be ignored [31].

2.3 Positioning Systems

2.3.1 Indoor Positioning Systems

Indoor positioning systems provide a raw layer of automation called automatic object location detection. To cite a few, one can weigh the location detection of products stored in a warehouse, location detection of fire fighters on a building on fire, location of medical personnel or equipment in a hospital. Since wireless information access is nowadays widely available, there is a high requirement for precise placement in wireless nets [32]. The process of determining a location is called location sensing, geo-location, position location, or radio location, if it uses wireless technologies.

Different applications may need different types of position data. They are physical location, symbolic location, absolute positioning, and relative position [33]. The physical location is expressed in the form of coordinates, which distinguish a period on a 2-D/3-D map. The widely used coordinate systems are the degree/minutes/seconds (DMS), degree decimal minutes, and universal transverse Mercator (UTM) system. Symbolic location expresses a location in a natural-language mode, such as in the office, in the third-level chamber, etc. Absolute location uses a shared reference grid for all located objects. A relative location depends on its own material body of reference. Relative location information is commonly based on the proximity to known reference points or base stations [32].
Various wireless technologies are employed for wireless indoor positioning. These may be sorted based on,
1) the location positioning algorithm and
2) the physical layer or location sensor infrastructure.
This means that, the wireless technology is employed to communicate with the mobile devices or static devices. In general, measurement involves the transmission and reception of signals between hardware elements of the organization. An indoor wireless positioning system consists of at least two separate hardware components like a signal transmitter and a measuring unit.

2.3.2 Outdoor Positioning System

Outdoor positioning technologies can be enforced in two ways as Self positioning and Remote location [3]. In the first approach, the mobile terminal uses signals, carried by the gateways or antennas which can be either terrestrial or satellite to compute its own location. More specifically the positioning receiver makes the appropriate signal measurements from geographically distributed transmitters and uses these measurements to define its location. A self-positioning receiver, therefore, “knows” where it is and applications collocated with the receiver can apply this data to make positioned based decisions such as those needed for vehicle navigation. Some of the self-positioning techniques are,

- GPS
- A-GPS
- D-GPS
- GNSS

The second technique is called remote positioning. In this case the mobile positioning can be located by measuring the signals moving to and from a set of recipients. More specifically, the receivers which can be set up at one or more locations measure a signal starting from, or reflecting off, the object to be placed. These signal measurements are utilized to define the distance and/or centering of the individual radio paths, and then the mobile terminal location is computed from geometric relationship [34].

2.4 Time Of Arrival

The most frequently used distant measurement method for accurate indoor positioning is Time-Of-Arrival (TOA) estimation of direct path using UWB technology [35]. Due to severe multipath conditions in indoor areas, estimation of
Chapter 2. Theoretical Framework

TOA of direct path results in small random and sometimes large errors. The small random errors are caused by paths arriving close to the detected first path. The large errors occur when the direct path goes below the detection threshold so the detected first path in the received multipath profile is erroneously considered to be the direct path. The TOA estimation error has two components, (1) the errors caused by multipath dispersion affecting any signal path (2) the errors caused by undetected direct path conditions [36].

A constrained Non-linear Least Squares solution for TOA based location estimation utilized the condition that NLOS range errors are always positive to set upper bounds on the true range [37]. The true location of the MS, \((x, y)\), therefore has to lie inside the circle of radius \(L_i, i=1,2...,N\), where \(N\) is the number of available TOA measurements. This condition implies that the MS location is constrained to the area of intersection of the range of circles given by the 'N' TOAs.
This chapter deals with the detailed description of the proposed method used in tracking the position of the player using TDOA estimation and Kalman Filtering techniques. The model imitating a football field with dimensions 120x60 meters with six base stations along with a player is initialized and then the TDOA are calculated from their TOA. In this thesis, the football player is in motion and shifts his position from time to time according to the game play. Three patterns of football player’s path is considered namely circular, linear and zig-zag. A number of sampling points are considered based on the shape of the path. The position of the player is estimated using Gauss-Newton method. This obtained position is then smoothened using Kalman Filtering technique. The speed of the player is analyzed and the path is recognized. This is summarized in the flow chart in the Figure 3.1.

![Flow Chart](image)

Figure 3.1: Proposed Solution
3.1 Simulation of the Model

The model of football field considered for simulation in MATLAB is shown in the Figure 3.2 with different specifications. The dimensions of the rectangular football field are considered to be 120x60 meters. Six base stations are considered (B₀ to B₅) out of which the reference base station is taken as B₀. Here, adjacent base stations are equidistantly placed along the football field. A player 'P' is considered whose initial position at time $t₀$ is shown in the Figure 3.2. The movement of the player is animated in different paths like Circle, Square and Zigzag that are simulated in MATLAB.

Figure 3.2: Model of Football field considered
3.2 Calculation of TDOA

The location of the football player is tracked using TDOA calculation, which is one of the most efficient techniques used for navigational purposes and a part of Multilateration. The player is attached with a transmitter which emits the radio frequency signal throughout the assigned game time with very short regular intervals. These signals are received by the BS, which are placed at the known locations. The time taken by the signal to reach the BS from an emitter at a particular time instant varies from base station to base station, as the BS are spatially separated. The time for a signal from emitter to base station is recorded using the data collectors at the BS. Using these TOA from all the base stations, a reference base station is considered and the TDOA is calculated [38]. The pictorial illustration of TDOA calculation for a player moving in a football field is shown in Figure 3.3.

![Figure 3.3: Illustration of TDOA calculation](image-url)
Chapter 3. Proposed Method

The initial position of the player is considered at time instance \( t_0 \) (represented in bold line). There is a change in position of the player at time instance \( t_0 + T_s \) (represented in dotted line).

### 3.2.1 Localizing the Cartesian co-ordinates of the player from TDOA measurements

The measured TDOA gives a whole set of locations from the BS. The Locus of the all possible emitter locations together form a one half of two sheeted hyperboloid. In comparison with the Reference base station, all other BS are considered to know the intersecting(meeting) points of the hyperboloid. These are the most possible locations of the player’s estimated positions. These estimations are precisely plotted with increase in the number of BS as the intersecting points tend to decrease. The below mathematical description is considered from [38] [39].

Consider \( t_{a0} \) is the reference TOA from reference base station and \( t_{a1}, t_{a2}, t_{a3}, t_{a4} \) and \( t_{a5} \) are the respective TOAs from other 5 BS as shown in Figure 3.3.

Now consider an emitter (player) at an unknown location \( \vec{P} = (x, y) \). The locations of the BS are given by \( \vec{B}_0 = (x_0, y_0) \), \( \vec{B}_1 = (x_1, y_1) \) and so on as \( \vec{B}_k = (x_k, y_k) \).

The distance from one of the base station to player’s location \( (D_k) \) is given by

\[
D_0 = |\vec{B}_0 - \vec{P}| = \sqrt{(x_0 - x)^2 + (y_0 - y)^2},
\]
\[
D_k = |\vec{B}_0 - \vec{B}_k| = \sqrt{(x_k - x)^2 + (y_k - y)^2},
\]
(3.1)

where, \( D_0 \) is the distance of the player from \( (x_0, y_0) \) i.e the reference point.

The distance, \( D_0 \) is the wave speed (V) times transit time \( (t_{a0}) \) at instance 0 as

\[
D_0 = V * t_{a0}.
\]
(3.2)

From these times, \( t_{d1}, t_{d2}, t_{d3}, t_{d4} \) and \( t_{d5} \) i.e. TDOA at different instances can be calculated as

\[
t_{d1} = t_{a0} - t_{a1},
\]
\[
t_{d2} = t_{a0} - t_{a2},
\]
\[
t_{d3} = t_{a0} - t_{a3},
\]
\[
t_{d4} = t_{a0} - t_{a4},
\]
\[
t_{d5} = t_{a0} - t_{a5}.
\]
(3.3)
Chapter 3. Proposed Method

In real time football field scenario, there are different factors influencing TDOA like multi-path propagation, signal interference, time jitters etc. In order to consider this error in the simulation model, a random error is generated and introduced to the original position estimates of the player.

The Range Difference between the BS with respect to the reference base station \(R_k\) is given by

\[ R_k = D_k - D_0, \quad (3.4) \]

\[ R_k = \sqrt{(x_k - x)^2 + (y_k - y)^2} - \sqrt{(x_0 - x)^2 + (y_0 - y)^2}, \quad (3.5) \]

where \(k = 1,2,3,4,5\). This defines the set of nonlinear hyperbolic equations whose solution gives the 2-D coordinates of the player.

Rearranging the equation 3.4 gives

\[ D_k^2 = (R_k + D_0)^2. \quad (3.6) \]

This set of equations can be solved to obtain the player’s coordinates as \((x, y)\).

3.3 Gauss-Newton Position Estimation

Gauss-Newton method is an iterative process of solving the problem of non-linear least-squares approximation. It can be applied as a method of locating a single-point. By solving the system of non-linear equations, the best estimates of the unknown variables are obtained [40]. The mathematical description shown below is considered from [41].

Consider a set of \(m\) transmitters located at positions \((x_k, y_k)\) spaced at the distance \(d_0\) to \(d_k\). Distance of each point to the reference base station is given by

\[ D_{x_0,y_0} = \sqrt{(x_0 - x_k)^2 + (y_0 - y_k)^2}, \quad (3.7) \]

where \(x_0\) and \(y_0\) are coordinates of the reference base station. Gauss-Newton method finds the value of the variables which minimizes the sum of squares in an iterative approach [41] represented as \(g(x)\) is given by

\[ g(x) = \sum_{k=1}^{m} r_k^2, \quad (3.8) \]

where \(r_k\), the set of residuals is given by

\[ r_k = d_k - \sqrt{(x_0 - x_k)^2 + (y_0 - y_k)^2}. \quad (3.9) \]
Gauss-Newton method requires the calculation of the Jacobian matrix of $r_k$. The partial derivatives of $r_k$ with respect to both $x_0$ and $y_0$ are determined as

$$\frac{\partial r_k}{\partial x_0} = (x_0 - x_k) \sqrt{(x_0 - x_k)^2 + (y_0 - y_k)^2}, \quad (3.10)$$

$$\frac{\partial r_k}{\partial y_0} = (x_0 - y_k) \sqrt{(x_0 - x_k)^2 + (y_0 - y_k)^2}. \quad (3.11)$$

The Jacobian is calculated at each iteration using the newest approximations of coordinates $x_k$ and $y_k$.

### 3.4 Kalman Filter Smoothening

A Kalman filter that linearizes about the current mean and covariance is referred to as an extended Kalman filter or EKF. Many of the practical scenarios are the non-linear systems, which are not appropriate for Kalman filters. Such cases require concept of extended Kalman filter. The basic idea of EKF is to focus on first-order nonlinear Taylor expansion around the status of the estimated, then transform the nonlinear system into a linear equation. It linearizes the nonlinear model around the previous state estimates using a first-order Taylor series approximation [6].

**Merits**

- Easy to implement.
- Good performance for objects in motion.
- Better adaptability for the uncertainty of noise

**Demerits**

- Status and measurement of noise slightly affects the filtering result.
- Improper estimation result in cumulative error, which may lead to divergence of filter.

In practice, Extended-Kalman Filter can lead to very reliable state estimation. The mathematical description is considered from [42] and [43]. Consider a non-linear discrete-time process in the standard state-space as

$$p_k = f(p_{k-1}, u_k, k) + w_{k-1},$$

$$q_k = h(x_k, u_k, k),$$

$$\tilde{q}_k = q_k + v_k. \quad (3.12)$$
where \( k \) is a discrete point in time, \( k-1 \) denotes immediate past time point, \( u_k \) is input vector, \( p_k \) is actual state vector, \( q_k \) is actual process output vector, \( \tilde{p}_k \) is measured process output vector, \( w_k \) and \( v_k \) are processed and output noise respectively, \( f(\cdot) \) and \( h(\cdot) \) are non-linear functions relating past state, current input, and current time to the next state and current output respectively.

![Figure 3.4: Input-Output of the Extended-Kalman Filter](image)

Here the inputs, measured outputs, assumptions on the process and output noise are given. The Extended Kalman Filter is then used to estimate unmeasured states (\( \hat{p}_k \)) and the actual process outputs (\( \hat{q}_k \)).

The EKF acquires a two step predictor-corrector algorithm [44].

- The projection of most recent state estimates along with estimate of error covariance are forwarded in time to compute the predicted estimate of the states at present time is performed in the first step.

- In the following second step, the correction of predicted state estimate is calculated by incorporating the most recent process measurements in the first step to generate an updated state estimate.

Since the process is non-linear in nature, the covariance prediction and update equations cannot use \( f \) and \( h \) directly. The Jacobian of \( f \) and \( h \) are used instead. They are defined as

\[
F_k = \left. \frac{\partial f}{\partial p} \right|_{(\hat{p}_{k-1}, u_k, k)},
\]

\[
H_k = \left. \frac{\partial h}{\partial p} \right|_{(\hat{p}_{k-1}, u_k, k)}.
\]

**Predictor step:**

\[
\hat{p}_k^- = f(\hat{p}_{k-1}, u_k, k),
\]

\[
\hat{P}_k^- = F_{k-1}P_{k-1}F^T_{k-1} + Q_k.
\]

(3.13)
Chapter 3. Proposed Method

**Corrector step:**

\[
K_k = \hat{P}_k^- H_k^T (H_k \hat{P}_k^- H_k^T + R_k),
\]
\[
\hat{p}_k = \hat{p}_k^- + K_k (\tilde{q}_k - h(\hat{p}_k^-, u_k, k)),
\]
\[
P_k = (I - K_k H_k) P_k^-,
\]  

(3.15)

where \(P_k\) is an estimate of the covariance of the measurement error, \(K_k\) is called the Kalman gain, \(\hat{x}_k\) is current estimate of the states after the prediction and correction steps are performed. \(\hat{y}_k\) can then be calculated. Both \(\hat{x}_k\) and \(P_k\) are stored and used in the predictor step of the next time period. The gain of the Extended Kalman Filter is tuned by varying the samples and as well as the best primary estimate which is very much closer to the original location of the football player.
In this chapter, the considered path patterns namely circular, linear and zig-zag are studied and the position estimates of the player moving in these paths are analyzed. Using TDOA, the position co-ordinates are extracted from hyperbolic functions. These coordinates are used by Gauss Newton method to estimate the position of the player moving in the football field. The estimated positions are smoothened by Kalman filtering technique to recognize the players movement and pattern in the selected paths. The estimated position as well as the recognized pattern in the path are extracted from the method by using the calculations described in chapter 3. Parameters such as sampling rate, accuracy and speed of the player are considered to analyze and compare the player’s movement and path. This chapter also includes the validation in which, the achieved results are validated by relating the simulated model to the real time football game.

4.1 Different paths of the player

The Circular, Linear and Zig-zag paths in which the player’s movement is considered, are plotted in MATLAB as shown in the figures 4.1, 4.2 and 4.3. These figures show the actual paths of the player’s movement. The circular path considered has a radius of 32.61 m².
Figure 4.1: Actual Circular path of the player

Figure 4.2: Actual straight line path of the player
Chapter 4. Results and Analysis

4.2 Position estimates of different paths

The locations of the player moving in different paths are estimated using Gauss-Newton and Kalman filter techniques. The estimates are then plotted.

4.2.1 Circular Path

Figure 4.4 shows comparison of position estimates from Gauss-Newton and Kalman filtering techniques with original mobile location of the player moving in a circular path within football field consisting of 6 base stations (represented with the black dots).

It can be observed from the Figure 4.4, that average of the estimated mobile locations of player using Kalman filter is relatively accurate to that of average Gauss-Newton estimates. The above plot in Figure 4.4 can be clearly observed in the magnified version shown in Figure 4.5 which clearly shows that position estimates from the Kalman filter are more closer to original mobile location of player than Gauss-Newton position estimates. Here, mobile location refers to the moving player in the field.
Chapter 4. Results and Analysis

Figure 4.4: Position estimates from Gauss-Newton and Kalman filter (Circular)

Figure 4.5: Magnified version of the position estimates of the player
4.2.2 Straight-line Path

Figure 4.6 shows comparison of position estimates from Gauss-Newton and Kalman filtering techniques with original mobile location of the player moving in a Straight-line path within football field consisting of 6 base stations shown in black dots.

It can be observed that average of the estimated mobile locations of player using Kalman filter is relatively accurate to that of average Gauss-Newton estimates. The plot in Figure 4.6 can be clearly observed in the magnified version shown in Figure 4.7 which clearly shows that position estimates from the Kalman filter are more closer to original mobile location of player than Gauss-Newton position estimates where mobile location refers to the moving player in the field.

Figure 4.6: Position estimates from Gauss-Newton and Kalman filter (Straight line path)
Chapter 4. Results and Analysis

4.2.3 Zig-zag Path

Figure 4.8 shows comparison of position estimates from Gauss-Newton and Kalman filtering techniques with original mobile location of the player moving in a zig-zag path within football field consisting of 6 base stations shown in black dots.

It can be observed that average of the estimated mobile locations of player using Kalman filter is relatively accurate to that of average Gauss-Newton estimates. The plot in Figure 4.8 can be clearly observed in the magnified version shown in Figure 4.9 which clearly shows that position estimates from the Kalman filter are more closer to original mobile location of player than Gauss-Newton position estimates where mobile location refers to the moving player in the field.
Chapter 4. Results and Analysis

Figure 4.8: Position estimates from Gauss-Newton and Kalman filter (Zig-zag)

Figure 4.9: Magnified version of the position estimates of the player
4.3 Error Estimates

Error estimates from the position tracking using Gauss-Newton and Kalman filtering are calculated for the player moving in different kinds of paths. The error estimates for Circular, Straight-line and Zig-zag paths are plotted in figures 4.10, 4.11, 4.12.

Figure 4.10: Error estimate of Gauss-Newton and kalman filter (Circular Path)
Chapter 4. Results and Analysis

Figure 4.11: Error estimate of Gauss-Newton and Kalman filter (Straight line)

Figure 4.12: Error estimate of Gauss-Newton and Kalman filter (Zig-zag)
Chapter 4. Results and Analysis

It is observed from the above figures that the magnitude of error estimate of the Gauss-Newton is relatively higher when compared to the error estimate of Kalman filter for the player moving in different paths. This means position estimate of Kalman filter is relatively accurate when compared to Gauss-Newton position estimates.

4.4 Accuracy Comparison

Figures 4.13, 4.14 and 4.15 displays the accuracies of Gauss-Newton and Kalman Filtering techniques with respect to circular, Straight-line and zig-zag paths of a player respectively.

![Command Window](image)

Figure 4.13: Accuracy comparison of proposed algorithms (Circular)

When path of the player is considered to be circular, the accuracies of the position estimates from Gauss-Newton and Kalman filtering techniques are obtained as 0.6531 and 0.8054 respectively.
Chapter 4. Results and Analysis

Figure 4.14: Accuracy comparison of proposed algorithms (Straight line)

When path of the player is considered to be linear, the accuracies of the position estimates from Gauss-Newton and Kalman filtering techniques are obtained as 0.6906 and 0.8429 respectively.

Figure 4.15: Accuracy comparison of proposed algorithms (Zig-zag)

When path of the player is considered to be zig-zag, the accuracies of the position estimates from Gauss-Newton and Kalman filtering techniques are obtained as 0.5376 and 0.7606 respectively.
The accuracies of adopted methods in different paths of the player are shown in Table 4.4.1 for comparison.

<table>
<thead>
<tr>
<th>Path of player</th>
<th>Method</th>
<th>Accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Circle</td>
<td>Gauss-Newton</td>
<td>65.31</td>
</tr>
<tr>
<td></td>
<td>Kalman Filtering</td>
<td>80.54</td>
</tr>
<tr>
<td>Straight line</td>
<td>Gauss-Newton</td>
<td>69.06</td>
</tr>
<tr>
<td></td>
<td>Kalman Filtering</td>
<td>84.29</td>
</tr>
<tr>
<td>Zig-zag</td>
<td>Gauss-Newton</td>
<td>53.76</td>
</tr>
<tr>
<td></td>
<td>Kalman Filtering</td>
<td>76.06</td>
</tr>
</tbody>
</table>

It can clearly inferred from table 4.4.1 that the Kalman filtering technique gives accurate position estimates when compared to Gauss-Newton method for a player moving in different paths.
Chapter 5
Validation and Discussions

5.1 Validation

Consider the player is moving in circular path, with diameter \( d \) of circle as 32 m. Then perimeter of the circle = \( \pi \times d = 100.5714 \) m. It is also assumed that the player is moving with his maximum velocity as 12.4 m/sec (sprinting). Then the time taken for the player to complete a round of the circle is 8.1105 secs. Now consider the number of samples. In first model we have taken 100 samples. Inter Sample Interval is 0.0806 sec. From the above data Sampling rate can be known as 12.3304 Hz. Basing on these assumptions, the results can be validated as below shown in Table 5.1.1. It can be observed that the results explicitly relate to the real-time motion of the player in the field, thus validating the achieved results as reliable.

<table>
<thead>
<tr>
<th>No. of Samples</th>
<th>Time to complete full circle (sec)</th>
<th>Speed of the player (m/sec)</th>
<th>Estimated State of the player</th>
</tr>
</thead>
<tbody>
<tr>
<td>100</td>
<td>8.11</td>
<td>12.4</td>
<td>Sprinting</td>
</tr>
<tr>
<td>150</td>
<td>12.17</td>
<td>8.27</td>
<td>Running</td>
</tr>
<tr>
<td>200</td>
<td>16.22</td>
<td>6.20</td>
<td>Jogging</td>
</tr>
<tr>
<td>500</td>
<td>40.55</td>
<td>2.48</td>
<td>Walking</td>
</tr>
</tbody>
</table>

5.2 Discussions

Research Question 1:
How well is a football player’s position tracked using advanced mathematical methods and techniques accurately?

The position of a football player is tracked using TDOA measurements along with Guass-Newton mathematical methods and Kalman Filter Smoothening technique. Depending upon the position estimates from the algorithms, the pattern
in the path of a football player is analyzed along with his state of motion. By this the main aim of the project is accomplished. It is inferred from the obtained results that Kalman Filter Smoothening technique gives relatively higher accuracy in all considered paths of the player which is shown in Table 4.4.1.

Research Question 2:
How well is the accuracy of the algorithm in localizing the position of a football player retained?

Gauss-Newton Method cannot localize the path of the player in Zig-zag movement. Kalman Filter Smoothening technique accurately predicted up to 84.29% in various paths of player. Based on the accuracy comparison between Gauss-Newton and Kalman filtering techniques, it is observed that Kalman Filter Smoothening technique gives relatively higher accuracy in all considered paths of the player.

Research Question 3:
How well is the simulated model related to the practical scenario of football game?

The simulated model of football field is constructed identical to the physical world measuring of 120m x 60m as shown in Section 3.1. Also, the practical paths like circular, straight-line and zig-zag are considered which are more relative to a football player movements in a real football match. Real-time noises like Multi-path propagation, Channel fading, Time jitters are also taken into consideration in the simulated model.
Chapter 6

Conclusions and Future works

This chapter deals with various conclusions inferred from the results obtained by simulating the model and the possible future extensions.

6.1 Conclusions

The simulated model of football field considered is constructed close to the real time scenario with the measurements of 120m x 60m in MATLAB. The position of a football player moving in different paths in this field is estimated using mathematical TDOA measurements and also Guass-Newton and Kalman Filter Smoothening techniques.

It is inferred that the Gauss-Newton Method cannot localize the path of the player in Zig-zag movement. Based on the number of samples, the speed of the player is also estimated. Further, the pattern of the movement can be recognized and the path of the player is then estimated. These conclusions are derived based on validating the results achieved. The accuracies of Gauss-Newton and Kalman filter techniques are also compared and concluded that Kalman Filter Smoothening technique gives relatively higher accuracy in all considered paths of the player.

6.2 Future works

The work can further be extended in following ways,

- The analysis can also be made on different movements of the player other than circular, linear and zigzag.
- Hybrid Techniques can also be used to track the position of the player and smoothen the output using various filtering techniques.
- Neural Networks and Fuzzy logics can also be implemented to detect the true position of the player along with the proposed algorithms.
References


References


