Data Fusion For Improved TOA/TDOA Position Determination in Wireless Systems

by

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Abstract

The Federal Communications Commission (FCC) that regulates all wireless communication service providers has issued modified regulations that all service providers must select a method for providing position location (PL) information of a user, requesting for E-911 service, by October 2000. The wireless 911 rules adopted by the FCC are aimed both for improving the reliability of the wireless 911 services and for providing the enhanced features generally available for wireline calls. From the service providers' perspective, effective position location technologies must be utilized to meet the FCC rules. The Time-of-Arrival (TOA) and the Time-Difference-of-Arrival (TDOA) methods are the technology that can provide accurate PL information without necessitating excessive hardware or software changes to the existing cellular/PCS infrastructure.

The TOA method works well when the mobile station (MS) is located close to the controlling base station. With certain corrections applied, the TOA method can perform reliably even in the presence of Non-Line-of-Sight (NLOS) condition. The TDOA method performs better when the MS is located at a significant distance from the controlling base station. However, under the NLOS environmental condition, the performance of the TDOA method degenerates significantly. The fusion of TOA and the TDOA method exhibits certain advantages that are not evident when only one of the methods is applied.

This thesis investigates the performance of data fusion techniques for a PL system, that are able to merge independent estimates obtained from TOA and TDOA measurements. A channel model is formulated for evaluating PL techniques within a NLOS cellular environment. It is shown that NLOS propagation can introduce a bias into TDOA measurements. A correction method is proposed for removing this bias and new corrected data fusion techniques are compared with previous techniques using simulation method, yielding favorable results.

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Chapter 1

Introduction

Position estimation of mobile users in cellular phone networks is becoming more important as the numbers of emergency calls originating from mobile telephone units increase. New Personal Communication Systems (PCS) are introducing new data and voice services [30]; however, the present wireless radio systems are still unable to provide accurate mobile user position location (PL) information to the Public Safety Answering Points (PSAP). This problem of providing reliable and accurate PL of mobile units in wireless communication systems has drawn considerable attention in the recent years as the deadline mentioned in a regulation adopted by the Federal Communication Commission is impending. Current regulation states that, by the October 2000 all the wireless carriers will have to identify a method for determining the location of the mobile unit making a E-911 call within a radius of no more than 125 meters rms [9]. Depending on the method selected, the accuracy requirements may be even more stringent, and hardware must be deployed over the next one to four years. This chapter discusses the motivation behind position determination requirements for mobile users in cellular system, an overview of different radio frequency based position location methods, and an outline of the research work contained in this thesis.

1.1 The Need for Location Information in Wireless Systems

In case of landline phones, the E-911 service provides the Public Safety Answering Point (PSAP) the number of the calling party. The Automated Number Identification (ANI) information enables the call back capability in case the emergency call is disconnected. A complete E-911 service not only provides the ANI but also enables the PSAP to identify an emergency call originating address through the use of an Automated Location Identification (ALI) database.

For the mobile users, although it is possible to identify the cell from where the E-911 call has been generated, it is not yet possible to identify the exact position in the cell from where the emergency call has been made.

In mid 90's, the Federal Communications Commission (FCC) addressed this problem issuing regulations outlining three staged phases, which all the wireless service providers must implement to provide the capability of universally available E-911 service with position determination.

The original regulation state that, in the first phase the wireless service providers have to achieve the capability to transmit Mobile Identification Number (MIN) of the handset generating 9-1-1 call to the PSAP without any interception by the carrier for credit checks or other validation process. Time frame allocated for this service was twelve months from the effective date of FCC rule, June 1996. In the second phase, the wireless service providers must provide a cell-site location mechanism in their wireless system along with providing the PSAP with the caller's phone number. In the third phase, the wireless service providers will have to achieve the target of identifying the location of the mobile users, attempted 9-1-1 calls, within a circle of radius of no more than 125 meters in at least 67 percent of all the cases [9]. The FCC regulation requires that all the wireless carriers achieve this goal by October 1, 2001.

In October 1999, the FCC revised its phase II requirements, offering service providers two alternative methods for position determination. Carriers have until October 1, 2000 to declare whether they will offer a network based or handset based solution to the position determination problem. For carriers offering network based solutions, an accuracy requirement specifies that, 67 percent of E-911 calls must be located with 100 meters, and 95 percent of E-911 calls must be located with 300 meters. This service must be available to 50% of the network within 6 months of a PSAP request and available to 100% of the network within 18 months of a PSAP request.

For carriers opting for a handset-based approach, accuracy requirements are 50 meters for 67% of the calls and 150 meters for 95% of the calls. Carriers providing handset-based position determination must begin selling phones with location technology by March 1, 2001, and must switch all subscriber equipment to enable location by December 31, 2004.

At least two commercial developers (U.S. Wireless and True Position) offer network-based solutions to position determination. Service providers opting for handset-based solutions will likely embed low cost Global Position System (GPS) receivers in their handsets [31]. Although it is not yet apparent which approach the industry will adopt, this thesis addresses the network-based approach. Although the deadline for providing the PL service is imminent, no single wireless service provider is even near to meet the requirements. Significant research work is aimed at finding a proven method to implement a measurement and to estimate the system without bringing in too much hardware or software modification in the existing cellular infrastructure.

1.2 Overview of Different Position Location Methods

There are a number of different radio frequency based techniques that can be used for wireless position location. The issue is, how effectively and efficiently a technique can be implemented so that it can be incorporated in the existing system easily without making major changes, either at the user end or at the service provider's end? Electromagnetic waves at radio frequency (RF) have the unique property of traveling through most objects. PL using radio frequency is performed by direct measurement of radio signals traveling between the base station and the mobile unit. The RF signal reflection and obstructed line of sight introduce error in the calculated location. However, only the radio frequency estimation systems offer the advantages of low cost, ease of integration and ability to work in harsh environmental conditions. Therefore, RF techniques that are practically viable for cellular systems are discussed below. The techniques can be broadly classified into two categories, namely:

- Modified Handset Techniques
- Unmodified Handset Techniques

1.2.1 Modified Handset Techniques

From the technical aspect, the modified handset techniques are easy to implement and accurate to determine a mobile location. The GPS-based position location, mobile-assisted Time of Arrival (TOA) technique and mobile-assisted Time Difference of Arrival (TDOA) techniques fall into this category. The GPS-based PL requires installation of a GPS receiver in the handset and transmitting the received GPS data on the reverse link to the base station (BS) for further processing and position determination [13]. The drawbacks of this technique include an increase in the size and weight of the handsets, and additional drain of the batteries in the mobile phones. Moreover, a GPS receiver needs to have at least four satellites constantly visible. In a heavily shadowed and covered urban environment, the line-of-sight between the mobile station and the satellites is impeded. Therefore, the GPS based solution is a feasible option for outdoor mobile units but not for indoor mobile units or units within urban canyons. In the mobile assisted TOA technique, the handset stamps the current time on any outgoing signal in the reverse channel. The base station determines the time required by the signal to reach the base station, and from that determines the distance between the base station and the mobile unit. If at least three base stations take part in this process then the triangulation method can be used to determine the mobile position. This requires that the mobile station and the base stations must be accurately synchronized. Although this is not impossible to achieve, it is not cost effective. The modified handset TDOA method proposed for the CDMA system utilizes the pilot tones transmitted by different base stations. Higher power transmission of the pilot tone allows extremely accurate tracking of the received signal. Since each cell site transmits a Pseudo Noise (PN) code with a unique code sequence, a mobile can differentiate each cell site's pilot tone. The mobile measures the arrival time differences of at least three pilot tones transmitted by three different cells. This gives rise to hyperbolic equations and by intersecting the hyperbolas, an estimation of the mobile unit's position can be found [10]. The estimation can then be transmitted back to the base station through reverse channel. Since all the processing must be done in the handset, additional hardware requirements are imposed on the handset.

1.2.2 Unmodified Handset Techniques

An unmodified handset solution requires that all the modifications will be made at the base stations and at the switching centers, thus allowing existing terminal equipment to be used. Prominent options include: Angle of Arrival (AOA), Time of Arrival (TOA) or Direction of Arrival (DOA), and Time Difference of Arrival (TDOA) techniques. It is also possible to combine two or more of these techniques to achieve a more accurate position location. Combined methods are commonly known as Hybrid Techniques [6].

The AOA method utilizes antenna-arrays to estimate the direction of arrival of the signal of interest. A single AOA measurement constrains the source along a line. The position of the signal source can be located at the intersection of two lines if two DOA estimates are available from two separate antennas. Although the basic principle of the AOA method seems very simple, the method has some drawbacks. For measurement accuracy, it is important that the mobile unit and the participating base stations all have Line-Of-Sight (LOS) to the mobile. This is not the usual case in cellular systems. Cellular systems have heavily shadowed channels like the ones encountered in urban environments.

In the unmodified handset TOA technique, when a base station detects a 9-1-1 user, it transmits a particular command or instruction signal to the user and asks the user to respond to that command signal. The total time elapsed between the transmission of the command signal and the reception of the acknowledgement signal is recorded at the base station. The measured round trip delay includes the propagation delay of the signal traveling in both directions, plus a processing delay and a response delay of the mobile handset. Therefore, if the delays associated with the handset were known, then subtracting the values from the measured round trip delay (RTD) time would give the RTD with sufficient accuracy. If two additional base stations take part in this process then the triangulation method can be used to find the position of the user at the intersection of the circles determined by the time delay measurements. Since this method relies on a time reference, it is highly susceptible to the timing error due to Non-Line-Of-Sight (NLOS) between the base station and the mobile unit.

The unmodified handset TDOA has the relative advantage over TOA in the sense that the TDOA does not require any time reference for determining RTD. The TDOA technique estimates the time difference of arrival of the signal from the source at multiple base stations. Two versions of the received signal at pairs of the base stations are cross-correlated. From the peak of this cross-correlator output, the time difference of the signal arriving at two base stations is determined. This time difference gives rise to a hyperbola between the two receivers. If the base stations and the mobile user are in the same plane, then the mobile lies on a line of the hyperbola. If another base station takes part in this process, another hyperbola is defined, and the intersection of the hyperbolas results in the position estimate of the source. The TDOA method is also referred as the Hyperbolic Position Location method. The advantage of this technique is that all processing takes place at the base station infrastructure level. Advantages of the method include: cost effectiveness, no need for an absolute time reference, capability with inexpensive antennas, and immunity to timing errors [10]. Any timing bias will be cancelled in the time difference operation. As a result, the TDOA methods work better than the TOA methods in the absence of LOS between base stations and the mobile unit [6].

In the hybrid techniques (HT), two or more of the techniques discussed earlier are combined to create a more accurate position location service. When AOA and TDOA are combined to form AOA-TDOA HT, multiple base stations receive signals from the mobile unit and the AOA estimates from each base station; and the TDOA estimates between multiple base stations are combined to determine target location. This type of method results in highly accurate position determination. However care must be taken that error from one method does not affect the overall position estimation. The AOA-TOA HT is most suitable when only one base station is able to receive the signal from the mobile [11]. Although this technique may not be as accurate as the AOA-TDOA HT, it may be the only unmodified handset PL solution possible when only one base station is able to receive the mobile signal [6].

This thesis focuses on the use of data fusion techniques to allow efficient combining of position determination data within hybrid schemes. Note that, data fusion is more than simple averaging of estimates, but takes into account the quality of the various estimates.

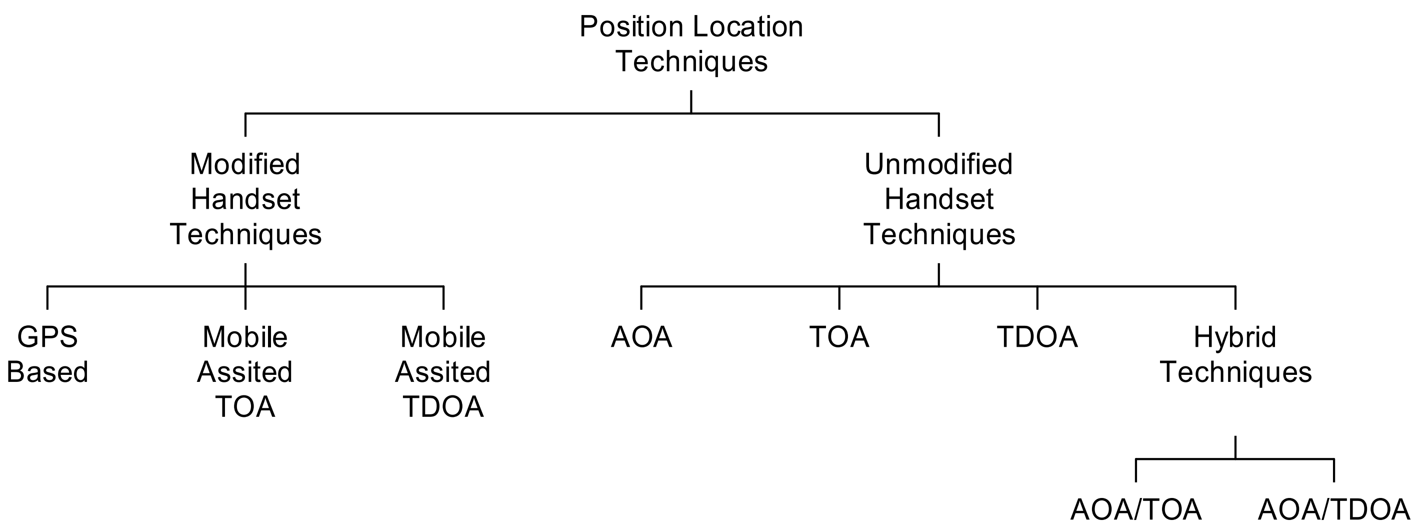

Figure 1.1: Wireless PL techniques

1.3 Research Outline

1.3.1 Purpose of Research

This research has two main objectives. First, we develop a model for the TDOA range measurements and to propose an algorithm that corrects the error of the range measurements in the TDOA method, in the absence of complete LOS between the base station and the mobile unit. Although a timing bias may be cancelled in the TDOA technique, additional timing delay due to NLOS propagation may still result in an erroneous solution. This research identifies a method to make an acceptable correction to the error introduced in the range measurements due to NLOS propagation between the base and the mobile. We propose an algorithm and validate the implementation of this algorithm under simple channel conditions and typical base station topographies. The second objective of this research work is to apply the data model and the correction algorithm to the Data Fusion Architecture for the PL problem proposed by Kleine-

Ostmann and Bell [23], and to validate the decision criterion for choosing the best estimate at level four of the data fusion model by simulation results.

1.3.2 Thesis Outline

This chapter provides an introduction to the position location problem and briefly discusses the different techniques considered to be the possible solution to the problem. Chapter 2 develops the TOA and the TDOA methods with greater mathematical rigor, presenting algorithmic descriptions of the two techniques. Chapter 3 gives an introduction to the Data Fusion Architecture and its application to the position location problem. Chapter 4 describes the different channel models used in the simulation, and Chapter 5 presents various simulation results based on this algorithm. Chapter 6 proposes the algorithm for error correction in TDOA range measurements due to Non-Line-Of-Sight, and presents some simulation results based on this algorithm. Finally, Chapter 7 concludes the thesis by discussing the outcomes and identifying some areas for further investigation and research work.

Chapter 2

Position Determination: Principles and Algorithms

Chapter 1 briefly described several position location (PL) technologies that are possible solutions to the mobile radio PL problems. This thesis will focus on the range-based techniques of TOA and TDOA. Because of the relative advantages of TOA and TDOA methods over other methods, these two techniques are widely used in RF PL system for the geo-location of mobile users. Therefore the basic principle and algorithm of only these two techniques are rigorously described in this chapter.

2.1 Time of Arrival (TOA) Techniques

The Time of Arrival technique exploits triangulation to determine positions of the mobile users. Position estimation by the triangulation is based on knowing the distance from the mobile to at least three base stations in the line of sight (LOS). The base stations determine the time signal takes from the source to the receiver either on the uplink or on the downlink. When 9-1-1 is dialed from a mobile unit, the controlling base station prompts the mobile to respond to a initial signal. The total time elapsed from the instant the command is transmitted to the instant the mobile responds is detected. This time consists of the sum of the round trip signal delay, and any processing and response delay within the mobile unit. When the processing delay is subtracted from the total measured time, total round trip delay is found. Half of the quantity would be the estimate of the signal in one direction. Multiplying this time with the traveling velocity of the electromagnetic waves would give the approximate distance of the mobile from the base station. The approximate distance to the mobile determined by two additional receivers could be used to determine the mobile position at the intersection of circles from multiple TOA measurements, as illustrated in Figure 2.1.

The mobile position can be determined accurately if there exists a complete LOS between the mobile station (MS) and the base stations. However the occurrence of non-line-of-sight (NLOS) propagation causes the signal to take a longer path to the base station receiver and the measured TOA is generally larger than the arrival time of an LOS signal. In such a circumstance, there is a need to detect NLOS and to correct the biased error in the TOA measurements before processing them.

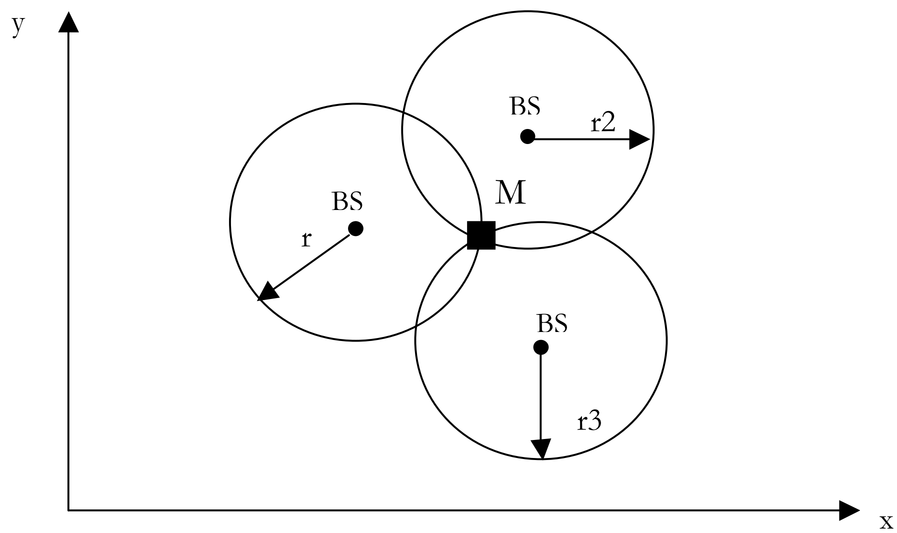

Figure 2.1: Example of TOA Location from Three Base Stations

2.1.1 Mathematical model of TOA measurements

TOA measurements can be interpreted as the range measurements between MS and BS [2]. The range measurements obtained from the arrival times are,

$$r_{TOA} = c\,\Delta t_{TOA}$$

Where,

$$c = Speed\ of\ Electromagnetic\ Wave = Speed\ of\ light = 3\times10^{8}\ m/\mathrm{sec}$$
$$r_{TOA} = Range\ Measurement$$
$$\Delta_{TOA} = Time\ of\ arrival$$

The range measurements can be modeled as,

$$r_{TOA} = r_m(t_i) = L_m(t_i) + n_m(t_i) + NLOS_m(t_i), \qquad (2.1)$$

where,

$$m = \text{BS index} = 1,2....M$$
$$i = \text{Sample time index} = 0,1,2.....(K-1)$$
$$K = \text{Number of measurements at different time } \mathrm{t_i}$$
$$L_m = \text{True distance between MS and BS}$$
$$n_m = \text{Standard measurement error}$$
$$NLOS_m = \text{Error due to Non-line-of-sight}$$

If the BS coordinates are (x_m, y_m) and the unknown coordinates of the mobile station are ($x(t_i)$, $y(t_i)$), then the true distance between the MS and the BS can be represented as,

$$L_m(t_i) = \sqrt{(x(t_i) - x_m)^2 + (y(t_i) - y_m)^2}.$$

If the measured ranges are smoothed by fitting them into a (N-1)th order polynomial, then $r_m(t_i)$ can be modeled as,

$$s_m(t_i) = \sum_{n=0}^{N-1} a_m(n) t_i^{\,n}$$

Where, $a_m(n)$ are the N unknown coefficients of the regression polynomial. These N unknown coefficients can be determined as follows:

$$\begin{bmatrix} a_m(0) \\ a_m(1) \\ \vdots \\ a_m(N-1) \end{bmatrix} = (\nu^T \nu)^{-1} \nu^T \begin{bmatrix} r_m(t_0) \\ r_m(t_1) \\ \vdots \\ r_m(t_{K-1}) \end{bmatrix},$$

where,

$$v = \text{Coefficient Matrix} = \begin{bmatrix} t_0^0 & t_0^1 & t_0^2 \cdots\cdots t_0^{N-1} \\ \vdots & \vdots & \vdots \cdots\cdots \vdots \\ t_{K-1}^0 & t_{K-1}^1 & t_{K-1}^2 \cdots\cdots t_{K-1}^{N-1} \end{bmatrix}.$$

It should be noted here that the standard error is assumed to have zero mean Gaussian distribution with variance σ_m^2. Moreover, it is considered that $n_m(t_i)$ has bounded region. That is,

$$n_m(t_i) \approx N(0, \sigma_m^2), \qquad \text{where} \;\; -\alpha_m \le n_m(t_i) \le \alpha_m$$

2.1.2 Correction of TOA Measurements in NLOS

As stated earlier, the NLOS term is considered to be an additional error, normally distributed with mean μ and variance $\sigma_{NLOS,m}^2$ [2]. The BS can detect the NLOS case by comparing the variance (or standard deviation) of the measured ranges with the variance (or standard deviation) of the measurement noise (standard measurement error). If the measured ranges have higher standard deviation than the standard deviation of the measurement noise, then the measured ranges are the data for the NLOS case. Wylie and Holtzman have suggested an error correction method for TOA measurements in NLOS situations [2]. The algorithm can be summarized as follows [5]:

1. Detect NLOS for a BS
2. Calculate D = maximum($s_m(t_i)$-$r_m(t_i)$) for the NLOS BS
3. Displace smoothed curve $\hat{s}_m(t_i) = s_m(t_i) - D + \alpha_m$ for the NLOS BS
4. No correction required for the LOS BS, that is $\hat{s}_m(t_i) = s_m(t_i)$

2.1.3 TOA Procedure for E-911

This TOA method can be used to provide E-911 service within a cellular network. A summary to steps required for E-911 requests follows:

1. Mobile user requests E-911 service
2. At certain time BS requests MS to respond to a beckoning signal
3. Acknowledgement of MS is received at the BS at a given time

4. From the time difference BS measures the ranges of MS over different time instance t_i
5. The measured ranges $r_m(t_i)$ are smoothed by fitting them into a $(N-1)^{th}$ order polynomial.
6. The standard deviation of $s_m(t_i)$ is calculated by BS and compared to the standard deviation of the standard measurement error to detect an NLOS case.
7. If an NLOS is detected, $s_m(t_i)$ is adjusted to compensate for error due to an NLOS.
8. Corrected values of $s_m(t_i)$ designated as $\hat{s}_m(t_i)$ are fed into the input of TOA estimator for position determination of mobile user.

2.1.4 Taylor Series Method used for TOA PL System

If multiple TOA measurements are available, the TOA position estimate may be over determined. In this case, the best estimate based on all available data may be determined by a Taylor series estimate. The optimum least square position estimate $(\hat{x}, \hat{y})$ is obtained by minimizing

$$F_i = \sum_{m=1}^{M} (\hat{s}_m(t_i) - \hat{L}_m(t_i))^2 , \tag{2.2}$$

where,

$$\hat{L}_m(t_i) = \sqrt{(\hat{x} - x_m)^2 + (\hat{y} - y_m)^2},$$
$$(x_m, y_m) = \text{Position of the m}^{\text{th}} \text{ BS.}$$

The non-linear equation that has to be linearized for each base station is given by:

$$f(\hat{x}, \hat{y}, x_m, y_m) = \hat{L}_m(t_i) = \hat{s}_m(t_i) - e_m(t_i).$$

The objective is to find a solution so that the error is minimized in mean-square sense.

Let

$$(x_v, y_v) = \text{ Exact equilibrium points,}$$
$$(\delta_x, \delta_y) = \text{Displacements near the equilibrium points,}$$
$$\hat{x} = x_v + \delta_x = x \text{ coordinate position estimate of the mobile user,}$$
$$\hat{y} = y_v + \delta_y = y \text{ coordinate position estimate of the mobile user.}$$

Now, ignoring the 2nd and higher order terms in Taylor series expansion, the equation becomes:

$$f_o + a_{m1}\delta_x + a_{m2}\delta_y = \hat{s}_m - e_m,$$

where,

$$f_o = f(x_v, y_v, x_m, y_m) = \sqrt{(x_v - x_m)^2 + (y_v - y_m)^2},$$

$$a_{m1} = \frac{\partial f}{\partial \hat{x}}\Big|_{x_v, y_v} = \frac{x_v - x_m}{\sqrt{(x_v - x_m)^2 + (y_v - y_m)^2}} = Taylor\ Coefficient,$$

$$a_{m2} = \frac{\partial f}{\partial \hat{y}}\Big|_{x_v, y_v} = \frac{y_v - y_m}{\sqrt{(x_v - x_m)^2 + (y_v - y_m)^2}} = Taylor\ Coefficient.$$

The linearized system of equations can be written in vector form as:

$$\mathbf{A\delta} = \mathbf{z} - \mathbf{e}\ ,$$

where,

$$\mathbf{z} = \hat{s}_m - f_o,$$

$$\boldsymbol{\delta} = [\delta_x \quad \delta_y]^T,$$

$$\mathbf{A} = \lfloor a_{m1} \quad a_{m2} \rfloor \quad \text{where, } m = 1,2\ldots\text{M} = \text{Number of BS}$$

The least-square error solution is obtain by,

$$\boldsymbol{\delta} = \left[A^T A\right]^{-1} A^T z\,.$$

Calculation starts with an initial guess for the equilibrium point (x_v, y_v), and update this value until the magnitude of $\boldsymbol{\delta}$ below a given threshold value [7].

2.2 Time Difference of Arrival (TDOA) PL Technique

Next we examine the TDOA or hyperbolic PL technique. Two distinct stages are involved in the hyperbolic position estimation technique. In the first stage, time delay estimation is used to find the time difference of arrival (TDOA) of acknowledgement signals from MS to BS's are determined. This TDOA estimate is used to calculate the range difference measurements between the base stations. In the second stage, an efficient algorithm is used to determine the position location estimation by solving the nonlinear hyperbolic equations resulting from the first stage.

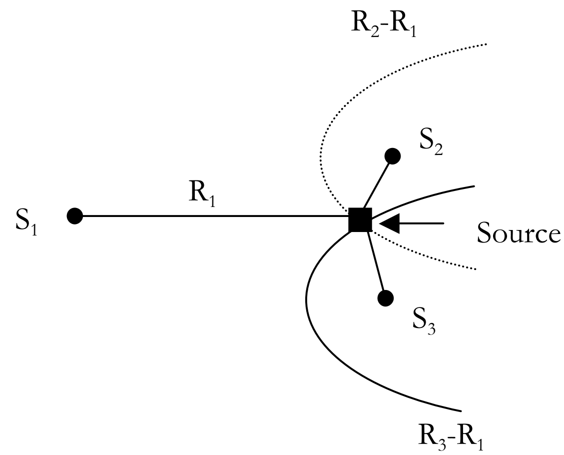

Figure 2.2: Hyperbolic Position Location Solution

TDOA can be estimated by two methods:

1. Subtracting the TOA measurements from the two BS's
2. Correlating two versions of the acknowledgement signal at the two BS's

The second method, commonly known as Generalized Cross-Correlation (GCC) method [12], is more robust and will be considered for this thesis.

Figure 2.3 shows block diagram for determining the TDOA estimate by the GCC technique.

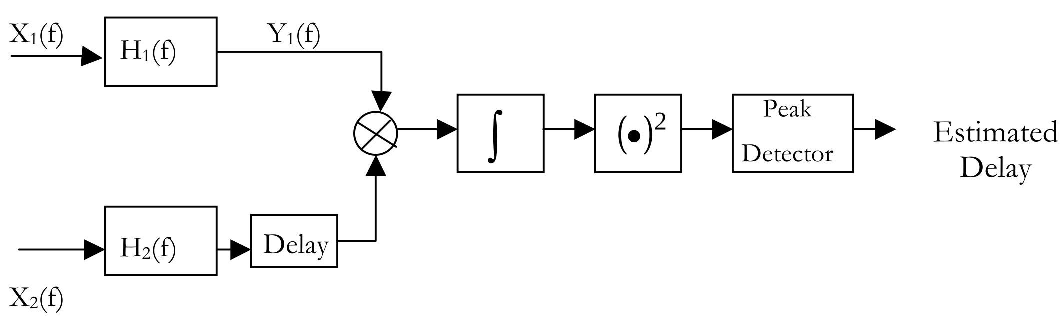

Figure 2.3: Delay estimation by GCC method

2.2.1 Mathematical Model for Hyperbolic Position Location

Let (x, y) be the source location and (X_i,Y_i) be the known location of i^{th} BS, where I = 2,3….M. M is the total number of BS taking part in position location. Moreover, assume that BS#1 is the controlling BS. The range difference between source and the i^{th} BS is

$$\begin{aligned} R_i &= \sqrt{(X_i - x)^2 + (Y_i - y)^2} \\ &= \sqrt{X_i^2 + x^2 - 2X_i x + Y_i^2 + y^2 - 2Y_i y} \\ &= \sqrt{X_i^2 + Y_i^2 - 2X_i x - 2Y_i y + x^2 + y^2}. \end{aligned}$$

Now, the range difference between base stations with respect to BS#1 is given by

$$\begin{aligned} R_{i,1} &= cd_{i,1} = R_i - R_1 \\ &= \sqrt{(X_i - x)^2 + (Y_i - y)^2} - \sqrt{(X_1 - x)^2 + (Y_i - y)^2}, \end{aligned} \tag{2.3}$$

where,

$c =$ Velocity of Electromagnetic wave $= 3\times10^8\, m/\text{sec}$

$d_{i,1} =$ TDOA between i^{th} BS and BS#1.

We know that

$$\begin{aligned} & R_{i,1} = R_i - R_1 \\ & \Rightarrow R_i = R_{i,1} + R_1 \\ & \Rightarrow R_i^2 = (R_{i,1} + R_1)^2 \\ & \Rightarrow R_{i,1}^2 + 2R_{i,1}R_1 + R_1^2 = X_i^2 + Y_i^2 - 2X_i x - 2Y_i y + x^2 + y^2 \\ & \Rightarrow R_{i,1}^2 + 2R_{i,1}R_1 = X_i^2 + Y_i^2 - 2X_i x - 2Y_i y + x^2 + y^2 - R_1^2 \\ & \Rightarrow R_{i,1}^2 + 2R_{i,1}R_1 \\ & = X_i^2 + Y_i^2 - 2X_i x - 2Y_i y + x^2 + y^2 - X_1^2 + Y_1^2 - 2X_1 x - 2Y_1 y + x^2 + y^2 \\ & \Rightarrow R_{i,1}^2 + 2R_{i,1}R_1 = X_i^2 + Y_i^2 - 2X_{i,1} x - 2Y_{i,1} y + x^2 + y^2 \quad \begin{bmatrix} (X_1, Y_1) = (0,0) \\ X_{i,1} = X_i - X_1 \\ Y_{i,1} = Y_i - Y_1 \end{bmatrix}. \end{aligned} \tag{2.4}$$

The above equation is linear with the source location (x,y) and the range of the mobile from the controlling base station R_1 as the unknown. If x and y can be expressed in terms of R_1 then the solution for R_1 can be obtained from the equation

$$R_1^2 = x^2 + y^2 \qquad [\text{since, } (X_1, Y_1) = (0,0)] \tag{2.5}$$

Knowing R_1, we can estimate the position location of the mobile.

2.2.2 Application of TDOA to the Cellular E-911 Problem

Within a cellular system, the above TDOA technique could be used to provide E-911 service through the following steps:

1. The mobile user requests E-911 service
2. The controlling base station detects the user and at least two additional base stations take part in the process.
3. Each base station takes a snapshot of the received signal at a synchronized time period.
4. The TDOA of signals is determined by cross-correlating two versions of the signals at pairs of base stations.
5. The peak of the cross-correlation output gives the estimation of the TDOA for the signal arriving at those two base stations.
6. The estimated TDOAs are transformed into range difference measurements between the base stations by using equation 2.2.
7. The transformation results in a set of hyperbolic equations (equation 2.3).
8. At least for I = 2,3, equation 2.3 can be used to express x and y in terms of R_1.
9. Equation 2.4 is used to find solution of R_1.

2.2.3 Mathematical Procedure for Taylor-Series Method

The Taylor series method can be employed to solve the TDOA hyperbolic equations. The Taylor-Series method is almost the same as the technique explained earlier for the TOA method. With a set of TDOA estimate, the method starts with an initial guess (x_o, y_o) and computes the deviation of the position location estimation

$$\begin{bmatrix} \Delta x \\ \Delta y \end{bmatrix} = (G_t^T Q^{-1} G_t)^{-1} G_t^T Q^{-1} h_t .$$

where,

$$h_t = \begin{bmatrix} R_{2,1} - (R_2 - R_1) \\ R_{3,1} - (R_3 - R_1) \\ \vdots \\ R_{M,1} - (R_M - R_1) \end{bmatrix},$$

and,

$$G_t = \begin{bmatrix} \frac{X_1 - x}{R_1} - \frac{X_2 - x}{R_2} & \frac{Y_1 - x}{R_1} - \frac{Y_2 - x}{R_2} \\ \frac{X_1 - x}{R_1} - \frac{X_3 - x}{R_3} & \frac{Y_1 - x}{R_1} - \frac{Y_3 - x}{R_3} \\ \vdots & \\ \vdots & \\ \frac{X_1 - x}{R_1} - \frac{X_M - x}{R_M} & \frac{Y_1 - x}{R_1} - \frac{Y_M - x}{R_M} \end{bmatrix}.$$

Q is the covariance matrix of the estimated TDOAs. Iteration starts with an initial value of $x = x_o$ and $y = y_o$. In the next iteration, x_o is updated to $x_o+\Delta x$, and y_o is updated to $y_o+\Delta y$. Iteration continues until deviation of x and y becomes negligibly small. Although the Taylor-Series method gives accurate results, it might not converge if the initial guess of x and y are not close to the exact value of x and y. For this reason, another method, commonly known as Chan's Method [8], is considered to be more appropriate for the TDOA PL system. The solution in Chan's method is in closed-form and is valid for both close and remote sources. However, both the Taylor Series Method and Chan's Method are useful when there is redundant information available for the PL solution. Since the Taylor Series Method linearizes equations by eliminating second and higher order terms, this might lead to significant error to the solution [13]. Chan's Method with three base station configuration is free from this problem. In order to understand the concept of Chan's Method, a mathematical model for Hyperbolic TDOA equations with three base station configuration is shown in the following section.

2.2.4 Mathematical Model for TDOA Equations in Chan's Method

For a three base station system, Chan's method producing two TDOAs to render solution for x and y in terms of R_1 is of the form

$$\begin{bmatrix} x \\ y \end{bmatrix} = -\begin{bmatrix} X_{2,1} & Y_{2,1} \\ X_{3,1} & Y_{3,1} \end{bmatrix}^{-1} \times \left\{ \begin{bmatrix} R_{2,1} \\ R_{3,1} \end{bmatrix} R_1 + \frac{1}{2} \begin{bmatrix} R_{2,1}^2 - K_2 + K_1 \\ R_{3,1}^2 - K_3 + K_1 \end{bmatrix} \right\},$$

where,

$K_1 = X_1^2 + Y_1^2,$

$K_2 = X_2^2 + Y_2^2,$

$K_3 = X_3^2 + Y_3^2,$

$R_{2,1} = cd_{2,1},$

$R_{3,1} = cd_{3,1}.$

In the above equation on the right side, all the quantities are known quantities except R_1. Therefore solution of x and y will be in terms of R_1. When these values of x and y are substituted into the equation, $R_1^2 = x^2 + y^2$, a quadratic equation in terms of R_1 is produced. Once the roots of R_1 are known, values of x and y can be determined. It should be noted that only the positive root of R_1 must be considered. One of the roots of the quadratic equation is either negative or too large to be within the cell radius.

2.3 Measure of PL Estimator Performance

Position estimator performance can be measured by several parameters, namely:

- Circular Error Probability (CEP)
- Geometric Dilution of Precision (GDOP)
- Mean Square Error (MSE)
- Cramer-Rao Lower Bound (CRLB)

CEP is based on the variances of the position estimate in the x direction and y direction. This gives an overall measure of the position estimator accuracy. GDOP is a measure of the estimator's performance depending on the actual position of the mobile relative to the base stations. Every position estimator performance can be evaluated by comparing estimator's MSE to the Cramer-Rao

Lower Bound (CRLB). CRLB is the theoretical limit for the variance of the estimator's output. We briefly consider the definition and value of each of these performance measures.

2.3.1 Circular Error Probability (CEP)

If an estimator is unbiased, CEP describes the scattering of the position estimate around the true position of the MS. CEP is defined as the radius of a circle around the estimator's position bias that contains half of the generated estimates [5], as illustrated in figure 2.4.

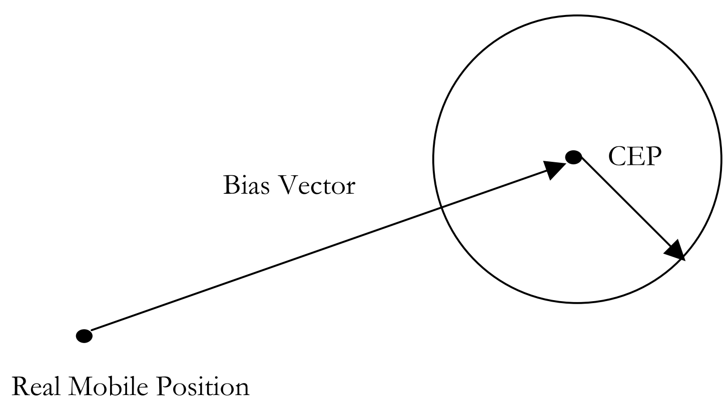

Figure 2.4: Circle of Error Probability

CEP, within an accuracy of 10%, is given by [3] as:

$$CEP \cong 0.75\sqrt{\sigma_x^2 + \sigma_y^2},$$

where,

$$\sigma_x^2 = \text{Variance of position estimate } \hat{x}$$
$$\sigma_y^2 = \text{Variance of position estimate } \hat{y}$$

2.3.2 Geometric Dilution of Precision (GDOP)

GDOP is the standard deviation of the range measurements [6]. Mathematically, it is defined as the ratio of the RMS position error to the RMS ranging error, that is:

$$GDOP = \frac{\sqrt{\sigma_x^2 + \sigma_y^2}}{\sigma_s}$$
$$\cong \frac{CEP}{0.75\sigma_s}.$$

From the above equation, it is evident that the GDOP is directly proportional to CEP, which means that if the scattering of the position estimate around the true position of the MS is small the estimator's output variance will be small as well. The smaller the Root Mean Square (RMS) position estimate error, the better the performance of the estimator.

2.3.3 Mean Square Error (MSE)

MSE is the square of the distance between a true mobile-position and an estimated mobile-position. Mathematically it is defined as,

$$MSE = (x - \hat{x})^2 + (y - \hat{y})^2,$$
$$RMS = \sqrt{MSE},$$

where, x and y are the mobile's real position. For most of the results in chapter 5 and 6, we will use RMS error as the performance measure of interest.

2.3.4 Cramer-Rao Lower Bound

In order to measure the accuracy of the position estimate, RMS position error of the estimator can be compared to the theoretical limit for unbiased estimators. Chan [8] derived the CRLB as,

$$\Phi = c^2 (G_t Q^{-1} G_t)^{-1},$$

where,

G_t = Taylor coefficients matrix evaluated at an initial guess (x_o, y_o),

Q = Covariance matrix of the smoothed and corrected range measurements that serve as estimator input data,

c = Velocity of electro-magnetic wave in free space.

The theoretical limit for the RMS position error of the estimator is given by,

$$RMS_{Limit} = \sqrt{trace(\Phi)}\ .$$

2.4 Chapter Summary

In this chapter we have presented a discussion of range-based measurement techniques. The TOA and TDOA techniques that will be used in the remainder of this thesis have been rigorously defined. The chapter has also presented a discussion of performance measures for TOA and TDOA techniques.

Chapter 3

Data Fusion

Data fusion means to combine the data obtained from different sensors, and relate information by accessing relevant databases, to achieve better accuracies and more specific inferences than could be found by the use of a single sensor alone [14]. The advent of sophisticated sensors, advanced processing techniques, and fast processing hardware are making implementation of data fusion practically a feasible option.

It is intuitive that when a same-source data is gathered by using multiple independent sensors, this data should result in a statistical gain over a single source data. In data fusion architecture, decision or inferences are made at different hierarchical levels. Identifying characteristics of an entity and its location are the basis of the decision or inference process. Therefore, hierarchical transformation between observed data and a corresponding decision or inference is the basic characteristic of data fusion technology.

Data fusion is widely used both in military application and civilian application. Position and velocity determination for a moving object from noisy time-series measurements is a classical statistical estimation problem [15], [16], [17]. Classic detection and estimation methods are typically used for raw data fusion techniques.

In the recent years data fusion technology has rapidly advanced from a loose collection of related techniques to an emerging engineering discipline with standard terminology [14]. Lack of unifying terminology impeded the technology transfer from one group to another in this field. In order to improve communications among military and civilian researchers and system developers, the Joint Director of Laboratories (JDL) established a data-fusion working group that devised generic data fusion architecture in 1972 [5].

3.1 JDL Data Fusion Architecture

The JDL data fusion architecture is a conceptual model. It identifies and categorizes the process, functions, and techniques applicable to data fusion. When developed, the JDL process model was intended to be very general and useful for multiple applications in different areas. For this reason it is considered to be functionally oriented model of data fusion. Figure 3.1 shows the top level of the JDL data fusion process model [14].

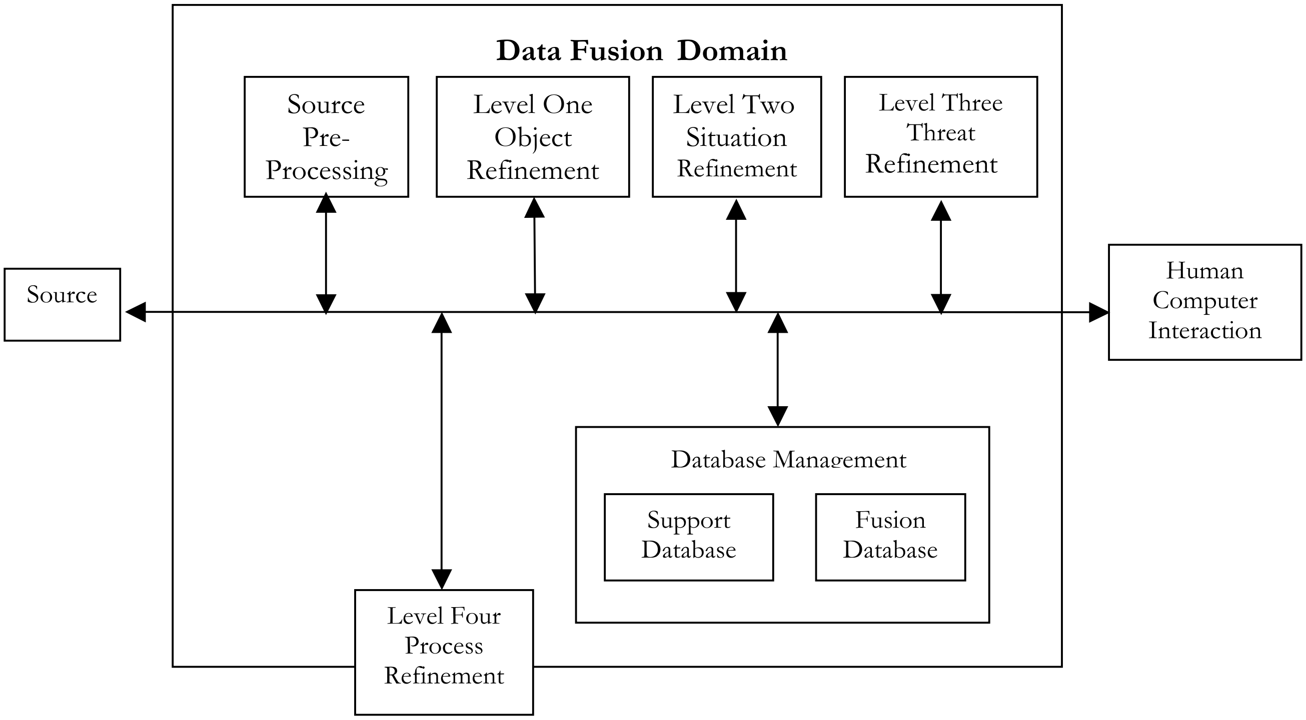

Figure 3.1: Top Level of the JDL Data Fusion Process Model

The model is conceptualized by the sources of information, human – computer interaction (HCI), source processing, Level-1 processing, Level-2 processing, Level-3 processing, and Level-4 processing. The separation of processes into different levels is an artificial partition. Real data fusion systems are implemented by integrating an interleaving the functions into an overall process.

Sources of Information, shown on the left side of figure 3.1, provide information at a variety of levels. Information may be a sensor data or *a priori* information from databases. Sensors may be local sensors associated with a data fusion system or distributed sensors linked electronically to a fusion system. A priori information may be reference information, geographical information or any other relevant information.

The data fusion process must work with the data that is most pertinent to the existing condition and at the same time reduce the processing load. This function is performed in the Source Pre-Processing block. A special case of source pro-processing is the synthesis of multiple component sensory array data to estimate the location and the velocity of a target [14]. In order to successfully accomplish this, all the data must be prescreened and allocated to an appropriate process.

Level-1 operates on raw data and performs multiple functions. It first transforms data to a consistent set of units and coordinates, then estimates the object's attribute, and refines prediction based on statistical estimation. In short, level-1 processing is responsible for combining locational, parametric and identity information to achieve refined representations of individual objects [14].

Level-2 does situation refinement focusing on relational information so as to determine the meaning of a number of separately collected entities. This level attempts to improve a description of current relationships among objects and events in the context of their environment [5].

Level-3 uses Fast-Time Engagement Models to aggregate estimation so as to predict the projection of current situation in future based on multi perspective assessment. If necessary, level-3 deduces alternative hypothesis from input data of the process.

Level-4 acts as a watchdog to other processes. It is also termed as *meta-process*, meaning that the process is concerned about other processes. It monitors the data fusion performance and identifying information to improve multi-level data fusion output.

Data base management acts as the heart of the JDL DF model. It performs data retrieval and storage, archiving, queries, and data protection so that it can support the entire process at all the levels.

HCI incorporates multimedia methods for human interaction. Communication of fusion system results may be through different types of media, like display via monitors, notification by alert or printing in text using printers.

The JDL DF model is helpful for common understanding, but does not help in developing architecture for real system [18]. Hall [14] proposed a hybrid approach that combines level one and level two fusion based on the JDL model.

3.2 Data Fusion Model for Position Location Estimation

Section 3.1 discussed the general JDL DF model, which is helpful in understanding the basic concept of DF process. Since the JDL DF model is a functionally oriented model, therefore to make this model applicable to position location problem, Kleine-Ostmann and Bell [23] have proposed an architecture using first, second, and fourth level fusion. Figure 3.2 shows the model proposed by Kleine-Ostmann and Bell.

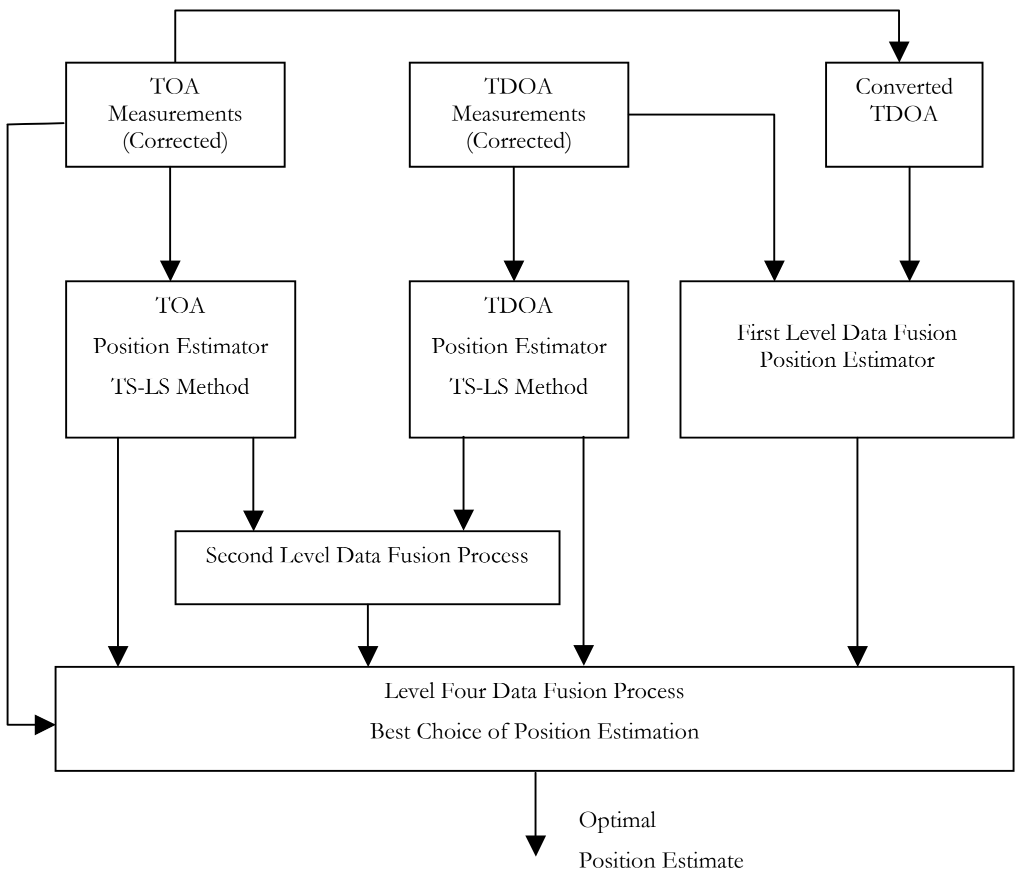

Figure 3.2: Proposed Data Fusion Model for Position Estimation

The main objective behind this technique is to fuse both TOA and TDOA data, obtained independently, in order to have an estimate better than either of the individual estimates. It should be noted that, in the proposed architecture, fusion is done with raw TOA/TDOA data as well as final position estimation generated by two different methods. It is important to mention that two different methods have two different error biases and variances. Therefore, care should be taken to weight TOA and TDOA measurement according to their quality, at least in terms of their variances.

The proposed structure estimates position of the E-911 mobile user by four different approaches before making a final choice. First estimation is done only from TOA measurements using the algorithm described in Section 2.1. Then estimation is made only from TDOA measurements using the algorithm described in the Section 2.2. Combining the raw TOA and TDOA data makes estimation from the first level data fusion. According to the data fusion standard, only a similar kind of data can be fused. Therefore, the TOA data must be converted to the corresponding TDOA data before fusing at the first level. This is accomplished by simply subtracting one set of TOA measurements from another set. The fourth position estimation is done at second level hierarchy. At this level Bayesian Inference is used to produce new improved estimate while combining the two position estimates form the TOA estimator and TDOA estimator. All these four estimates are then fed into level-4 processor, which decides which one of the four position estimates offers the best accuracy.

3.2.1 First Level Data Fusion

At the first level data fusion process, independent TOA measurements are converted to the corresponding TDOA measurements. These converted measurements are then combined with the independent TDOA measurements. Since the system we are considering generate an over-determined system of equations, therefore weighted least-square (WLS) estimator is employed to minimize the sum of the weighted squares of the errors. This kind of estimator is implemented for independent TDOA estimator described in the Chapter 2. The only difference is that the matrix G_t is augmented with additional rows for TDOA measurements resulting from independent TOA measurements. Now the new solution is obtained from more measurements.

3.2.2 Second Level Data Fusion

The second level data fusion utilizes the Bayesian Inference to improve an estimate with known statistics once new data is available [26]. If x_o and σ^2_o are the mean and variance respectively of the TOA estimator output, and x_m and σ^2_m are the mean and variance respectively of the TDOA estimator output, then x_c would be the mean and σ^2_c would be the variance of a single estimate using the Bayesian Inference. The probability distribution of the old estimate is updated depending on the probability distribution of new data and the amount of data available. Figure 3.3 shows the principle of the Bayesian Inference. In Figure 3.3 the center of mass x_c serves as an improved estimate over x_o and x_m, and the variance of new distribution indicates the weight of reliability of the improved estimate.

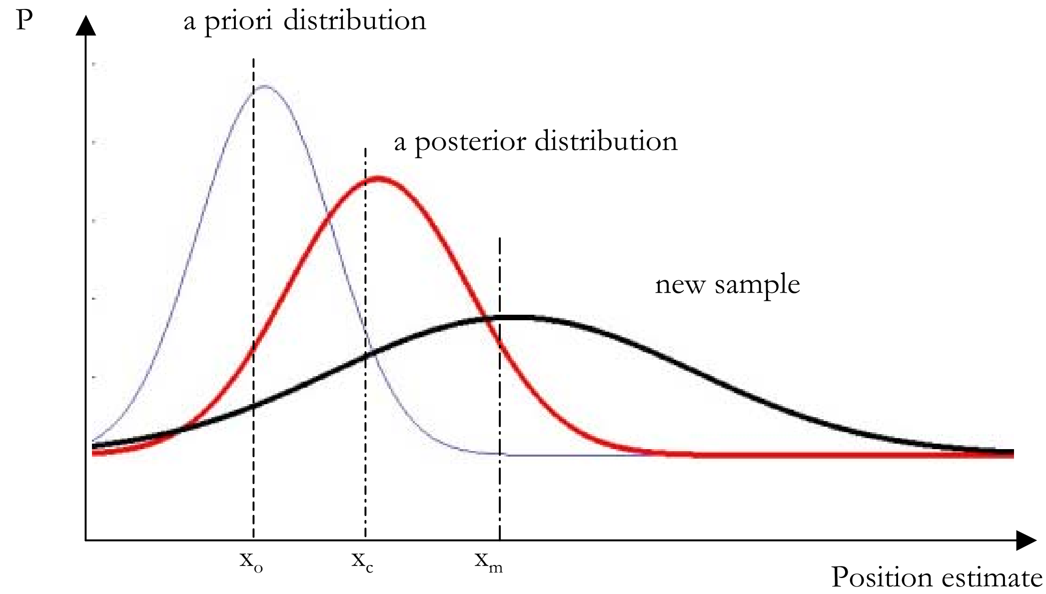

Figure 3.3: Bayesian Inference

Since both TOA and TDOA measurements are assumed to have Gaussian distribution [19], the center of mass of new distribution or, in other words, the fused position estimate becomes,

$$x_c = \frac{\frac{x_o}{\sigma_o^2} + \frac{x_m}{\sigma_m^2}}{\frac{1}{\sigma_o^2} + \frac{1}{\sigma_m^2}} = x_o + \frac{\sigma_o^2}{\sigma_o^2 + \sigma_m^2}\left(x_m - x_o\right)$$

the variance σ^2_c is given by,

$$\sigma_c^2 = \frac{1}{\frac{1}{\sigma_o^2} + \frac{1}{\sigma_m^2}}$$

Simulation results using this proposed architecture is presented in the following chapter.

3.2.3 Level Four Data Fusion: The final choice

Level four is the process where decision is made, which one of the all estimates represents the best choice. Solely evaluating the variance of each estimator output makes this decision. The second level estimate is expected to show reduced variance and hence be more reliable. Although the TDOA estimator has an inherent characteristic to be more tolerant to error bias introduced due to NLOS between BS and MS, it performs poorly when MS is very close to the BS.

3.3 Chapter Summary

In this chapter we have summarized the basic concepts of data fusion that will be used in chapters 5 and 6 of this thesis to combine TOA and TDOA estimates of mobile position within an E-911 system. This chapter outlined the different levels of data fusion that are available for combining data from disparate sources.

Chapter 4

The Channel Models

The effects of the mobile radio channel dominate the performance of a wireless communication system. The path along which a signal travels between a transmitter and a receiver could be either a simple line-of-sight one or a highly obstructed one. High rise buildings, mountains, or vegetation causes this obstruction along the path. Therefore, modeling the radio channel has been one of the most challenging parts of mobile radio system design. Often this modeling follows a statistical approach [20]. This chapter develops the channel models employed in chapters 5 and 6 to evaluate data fusion techniques for combining TOA and TDOA position estimates. The effects considered in this model include the path loss, result of AWGN and multi-path channels, as well as generation of received signals at the base stations.

Received Signal Models

4.1.1 TOA Received Signal Model

The range measurements between the base station and the mobile unit are linearly proportional to the TOA measurements. Although electromagnetic waves pass through different kind of medium while traveling along the path from a transmitter to a receiver, their speed can be considered constant, as the obstructed path length is much smaller than the traveling path in the air. Figure 4.1 illustrates this concept. When there is a complete LOS between the base station and the mobile unit, only the standard measurement noise affects the true range measurements. This standard measurement noise is assumed to have a distribution, which is similar to Gaussian distribution but with fine support region. However, in our simulation we have simulated the standard noise by a zero mean Gaussian random variable. Figure 4.2 shows the probability distribution function of standard measurement noise. In case when there is NLOS between the base station and the mobile unit, the measured ranges would be biased and the variance would be higher than the one obtained in LOS case. This appears to be an additional noise in the measured ranges. The empirical measurements have shown that NLOS error has a distribution like the one shown in Figure 4.3, which appears to be a single sided Gaussian distribution with bounded region. Therefore, the range measurements of TOA PL system is modeled as in equation 2.1:

$$r_{TOA} = r_m(t_i) = L_m(t_i) + n_m(t_i) + NLOS_m(t_i),$$

where,

$m = \text{BS index} = 1,2....\text{M},$

$i = \text{Sample time index} = 0,1,2.....(K-1),$

$K = \text{Number of measurements at different time } \mathrm{t_i},$

$L_m = \text{True distance between MS and BS},$

$n_m = \text{Standard measurement error} \approx \mathrm{N}(0, \sigma_\mathrm{m}) \qquad -\alpha_m \leq n_m(t_i) \leq \alpha_m,$

$NLOS_m = \text{Error due to Non-line-of-sight},$

$\approx \mathrm{N}(\mu, \sigma_{\mathrm{NLOS}}) \qquad 0 \leq \mathrm{NLOS_m}(t_i) \leq \beta_m$

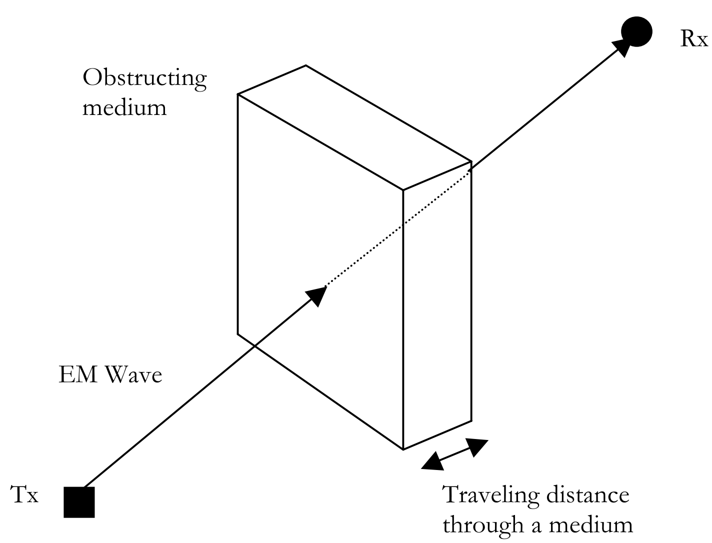

Figure 4.1: Propagation of EM Waves through different Medium

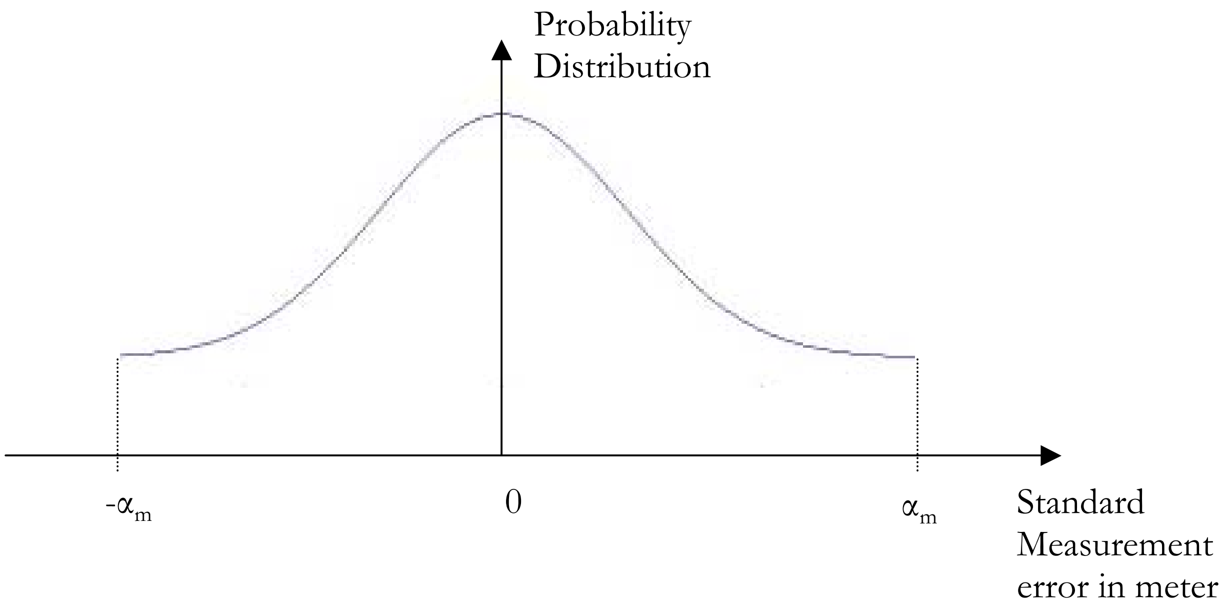

Figure 4.2: Probability Distribution of Standard Measurement Error

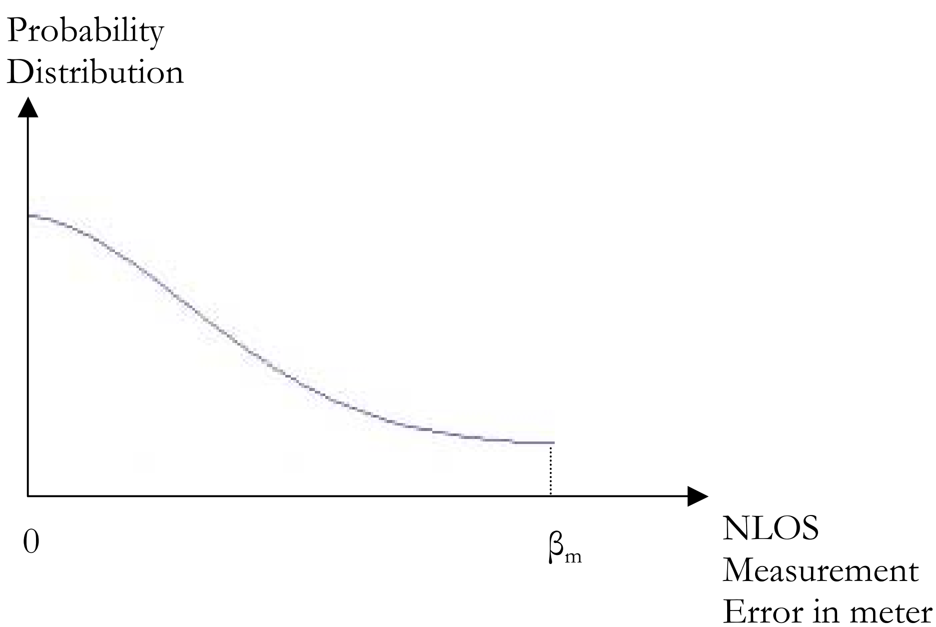

Figure 4.3: Probability Distribution of NLOS Measurement Error

4.1.2 TDOA Received Signal Model

The received signals at the base stations are the delayed versions of the transmitted signal from the mobile unit with noise superimposed on the signals. Assuming a four base station configuration, with base station #1 as the controlling base station, then for the propagation delays d_1, d_2, d_3, and d_4 at base stations 1, 2, 3 and 4 respectively, the relative delays with respect to the controlling base station are given by,

$$\begin{aligned} d_{21} &= d_2 - d_1, \\ d_{31} &= d_3 - d_1, \\ d_{41} &= d_4 - d_1. \end{aligned}$$

Each base station generates a particular sequence of BPSK signal, which is sampled and shifted accordingly to the relative delays. Delays are determined based on the distance of the mobile from each of the participating base stations. The signal passed through the Additive White Gaussian Noise (AWGN) channel, where noise power is scaled according to the Signal-to-Noise Ratio (SNR) of the received signal.

The general model for the received signals at different base stations are given by,

$$\begin{aligned} r_1(t) &= A_1 s_1(t - d_1) + n_1(t), \\ r_2(t) &= A_2 s_1(t - d_2) + n_2(t), \\ r_3(t) &= A_3 s_1(t - d_3) + n_3(t), \\ r_4(t) &= A_4 s_1(t - d_4) + n_4(t), \end{aligned} \tag{4.1}$$

where A_i [i = 1, 2, 3, 4] is the amplitude scaling of the signal and $n_i(t)$ [i = 1, 2, 3, 4] is the noise and the interfering signals. Since BS#1 is the controlling base station, therefore $d_1 < d_i$ [i = 2, 3, 4]. If the delay time and the scaling amplitudes are referred to the controlling base station, then the received signals at the neighboring base stations would be time shifted versions of the received signal at the controlling BS#1. The models of equation 4.1 can be rewritten as:

$$
\begin{aligned}
r_1(t) &= s_1(t) + n_1(t), \\
r_2(t) &= s_1(t - d_{21}) + n_2(t), \\
r_3(t) &= s_1(t - d_{31}) + n_3(t), \\
r_4(t) &= s_1(t - d_{41}) + n_4(t).
\end{aligned}
\tag{4.2}
$$

Since a log-distance path loss model is used, therefore each received signal power levels are adjusted depending on the channel path loss exponent and distance from the mobile unit to the base station. The TDOA estimator then processes the received signals where the hyperbolic location algorithm is used to provide an estimate of the mobile's position location. Figure 4.4 [21] shows the block diagram of the simulator used for generating TDOA signals and determining position estimate of the mobile unit.

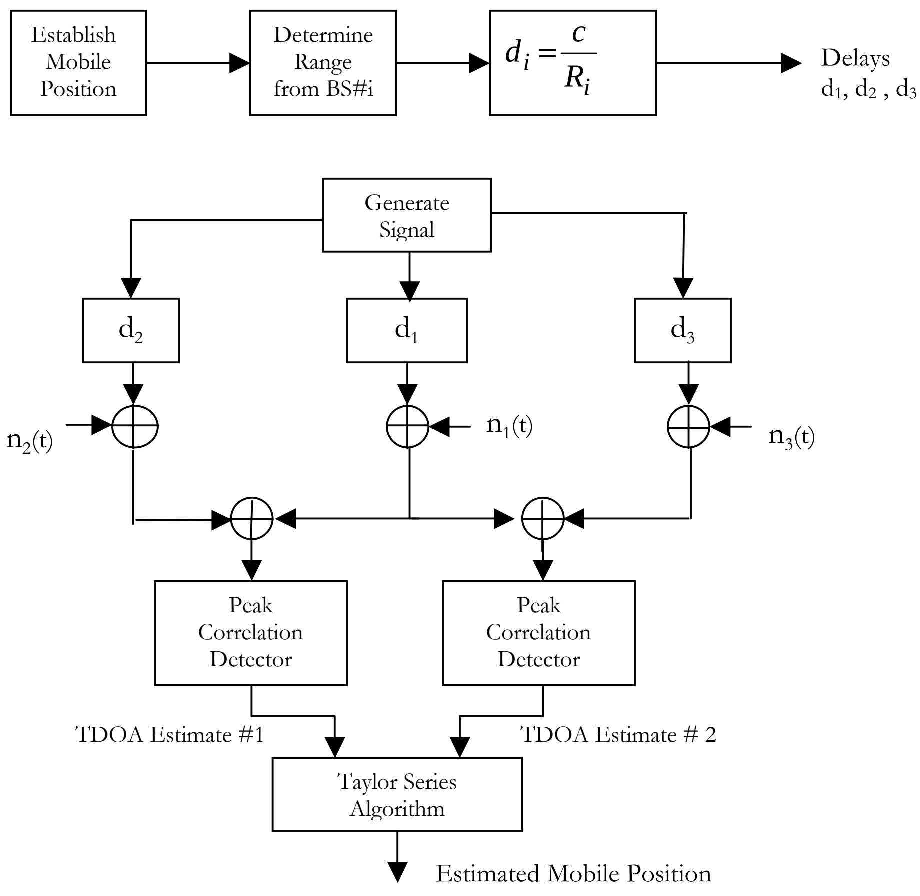

Figure 4.4: Block Diagram of TDOA Simulator

4.2 Path Loss Model

The log-distance path loss model has been developed based on theoretical analysis as well as practical measurements. The model indicates the average received signal power that decreases logarithmically with distance. If d_0 is the close-in reference distance and n is the path loss exponent, then the average large-scale path loss for an arbitrary transmitter-receiver separation distance d is given by:

$$PL(dB) = PL(d_0) + 10\,n \log\left(\frac{d}{d_0}\right) \quad [20]. \tag{4.3}$$

In order to avoid near-field effects, the close-in reference distance must be chosen in such a way that it lie in the *Fraunhofer region*. The near-field effects otherwise may alter the reference path loss. The dimension of the transmitting antenna and the operating frequency defines the far-field distance. The far-field distance is given by

$$d_f = \frac{2D^2}{\lambda}, \tag{4.4}$$

where, D is the maximum dimension of the transmitting antenna and λ is the wavelength at the operating frequency. With PCS carrier frequency of 1900 MHz, and half-wave dipole antenna, the Fraunhofer distance is 0.08 meter. For our simulation, 100 meter is the close-in reference distance for macro-cellular environment. If P_tG_t is the EIRP of mobile unit transmitter, then the power at a distance d_0 is given by

$$P_r(d_0)\ \text{dBm} = P_t + G_t + G_r - 20\log\left(\frac{4\pi d_0}{\lambda}\right), \tag{4.5}$$

where, G_r is the receiving antenna gain and λ is the wavelength at the operating frequency. The signal power received in a base station, located at a distance d from the mobile unit is given by,

$$P_r(d)\ \text{dBm} = P_r(d_0)\ \text{dBm} - 10n\log\left(\frac{d}{d_0}\right).$$

4.3 Additive White Gaussian Noise (AWGN) Channel

The received signal at each base station is the delayed version of transmitted signal added with the Additive White Gaussian Noise. The SNR of the received signal is given by,

$$SNR = \frac{P_s}{P_n}$$

Where, P_s is the received signal power and P_n is the noise power. The noise power at the receiver front end is defined as

$$P_n = kTB,$$

where,

k = Boltzman's constant = 2.38×10^{-23} J/$^{o}K / Hz$,

T = Thermal noise temperature in Kelvin,

B = Equivalent noise bandwidth of the transmitted signal.

In a digital communication system, E_b/N_o is often referred to as SNR, where E_b is the bit energy and N_o is the noise power spectral density [19]. The bit energy in terms of transmit signal power is given by

$$E_b = P_s \, T_{Bit}, \tag{4.6}$$

where, T_{Bit} is the bit duration. In the CDMA system, the PN spreading sequence provides a processing gain of N. Processing gain is the number of chips used to spread single bit energy over the frequency spectrum [29]. If N_s is the number of samples per bit, then T_{Bit} is equivalent to the product of number of chips per symbol and samples per bit.

$$T_{Bit} = N \, N_s \tag{4.7}$$

For AWGN channel, the noise power is given by,

$$\sigma_n^2 = \frac{N_0}{2}$$
$$\Rightarrow N_0 = 2\sigma_n^2 \tag{4.8}$$

From equation (4.6), (4.7) and (4.8)

$$\frac{E_b}{N_0} = \frac{P_s\, T_{Bit}}{2\sigma_n^2} = \frac{P_s\, N\, N_s}{2\sigma_n^2},$$
$$\Rightarrow \quad \sigma_n^2 = \frac{P_s\, N\, N_s}{2\left(\frac{E_b}{N_0}\right)}. \tag{4.9}$$

Since unity power signal is used for simulation, therefore $P_s = 1$ and noise power for a given SNR is obtained from

$$\sigma_n^2 = \frac{N\, N_s}{2\left(\frac{E_b}{N_0}\right)}. \tag{4.10}$$

A zero mean Gaussian noise with a variance given by equation (4.10) is added to the delayed version of transmitted signal from the mobile unit to represent received signals at the corresponding base stations.

4.4 Chapter Summary

This chapter has summarized channel models employed to simulate wireless propagation effects within a cellular environments. These channel models are employed in Chapter 5 to evaluate data fusion of TOA and TDOA position estimates and then again in Chapter 6 to evaluate data fusion with TDOA estimates corrected for the LOS cases.

Chapter 5

Data Fusion With Uncorrected TDOA

This chapter presents partial simulation results related to the PL solution for data fusion with uncorrected TDOA. In Chapter 6, we consider the extension of these results to the case where TDOA measurements are corrected for NLOS propagation. Some assumptions are made regarding the mobile user position as well the CDMA system while developing the PL simulator. The E-911 user is assumed to be stationary in all simulation cases. This reflects the physical scenario where a car may be broken on a highway, and the driver may be asking for the service while seating inside or standing beside the car. The sections 5.2 and 5.3 present simulation results that validate the performance of the TOA and TDOA simulator. Finally, the performance of the data fusion simulator with corrected TOA and uncorrected TDOA measurements is discussed.

5.1 Simulation Models

The base stations configuration used for all simulations is shown in figure 5.1. There are four participating base stations, and three of them are uniformly spaced around a circle and the other one is located at the center of the circle.

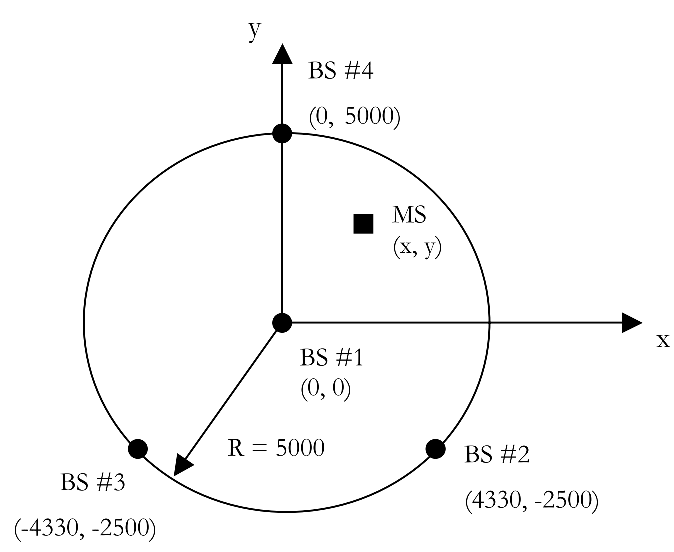

Figure 5.1: Base Stations Configuration

Base station #1 is assumed to be the controlling base station, meaning that the mobile user is within the cell where the BS#1 is the serving base station. It is also assumed that the controlling base station will always be at the center of the coordinate system. Since it is assumed that the system is operating in the CDMA environment, the mobile unit transmitter is modeled as the one shown in Figure 5.2. In an ealier chapter we mentioned that, a half-wave dipole antenna with unity gain and maximum transmiiter power of 1 Watt will be used in all simulations. The carrier frequency of 1900 MHz, and a chip rate of 1.2288 Mcps are used which indicate the operation of the CDMA system in the PCS band. One important thing is worth mentioning that, a perfect RF modulation and demodulation is assumed throughout this research work. 1.2288 Mcps chip rate indicates the modulating signal bandwidth to be 1.2288 MHz. A Non-Return to Zero (NRZ) waveform with unit amplitude are assumed for both PN spread sequence and message signal. It is well known that, sampling plays an important role in digital communication. In order to have sufficient Signal-to-Aliasing Ratio (SAR), an over sampling rate of 10 samples/symbol is used in all simulations. Figure 5.3 shows a plot of SAR vs Sample-per-Symbol. Since base band binary system operate with a true SNR of the order of 10 dB, sampling rate must be such that the SAR is much greater than 10 dB. This is to ensure that aliasing error does not affect the simulated performance of the system [22]. From figure 5.3 we find that, SAR is close to 17 dB for sampling rate of 10 samples per symbol. For all simulations over sampling rate of 10 samples/symbol is used. In CDMA One cellular standard, the long PN spreading sequence introduces a processing gain of 4 per symbol after rate 1/3 convolutional encoder. A 64-ary orthogonal modulator introduces an additional processing gain of 32 per symbol. Therefore, the over all processing gain in CDMA One cellular standard is 128. In all our simulations, we have assumed a constant processing gain of 128. Closed-loop power control is also assumed for every simulation. This indicates that, the total power level of each user on the receiving antenna of the primary base station is equal, thereby eliminating any near-far problem encountered in CDMA system. It is assumed that, unless specified, the controlling base station has to maintain a Signal-to-Noise Ratio of 10 dB from all users within the cell.

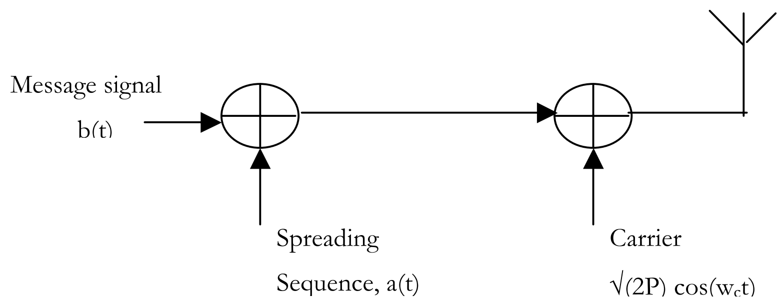

Figure 5.2 (a): Transmitter Model of Mobile Unit

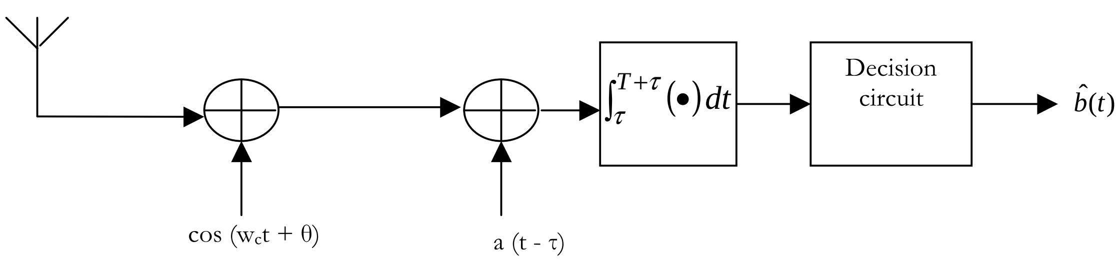

Figure 5.2 (b): Receiver Model of Direct Sequence Spread Spectrum Signal

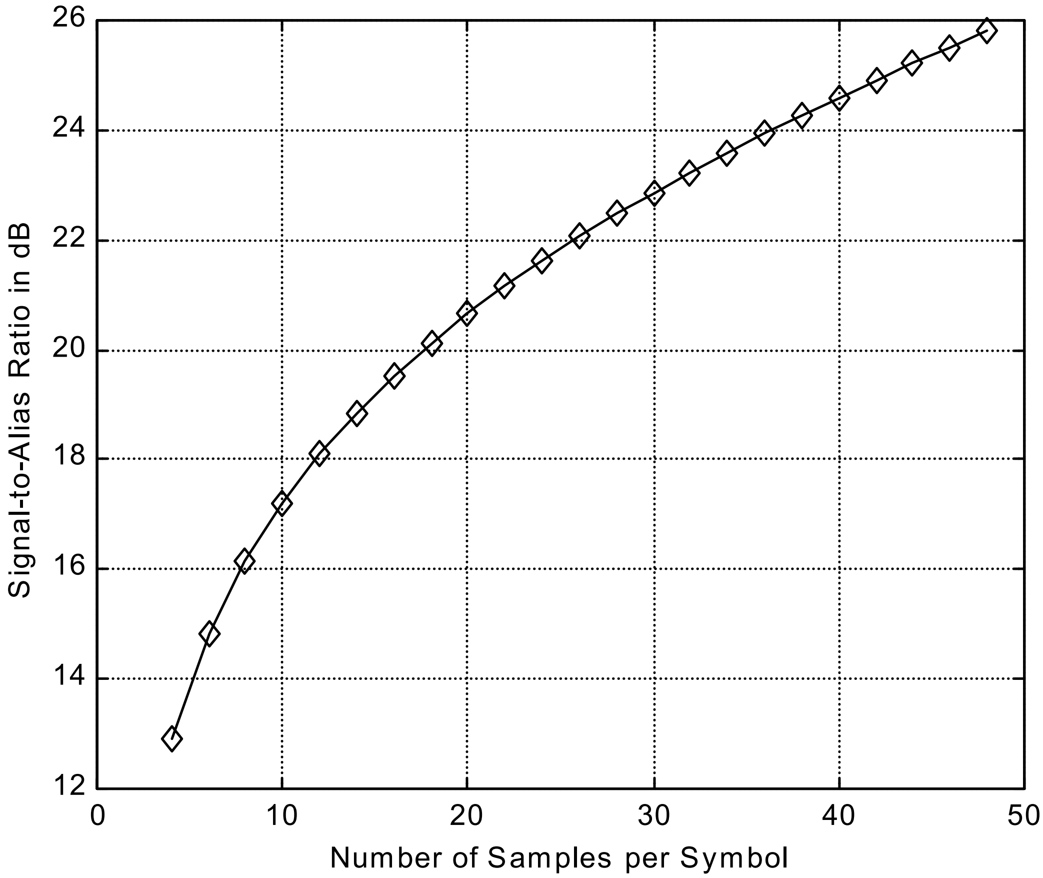

Figure 5.3: SAR vs. Samples/Symbol for NRZ Waveform

5.2 Validation of TOA Simulator Performance

The Wylie-Holtzman data model will be used to synthesize the TOA ranges. Once the true distance between the mobile user and the base station is determined, the standard measurement noise and the NLOS noise, where applicable, are added to the true range. In order to validate that the simulator is working properly, mobile trajectory estimation test is performed. The simulator makes necessary measurements to determine NLOS case and then takes appropriate steps to correct the errors introduced due to non-line of sight between the mobile and the base station. The starting point of the mobile trajectory is (300, 300) and velocity of the mobile is (v_x = 9.7m/sec, v_y = 16.8 m/sec). The estimator would estimate mobile trajectory from a series of measurements taken at different time. As we assumed earlier that the mobile requesting for E-911 service is stationary, it is not always necessary to estimate the entire trajectory of the mobile user. Once we validate that the simulator is working properly, the velocity of the mobile will be set to zero and the performance of the Taylor-Series Least-Square estimator will be evaluated based on the mean and variance of the position estimates obtained at different mobile locations.

5.2.1 Mobile Trajectory Estimation

In this simulation we assume that the mobile is moving along a straight line. Therefore at any given instant *t*, the mobile position is obtained from the equation 5.1.

$$\begin{aligned} x(t) &= x_o + v_x t \\ y(t) &= y_o + v_y t \end{aligned} \tag{5.1}$$

250 samples are taken at an interval of 0.5 second. The values used for the standard measurement noise and NLOS noise are taken from the ones provided in the reference number 4. The standard measurement noise is independent identically distributed Gaussian random variable with zero mean and 150 meter standard deviation. The NLOS error is described as a positive sided Gaussian random variable with 513 meters mean and 436 meter standard deviation. The values for α_m and β_m are 400 meters and 1300 meters respectively. It is assumed that the BS#2 and the BS#4 always had NLOS measurement while the BS#1 and the BS#3 always had complete LOS. Figure 5.5 shows the plot of real mobile trajectory and the estimated mobile trajectory.

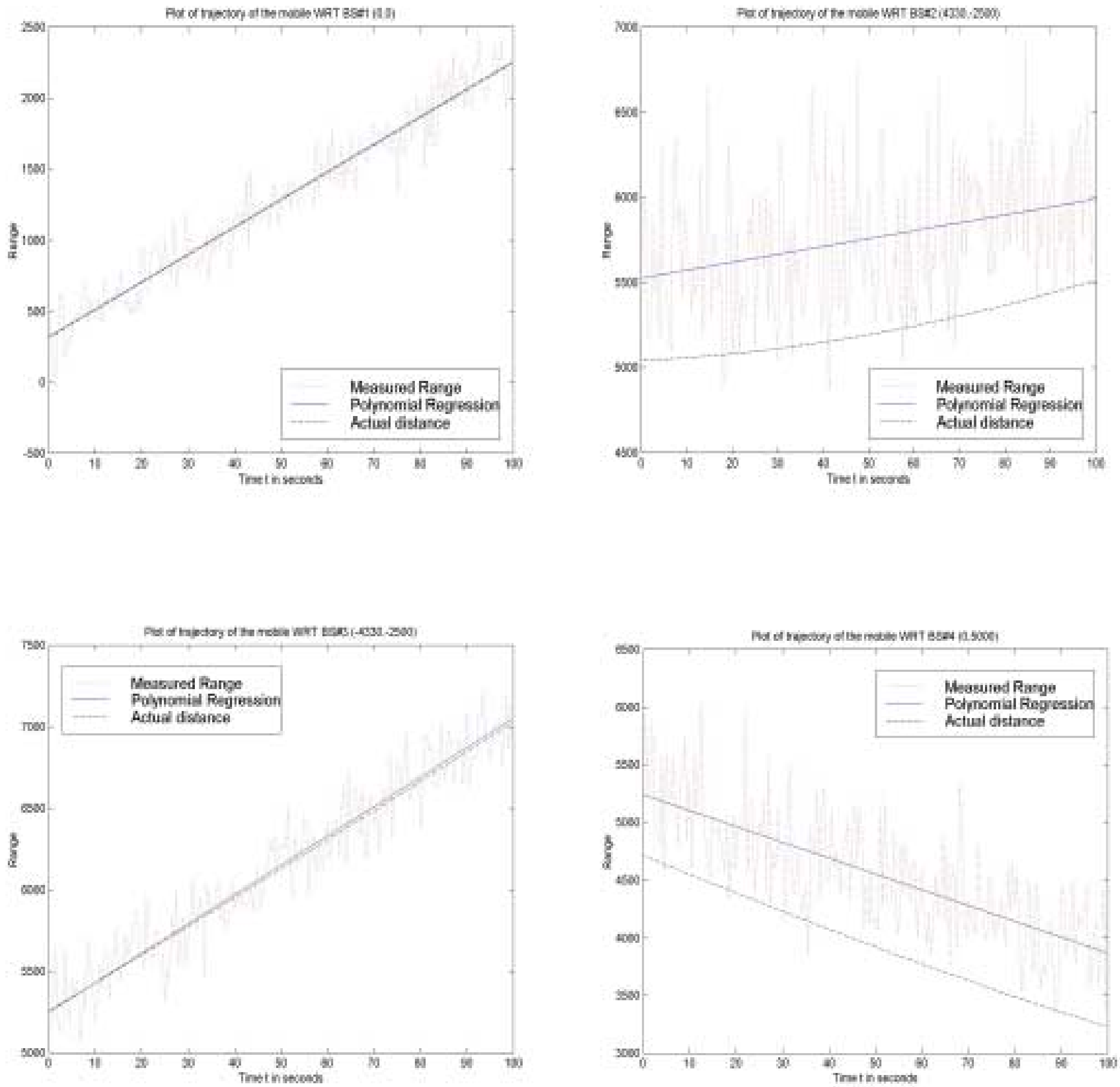

Figure 5.4: Trajectory of the Mobile With Respect to Different Base Stations

Fitting the measured ranges into a straight line by using Nth order polynomial fit, smooth the ranges. In the presence of the NLOS error, the measured ranges will deviate from the smooth values by a quantity, which is much greater than the standard deviation of the standard noise error. This in turn means that the standard deviation of the measured ranges in case of an NLOS would be much greater than the standard deviation of range measurements in case of an LOS. This hypothesis is used to determine the base station having an NLOS. The threshold value for comparing the standard deviation of the measured ranges from the smooth values is taken to be 300 meter. Table 5.1 and 5.2 show results that validate that it is possible to identify the NLOS measurements using the hypothesis test. Table 5.2 shows results demonstrating the situation that all the four base stations have NLOS.

Table 5.1: Standard Deviation of TOA Measurements from Smoothed Curves

BS#	NLOS	$\hat{\sigma}_m$
1	No	146.3
2	Yes	380.8
3	No	133.74
4	Yes	343.7

Table 5.2: Standard Deviation of TOA Measurements from Smoothed Curves

BS#	NLOS	$\hat{\sigma}_m$
1	Yes	369.4
2	Yes	345.5
3	Yes	377.2
4	Yes	388.8

From Table 5.1 it is evident that the BS#2 and the BS#4 are identified to have an NLOS. Once an NLOS is identified to exist for these two base stations, the Wylie-Holtzman algorithm is used to eliminate the bias in the data introduced by the NLOS error. Figure 5.5 shows plot of maximum and minimum values of the standard measurement noise as a function of number of trials. 250 samples in each trial are used to determine the maximum and minimum value of noise. This figure gives an idea about the bound of the standard measurement noise used in this simulation. The mean value of the upper bound of the standard measurement noise is 422 meter. Therefore the smooth curves for the base stations having an NLOS will be shifted by this value.

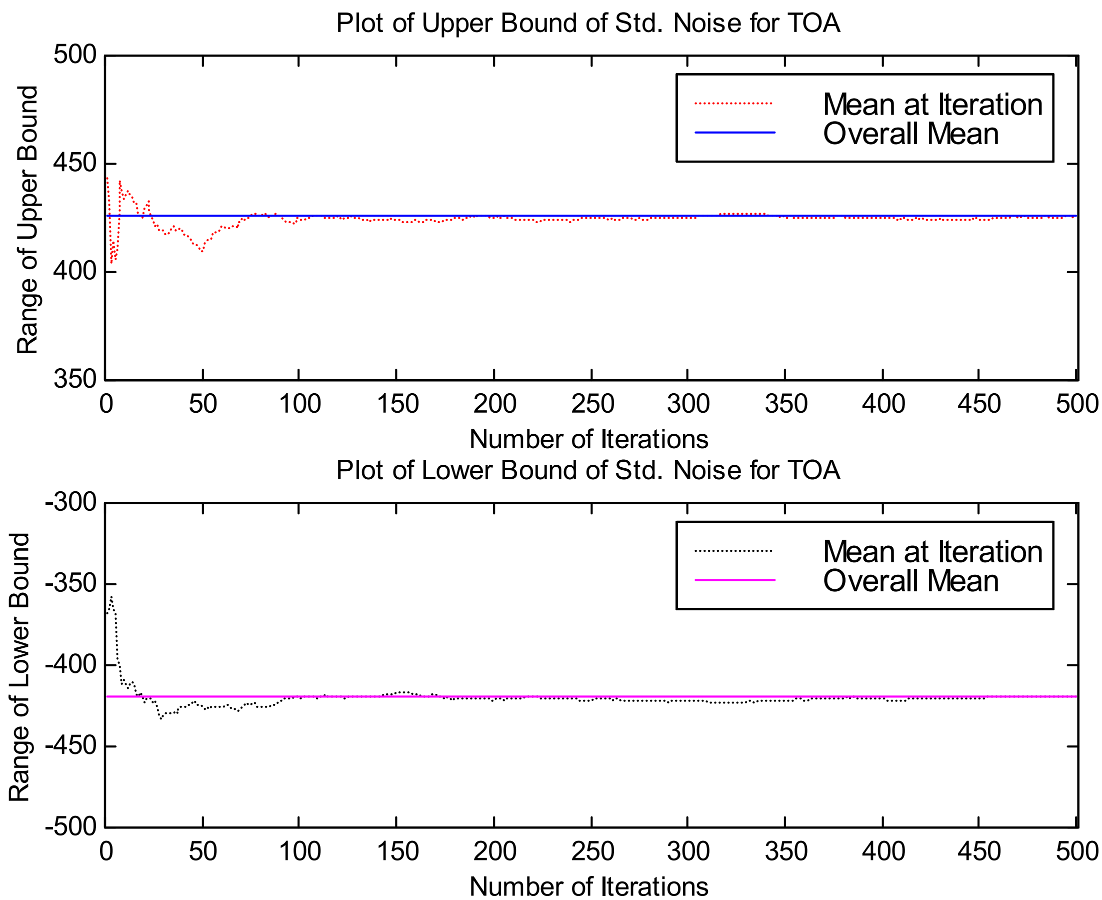

Figure 5.5: Upper and Lower Bound of Standard Measurement noise of TOA ranges

In the Figure 5.4, the dotted lines are the measured ranges, the solid lines are the smoothed range measurements and dash-dotted lines represent a true mobile trajectory. Figure 5.6 shows the output of the Least-Square estimator for different kind of inputs. The solid line indicates the real mobile trajectory. The dash-dotted line shows the output of an LS estimator with the uncorrected smoothed range measurements fed as the input, and the dashed line represents the estimated trajectory when the Wylie-Holtzman algorithm is applied to the uncorrected input the estimator input. In order to compare the improvement obtained by the Wylie-Holtzman algorithm, mobile trajectory is estimated when all the participating base stations have complete line of sight with the mobile. The dotted line represents this trajectory. The figure shows the improvement obtained by the Wylie-Holtzman algorithm and indicates that the TOA position estimator simulator functions properly. Figure 5.6 further strengthen the argument that, Wylie-Holtzman algorithm indeed makes significant improvement to the estimated position determination in TOA PL system even when there is NLOS between the mobile user and the base station.

Table 5.3 shows the performance of the TOA PL estimator, comparing the mean and the standard deviation of the location error of the PL estimates with the Wylie-Holtzman algorithm to the output of an LS estimator without any NLOS error correction. The results are also compared to the LS estimator performance when all the base stations have LOS. The error values are finally compared to the theoretical lower bound of the PL estimator. Obviously the best result is obtained when all the four base stations have LOS. Under this condition, the variances of the estimates are close to CRLB. Lower the error between the CRLB and the estimates better the performance. The estimates vary significantly for NLOS case. The Wylie-Holtzman algorithm reduces the error bias but introduces additional variance into the estimate.

Table 5.3: TOA Estimator Performance on Mobile Trajectory Estimation

	Not Corrected	**Corrected**	**Line-of-Sight**	$\sqrt{CRLB}$
μ_{xo}	-286.3042	21.7950	19.2684	-
σ_{xo}	53.0609	54.1237	17.3975	15.90
μ_{yo}	-68.4564	7.0271	8.2272	-
σ_{yo}	27.9718	53.9249	14.1523	14.20
μ_{vx}	2.4708	-0.2063	-0.2320	-
σ_{vx}	0.8655	0.6125	0.3072	0.27
μ_{vy}	0.5837	-0.0941	-0.0967	-
σ_{vy}	0.4931	0.5612	0.2387	0.25

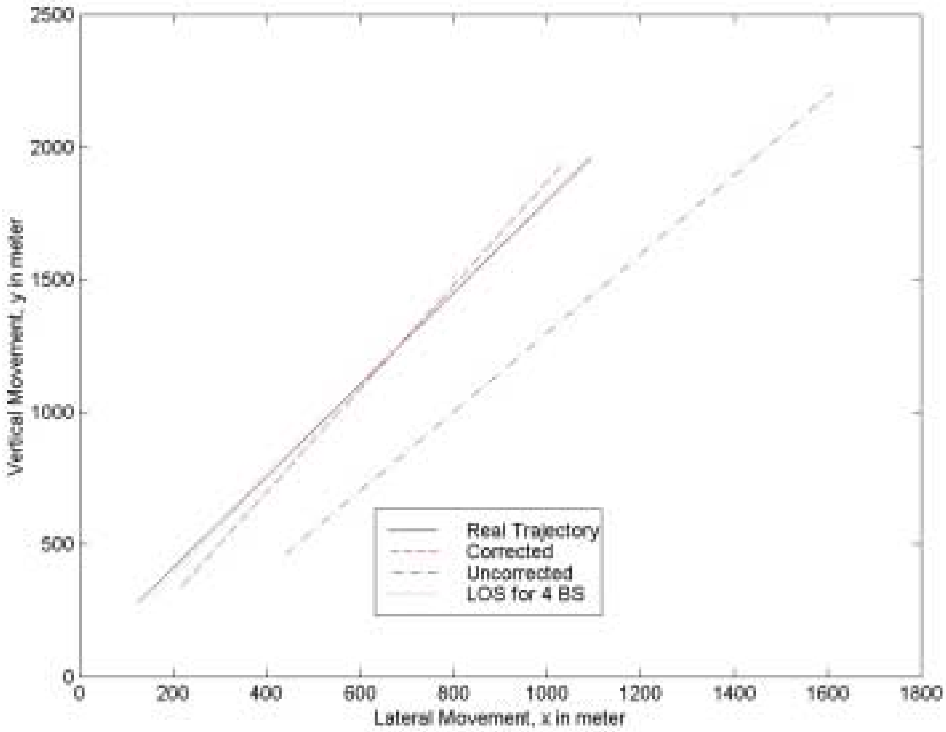

Figure 5.6: Estimated Mobile Trajectory with and with out TOA Range Correction

5.2.2 Evaluation of the Estimator's Performance for Position Estimation

In section 5.2 we mentioned that, for an E-911 service, it is not necessary to estimate the entire trajectory of the mobile. Most applications of position estimators require determining only the position estimates. In order to simulate this situation we set the velocity of the mobile to zero, and calculate several position estimate mean and variance. This will give a chance to evaluate the performance of an absolute position estimator.

Although the estimator is no longer estimating the mobile trajectory, the Wylie-Holtzman correction algorithm still holds, and the smoothed curve and the corrected curve shown in figure 5.6 become horizontal lines. The estimator directly outputs the estimate of the x-coordinate and the y-coordinate of the mobile. These values are used to calculate the mean and variance of the estimates. Each calculation uses 200 samples. Table 5.4 shows the estimated position location as well as the range bias and the range standard deviation. CRLB is also included to compare the standard deviation to the lower limit. The table indicates that the individual TOA PL estimator is able to meet the FCC regulation.

Table 5.4: TOA Estimator Performance at Different Mobile Location

	MS Location (MS Close to BS#1)	**MS Location** (MS Far From All BS)	**MS Location** (MS at the edge of the cell)
Real Position (x_0, y_0)	600, 900	2000, 2000	600, 2500
Estimator Mean $(\hat{x}, \hat{y})$	615, 897	2009, 2003	683, 2516
Estimator Standard Deviation (σ_x, σ_y)	56, 36	44, 22	161, 29
Range Bias, R	15.3	10.4	85
Range Standard Deviation, σ_r	66.3	49	164
$\sqrt{CRLB}$	42.5	31.4	22.23

5.3 Validation of TDOA Simulator Performance

The simulator's performance is evaluated under two different conditions. In this section our objective is to trace the output of the simulator when all the base stations have an LOS with the MS, as well as when few of the base stations have an NLOS with the MS. The starting point of the trajectory and the velocity of the mobile are same as the ones used in evaluating the performance of the TOA simulator. In Section 2.2, we mentioned that the TDOA range measurements can be obtained either by subtracting TOA's at two base stations, or by correlating two versions of the received signal at two base stations. Figure 5.7 shows plot of range differences obtained by the GCC method as well as by subtracting TOA's at two base stations. While using the GCC method to determine the range differences, we have used the channel model described in the Sections 4.2 and 4.3.

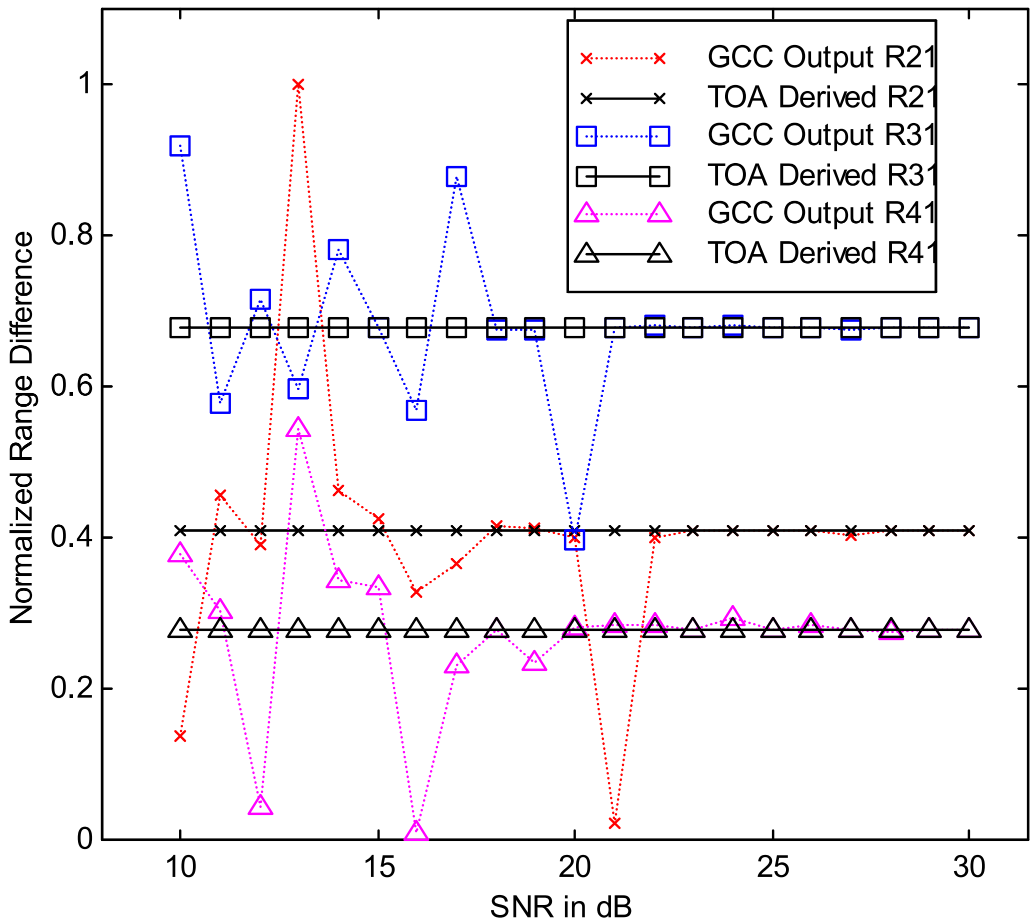

Figure 5.7: Normalized Range Differences vs. Signal-to-Noise Ratio

From Figure 5.7, we find that, at high SNR the TDOA range measurements from the cross correlator output match with the values obtained from the models. In simulations, TDOA range measurements obtained by using the GCC method take longer time than the measurements obtained from the TOA measurements. Therefore subtracting the synthesized TOA range measurements generates the TDOA range measurements in the simulations. In the next chapter we will propose a data model that can be unswervingly used to synthesize TDOA range measurements. Once again, when we validate that the simulator is working properly, the velocity of the mobile will be set to zero and the performance of the Taylor-Series Lease Square estimator will be evaluated at different mobile positions.

5.3.1 Mobile Trajectory Estimation

Since we are again considering that the mobile is moving along a straight line, therefore the trajectory is expressed by the equation 5.1. The trajectory consists of 250 samples taken at a sampling rate of 2 samples/sec. The values used for generating standard measurement noise and NLOS noises are same as the ones mentioned in section 5.2.1. The BS#1 is the controlling base station, so all the range differences are calculated with respect to the range of the mobile from the BS#1. More over, we will assume that the BS#1 has a complete LOS with the MS. Figure 5.9 shows the plot of range differences as a function of time. One distinct difference between the TOA estimator and the TDOA estimator is that, the raw TDOA range measurements are directly fed as the input to the TDOA estimator. It is obvious that, if any base station has an NLOS with the MS, the corresponding range difference will contain an error bias. The BS#3 has an NLOS with the MS and thus the range difference R_{31} contains NLOS-error bias. We already mentioned in section 5.2.1 that, the standard deviation of the range measurements in the presence of NLOS is much greater than the standard deviation of the standard noise error. Since TDOA range measurements are derived from the TOA range measurements, it is intuitive that the same reasoning will hold for TDOA range measurements. Table 5.5 and 5.6 shows the standard deviation of the range differences at different base stations configurations. Table 5.5 shows the standard deviation of the range differences when the controlling base station has a complete LOS. Under this condition the range differences can have at most one NLOS error bias. Table 5.6 indicates the standard deviation of the range differences when the range differences can have at most 2 NLOS error bias. The tables 5.5 and 5.6 show important results that will be used for hypothesis testing in determining presence of an NLOS error in the measured TDOA ranges.

Figure 5.8 shows the output of the Taylor-Series Least Square estimator for a different kind of inputs. The solid line indicates the real mobile trajectory, the dashed line shows the estimated trajectory when biased smoothed range differences are fed as the input to the estimator, and dotted line represents the estimated trajectory when the unbiased range differences are used as the input to the estimator. The figure shows that the TDOA range measurements are vulnerable to an NLOS error, and considerable improvement can be obtained if any correction is made to eliminate the bias incorporated into the NLOS TDOA range measurements.

Table 5.5: Standard Deviation of TDOA Range Measurements from Smoothed Curve

BS#I	**NLOS**	$\hat{\sigma}_m$ of R_{i1}
1	No	-
2	No	198
3	Yes	452
4	No	213

Table 5.6: Standard Deviation of TDOA Range Measurements from Smoothed Curve

BS#I	**NLOS**	$\hat{\sigma}_m$ of R_{i1}
1	Yes	-
2	No	430.5
3	Yes	586.7
4	Yes	546.2

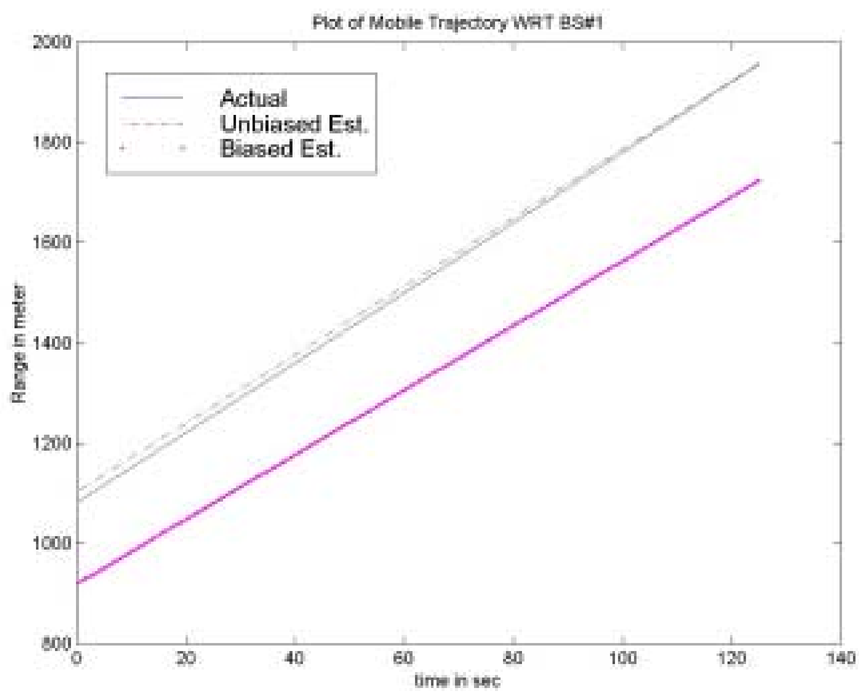

Figure 5.8: Estimated Trajectory with and without NLOS Error Bias in TDOA Range Measurement

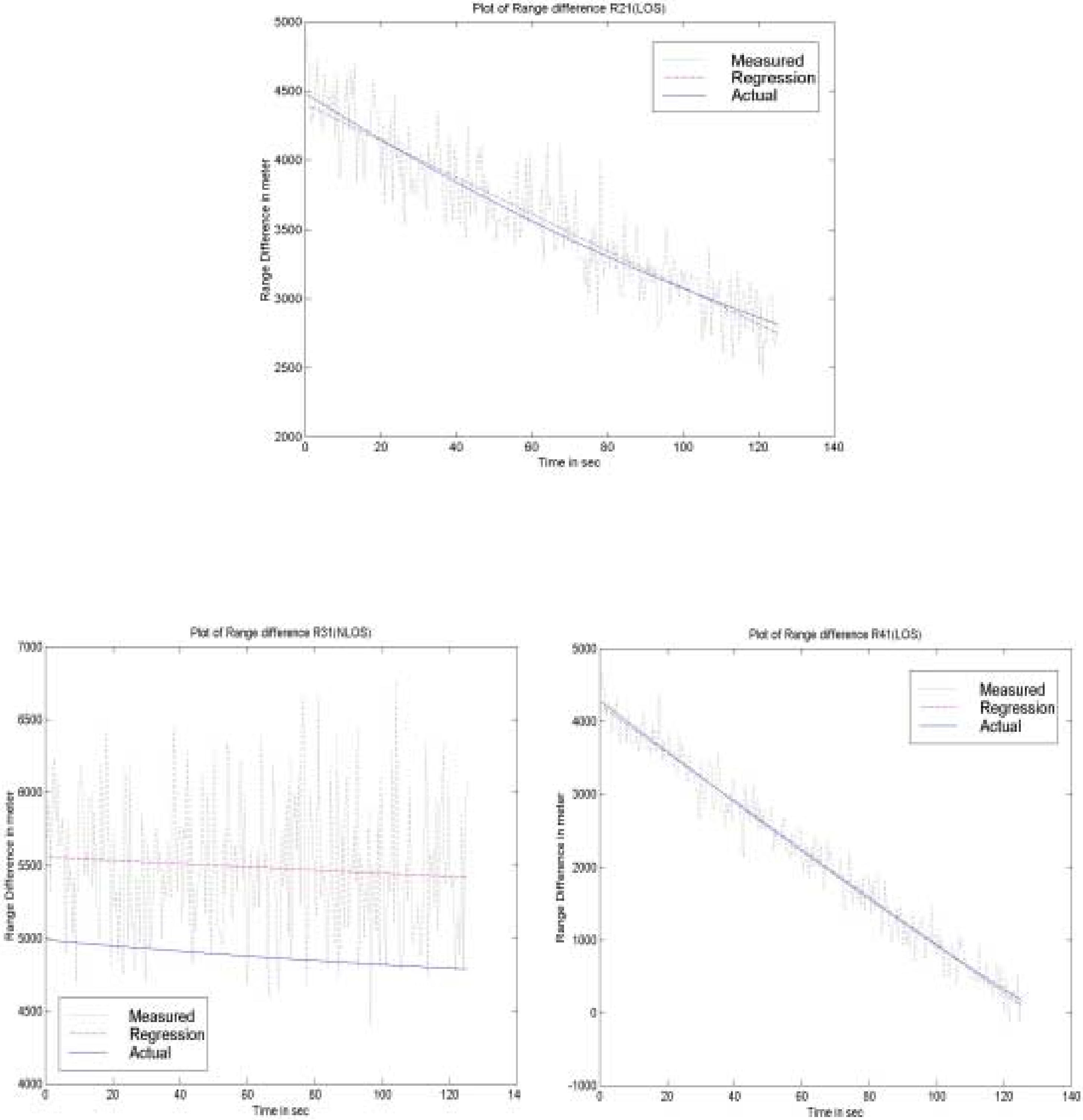

Figure 5.9: Plot of TDOA Range Differences vs. Time

5.3.2 Evaluation of the Estimator's Performance for Position Estimation

In the previous section we have demonstrated that the TDOA simulator is functioning properly. Most of the position identification applications such as to inform about a road accident or a fire incidence, require only the position estimates. Therefore the velocity of the mobile unit in the simulator will be set to zero and the simulator's output will be recorded at different mobile locations. The estimator directly outputs the x –coordinate and the y-coordinate of the mobile. These values of the estimates will be used to calculate the mean and variance of the estimates. Table 5.7 shows the mean of the estimated positions as well as the range bias and the range standard deviation. CRLB is also included to compare the standard deviation to the lower limit. The biased results are presented on the assumption that BS#3 and BS#4 have NLOS with the MS.

Table 5.7: TDOA Estimator Performance at Different Mobile Location

		MS Location	**MS Location (MS Far From All BS)**	**MS Location (MS at the edge of the cell)**
Real Position (x_0, y_0)		600, 900	2000, 2000	600, 2500
Estimator Mean $(\hat{x}, \hat{y})$	**Unbiased**	599, 904	1999, 2008	599, 2523
	Biased	671, 594	1986, 1620	776, 2267
Estimator Standard Deviation (σ_x, σ_y)	**Unbiased**	120.3, 102	162.5, 113.3	204.6, 108.5
	Biased	130.4, 219	184.4, 284.8	222.6, 240.7
Range Bias, R	**Unbiased**	5	8	23
	Biased	314	380	292
Range Standard Deviation, σ_r	**Unbiased**	157.7	198	231.6
	Biased	254.9	339.3	327.8
$\sqrt{CRLB}$	**Unbiased**	158.8	197.2	202.6
	Biased	268.8	345.7	319.8

The TDOA estimator performs well when the MS is considerably away from the controlling base station. We mentioned before that, TDOA estimates suffer from high GDOP when the MS is close to the controlling base station. The degradation of the TDOA estimates, when the MS is in close proximity of the BS, is due to numerical instability of the equations that actually model the TDOA triangulation. Table 5.8 shows the TDOA estimator's performance at some locations when mobile is very close to its controlling base station.

Table 5.8: TDOA Estimator's Performance When MS is Very Close to the Controlling BS

	MS Location	**MS Location**	**MS Location**	**MS Location**	**MS Location**
Real Position (x_0, y_0)	25, 25	50, 50	150, 150	200, 200	300, 300
Estimator Mean $(\hat{x}, \hat{y})$	44, 39	48, 59	148, 141	192, 188	291, 308
Estimator Standard Deviation (σ_x, σ_y)	102, 98	97, 97	129, 108	124, 105	118, 112
Range Bias, R	23	10	9	14	12
Range Standard Deviation, σ_r	141.7	137.4	167.7	162.4	162.7
$\sqrt{CRLB}$	158.8	155	171.8	162.2	162.5

5.4 Implementation of Data Fusion Model in Position Location

We have already discussed in Chapter 3 the data fusion model applicable to the PL problem. In this section we will briefly discuss how the model has been simulated using MATLAB codes. The TOA measurements have been simulated by first determining the true distances between the MS and the base stations. Then the TOA range measurement model present in the Section 2.1.1 is used to generate a complete TOA data. The TDOA measurements are generated from the TOA data and hence in contrast to the real life situation, the TDOA data cannot be assumed to be independent of the TOA data. Once again we should mention that the TOA estimator takes the smoothed TOA measurements as its input, where as the TDOA estimator takes raw measurements as its input. The raw TOA measurements of the TOA module are used to form additional TDOA data. In the first level data fusion module, these converted TDOA data are combined with the original TDOA measurements. The combined TDOA data is used as the input to the Taylor-Series Least Square estimator, similar to the one implemented in the TDOA module. The means of both the TOA estimates and the TDOA estimates are combined in the second level data fusion stage. In this stage, the TOA estimate is granted as the original estimate and is updated with the additional TDOA estimate. The level-four process chooses the best estimate among all the four estimates. In this simulation, the final decision about the optimum estimate is made on the basis of estimators' variances. The output of the estimator with lowest variance will be chosen as the best estimate in the level-four process.

Tables 5.9, 5.10 and 5.11 show the different estimators' output at different MS locations. The tables also indicate the decisions made at the level-four process of the data fusion architecture about the best position estimates. Tables 5.12 and 5.13 represent estimators' output when the MS is close to its controlling base station, BS#1. The results in the Tables 5.12 and 5.13 show that, although the first level estimator range biases are minimum, the estimates are not chosen as the best estimates. This reveals that, the present method of deciding best estimate, based on range standard deviation, needs to be modified.

Table 5.9: Estimators' Output in Data Fusion Architecture at MS (600, 900)

		TOA Estimator	TDOA Estimator	TOA/TDOA 1st level fusion	TOA/TDOA 2nd level fusion
Actual Position (x_0, y_0)		(600, 900)	(600, 900)	(600, 900)	(600, 900)
Estimator mean $(\hat{x}, \hat{y})$	**Unbiased**	(708, 977)	(613, 902)	(621, 920)	(706, 977)
	Biased	-	(1010,1113)	(855, 1047)	(710, 977)
Standard Deviation (σ_x, σ_y)	**Unbiased**	17, 9	113, 105	97, 83	16.8, 9.1
	Biased	-	223, 144	161, 101	15.7, 22.3
Range bias R	**Unbiased**	132	14	29	131
	Biased	-	462	294	134
Range Standard Deviation σ_r	**Unbiased**	19.3	154.7	128	19
	Biased	-	265.8	189	19
Choice	**Unbiased**		•		
	Biased		•		

Table 5.10: Estimators' Output in Data Fusion Architecture at MS (2000, 2000)

		TOA Estimator	TDOA Estimator	TOA/TDOA 1st level fusion	TOA/TDOA 2nd level fusion
Actual Position (x_0, y_0)		(2000,2000)	(2000,2000)	(2000,2000)	(2000,2000)
Estimator mean $(\hat{x}, \hat{y})$	**Unbiased**	(2173,2104)	(1988,2003)	(2030,2021)	(2167,2104)
	Biased	-	2588, 2371	2385, 2240	2176, 2105
Standard Deviation (σ_x, σ_y)	**Unbiased**	27, 9	158, 126	140, 102	26.5, 9.3
	Biased	-	344, 233	228, 153	19.4, 7.9
Range bias R	**Unbiased**	201	12	37	197
	Biased	-	695	454	204
Range Standard Deviation σ_r	**Unbiased**	29	202	173	29
	Biased	-	416	274	29
Choice	**Unbiased**		•		
	Biased		•		

Table 5.11: Estimators' Output in Data Fusion Architecture at MS (600, 2500)

		TOA Estimator	TDOA Estimator	TOA/TDOA 1st level fusion	TOA/TDOA 2nd level fusion
Actual Position (x_0, y_0)		(600, 2500)	(600,2500)	(600,2500)	(600,2500)
Estimator mean $(\hat{x}, \hat{y})$	**Unbiased**	(857, 2630)	(612, 2585)	(642, 2581)	(854, 2628)
	Biased	-	1109, 2778	957, 2682	857, 2634
Standard Deviation (σ_x, σ_y)	**Unbiased**	15, 28	129, 132	104, 98	14.7, 25.8
	Biased	-	297, 172	202, 107	18.3, 32.1
Range bias R	**Unbiased**	288	86	91	285
	Biased	-	580	401	291
Range Standard Deviation σ_r	**Unbiased**	32	185	143	31
	Biased	-	344	228	32
Choice	**Unbiased**		•		
	Biased		•		

Table 5.12: Estimators' Output with Unbiased Input at MS (25, 25)

	TOA Estimator	**TDOA Estimator**	**TOA/TDOA 1st level fusion**	**TOA/TDOA 2nd level fusion**
Actual Position **(x_0, y_0)**	(25, 25)	(25, 25)	(25, 25)	(25, 25)
Estimator mean $(\hat{x}, \hat{y})$	(36, 18)	(32, 17)	(29, 22)	(36, 18)
Standard Deviation (σ_x, σ_y)	7, 9	95, 100	70, 73	11, 8
Range bias R	13	11	5	13
Range Standard Deviation σ_r	11	138	101	14
Choice	•			

Table 5.13: Estimators' Output with Unbiased Input at MS (150, 150)

	TOA Estimator	TDOA Estimator	TOA/TDOA 1^{st} level fusion	TOA/TDOA 2^{nd} level fusion
Actual Position **(x_0, y_0)**	(150, 150)	(150, 150)	(150, 150)	(150, 150)
Estimator mean $(\hat{x}, \hat{y})$	(157, 133)	(158, 156)	(153, 146)	(157, 133)
Standard Deviation (σ_x, σ_y)	7, 6	107, 105	84, 75	4, 8
Range bias R	19	10	5	19
Range Standard Deviation σ_r	10	150	112	9
Choice				•

5.5 Chapter Summary

In this chapter, we have presented preliminary results showing the performance of TOA and TDOA position determination for a typical cellular environment. Throughout these simulations, the TOA measurements were normalized for NLOS propagation using the Wylie-Holtzman correction method. In the next chapter, we show how this method may be extended to correct TDOA measurements.

Chapter 6

TDOA Data Model and Extension of Wylie-Holtzman Algorithm to TDOA Ranges

In this chapter we will propose a data model that can be used to synthesize the TDOA range measurements. We will also show that, the Wylie-Holtzman algorithm to the TOA range measurements cannot be applied directly to the TDOA range measurements. We would also propose and validate a proposed correction method by presenting some simulation results. At the end of the chapter, the performance of the data fusion simulator with the corrected TOA and TDOA measurements will be discussed.

6.1 Data Model for TDOA Range Measurements

Initially we will assume that the controlling base station has a complete LOS with the MS. The range difference between base stations with respect to the controlling base station is given by the equation 2.2. The range measurements R_i can be modeled according to equation 2.1. For our convenience we will rewrite equation 2.1 below.

$$R_i = L_i(t_p) + n_i(t_p) + NLOS_i(t_p), \tag{6.1}$$

where,

$$\begin{aligned}
&i = \text{BS index} = 1,2....\text{M},\\
&p = \text{Sample time index} = 0,1,2.....(K-1),\\
&K = \text{Sets of measurements at different time t}_\text{p},\\
&L_i = \text{True distance between MS and BS},\\
&n_i = \text{Standard measurement error},\\
&NLOS_i = \text{Error due to Non-line-of-sight.}
\end{aligned}$$

Since we are assuming that the controlling base station has a complete LOS with the MS, therefore the general form of range difference with respect to BS#1 is given by the equation 6.2.

$$R_{i1} = L_i(t_p) - L_1(t_p) + n_i(t_p) - n_1(t_p) + NLOS_i(t_p) \tag{6.2}$$

The standard noise has a zero mean Gaussian distribution. Therefore the expectation of $n_i(t_p) - n_1(t_p)$ is

$$E[n_i - n_1] = E[n_i] - E[n_1] = 0 .$$

The variance is given by

$$\begin{aligned} E\left[(n_i - n_1)^2\right] &= E\left[n_i^2 + n_1^2 + 2\,n_i\,n_1\right] \\ &= E\left[n_i^2\right] + E\left[n_1^2\right] + E\left[2 n_i n_1\right] \\ &= \sigma^2 + \sigma^2 \\ &= 2\,\sigma^2. \end{aligned}$$

Therefore, when the controlling base station has LOS, the TDOA range differences can be modeled as follows

$$R_{i1} = L_{i1}(t_p) + n_{i1}(t_p) + NLOS\,(t_p)\ , \tag{6.3}$$

where,

$i =$ BS index $= 1,2....$M,

$p =$ Sample time index $= 0,1,2.....(K-1)$,

$K =$ Sets of measurements at different time $\mathrm{t_p}$,

$L_{i1} =$ True Range difference

$n_{i1} =$ Standard measurement error $\approx \mathrm{N}(0, 212.13)$,

$NLOS_i =$ Error due to Non-line-of-sight.

The standard measurement noise has a zero mean Gaussian distribution with the standard deviation of 212 meter. In a Line-of-Sight environment, the base station measures range differences in the presence of the standard system measurement noise. There will be no Non-Line-of-Sight error under that condition and NLOS (t_p) in equation 6.3 can be set to zero. The mean and standard deviation of NLOS noise will remain on the order of 513 meter and 436 meter, respectively. Even when the controlling base station would have the NLOS, the TDOA range model would remain same, except that an additional NLOS would appear in the equation 6.3. The distribution of the NLOS error would then change and would have a different mean and standard deviation.

6.2 Simulation Model

The simulation model, used to present results in the subsequent sections, would be almost same as the one mentioned in section 5.1. The L parameter of the TDOA ranges would be measured using the Euclidian distance approach. BS#1 is the controlling base station and is located at the center of the coordinate system. The other three participating base stations are uniformly spaced around a circle. The base stations configuration is same as the one depicted by the Figure 5.1.

6.3 Correction of TDOA Range Measurements Biased by NLOS Error

In the previous section we mentioned that, when there is a complete LOS between the base stations and the MS, the measured range differences would include the standard system measurement noise. Under such condition the range differences would not be biased by the NLOS noise. However, when there is an LOS of the MS with the controlling base station, but has NLOS between the MS and the participating base stations, the measured range differences would definitely contain NLOS error bias. The NLOS problem tends to be the key source of error in the range measurements [2]. First we would like to determine whether the range difference measurements contain the NLOS error bias, and then would try to reduce the amount of bias as much as possible. This would enable to determine the mobile coordinates more accurately by TDOA PL estimator even in the presence of NLOS environment.

6.3.1 Identification of NLOS Bias in TDOA Range Measurements

The NLOS bias in the TDOA range measurements can be identified if we have the *a priori* knowledge of the standard deviation of the standard measurement error. At the controlling base station, the range difference measurements are smoothed by polynomial regression. By comparing the standard deviation of a sample statistic to the known standard deviation of that statistic under the null hypothesis, we can determine the existence of an NLOS error bias in the measurements [2]. When there is a complete LOS between the MS and the base stations, the range measurements are affected by the standard measurement error in a very predictable manner. In such circumstance, the measured range difference would deviate from the true range difference by the standard deviation of the standard measurement error $n_{i1}(t_p)$. If we perform an Nth order polynomial fit to the measured range differences, we can expect that,

$$\hat{\sigma}_{i1} = \sqrt{\frac{1}{K}\sum_{p=0}^{K}\left(S_{i1}(t_p) - R_{i1}(t_p)\right)^2} \cong \sigma_{i1},$$

where,

σ_{i1} = Standard Deviation of the standard measurement error.

In the presence of the NLOS error, the measured range differences would deviate from the smoothed curves, so that $\hat{\sigma}_{i1} >> \sigma_{i1}$. The large standard deviation will be used to differentiate between the LOS case and the NLOS case.

6.3.2 Extension of the Wylie-Holtzman Algorithm to the TDOA Range Measurements

In the presence of an NLOS environment, the measured range differences are corrupted by both the standard measurement error and the NLOS error. We have modeled the TDOA ranges in the section 6.1, and in equation 6.3 we have shown that, the standard measurement error and the NLOS error can be modeled as a random variable. Equation 6.4 shows the range of the random variable.

$$-2\alpha_i < n_{i1}(t_p) + NLOS(t_p) < 2\alpha_i + \beta_i \tag{6.4}$$

Once we have the raw TDOA data, we can smooth the data by using an N^{th} order polynomial fit. It is worth mentioning that the effect of the NLOS error is only to bias the data [2]. If we extend the Wylie-Holtzman algorithm to the TDOA range measurements, then from the equation 6.4 we can deduce that, the maximum deviation of the measured range difference below the smoothed curve would be approximately $L_{i1}(t_p)$ - $2\alpha_i$. Therefore, by vertically displacing the smooth curve down by $\max(S_{i1}(t_p) - R_{i1}(t_p))$ and moving the curve up by $2\alpha_i$ would reduce the bias in the range measurements introduced by the NLOS error. Now we will derive the expression for the TDOA range correction from the Wylie-Holtzman algorithm given for TOA range correction.

According to equation 2.1

$$R_i(t_p) = L_i(t_p) + n_i(t_p) + NLOS_i(t_p). \tag{6.4}$$

As we are assuming that BS#1 has LOS and i^{th} BS has an NLOS, therefore range equation for BS#1 becomes

$$R_1(t_p) = L_1(t_p) + n_1(t_p). \tag{6.5}$$

If $S_m(t_p)$ is the smoothed version of $R_m(t_p)$, then according to Wylie-Holtzman algorithm, the corrected ranges of equation 6.4 becomes

$$\hat{S}_i(t_p) = S_i(t_p) - \max(S_i(t_p) - R_i(t_p)) + \alpha_i . \tag{6.6}$$

For equation 6.5

$$\hat{S}_1(t_p) = S_1(t_p) . \tag{6.7}$$

Subtracting equation 6.7 from equation 6.6, we get,

$$\begin{aligned} \hat{S}_i(t_p) - \hat{S}_1(t_p) &= S_i(t_p) - S_1(t_p) - \max(S_i(t_p) - R_i(t_p)) + \alpha_i \\ \hat{S}_{i1}(t_p) &= S_{i1}(t_p) - \max(S_i(t_p) - R_i(t_p)) + \alpha_i \end{aligned} \tag{6.8}$$

Now

$$\begin{aligned} S_i(t_p) - R_i(t_p) &= S_i(t_p) - R_1(t_p) - R_i(t_p) + R_1(t_p) \\ &= S_i(t_p) - R_1(t_p) - R_{i1}(t_p) \\ &= \left[S_{i1}(t_p) + S_1(t_p)\right] - R_1(t_p) - R_{i1}(t_p) \\ &= S_{i1}(t_p) - R_{i1}(t_p) + S_1(t_i) - R_1(t_p) \\ &= S_{i1}(t_p) - R_{i1}(t_p) + L_1(t_p) - \left[L_1(t_p) + n_1(t_p)\right] \qquad \begin{bmatrix} \text{From Equation 6.5} \\ S_1(t_p) \equiv L_1(t_p) \end{bmatrix} \\ &= S_{i1}(t_p) - R_{i1}(t_p) - n_1(t_p), \\ \max(S_i(t_p) - R_i(t_p)) &= \max(S_{i1}(t_p) - R_{i1}(t_p) - n_1(t_p)) \\ &= \max(S_{i1}(t_p) - R_{i1}(t_p)) - \max(n_1(t_p)) \\ &= \max(S_{i1}(t_p) - R_{i1}(t_p)) - \alpha_1 . \end{aligned}$$

From equation 6.8, we get

$$\begin{aligned} \hat{S}_{i1}(t_p) &= S_{i1}(t_p) - \max(S_{i1}(t_p) - R_{i1}(t_p)) + \alpha_1 + \alpha_i \\ &= S_{i1}(t_p) - \max(S_{i1}(t_p) - R_{i1}(t_p)) + 2\alpha_i . \qquad [\alpha_1 = \alpha_i] \end{aligned}$$

The final expression for TDOA range correction thus becomes

$$\hat{S}_{i1}(t_p) = S_{i1}(t_p) - \max(S_{i1}(t_p) - R_{i1}(t_p)) + 2\alpha_i \tag{6.9}$$

The above expression tells us that, in order to reduce the bias introduce by an NLOS error, we have to first smooth the TDOA measurement by N^{th} order polynomial fit. Then we have to deviate the smoothed curve down by the amount $\max(S_{i1}(t_p) - R_{i1}(t_p))$ and pull up the curve by the amount $2\alpha_i$. The value $2\alpha_i$ is the limit of standard measurement error of the TDOA PL estimator. Figure 6.1 shows the plot of the range differences as a function of time. We are assuming that BS#2 has NLOS, and therefore the range difference R_{21} will contain an NLOS error bias. The extended Wylie-

Holtzman algorithm is applied to the range difference. We have also plotted the corrected smoothed curve of the range measurements so that the curve can be compared to the plot of true range differences.

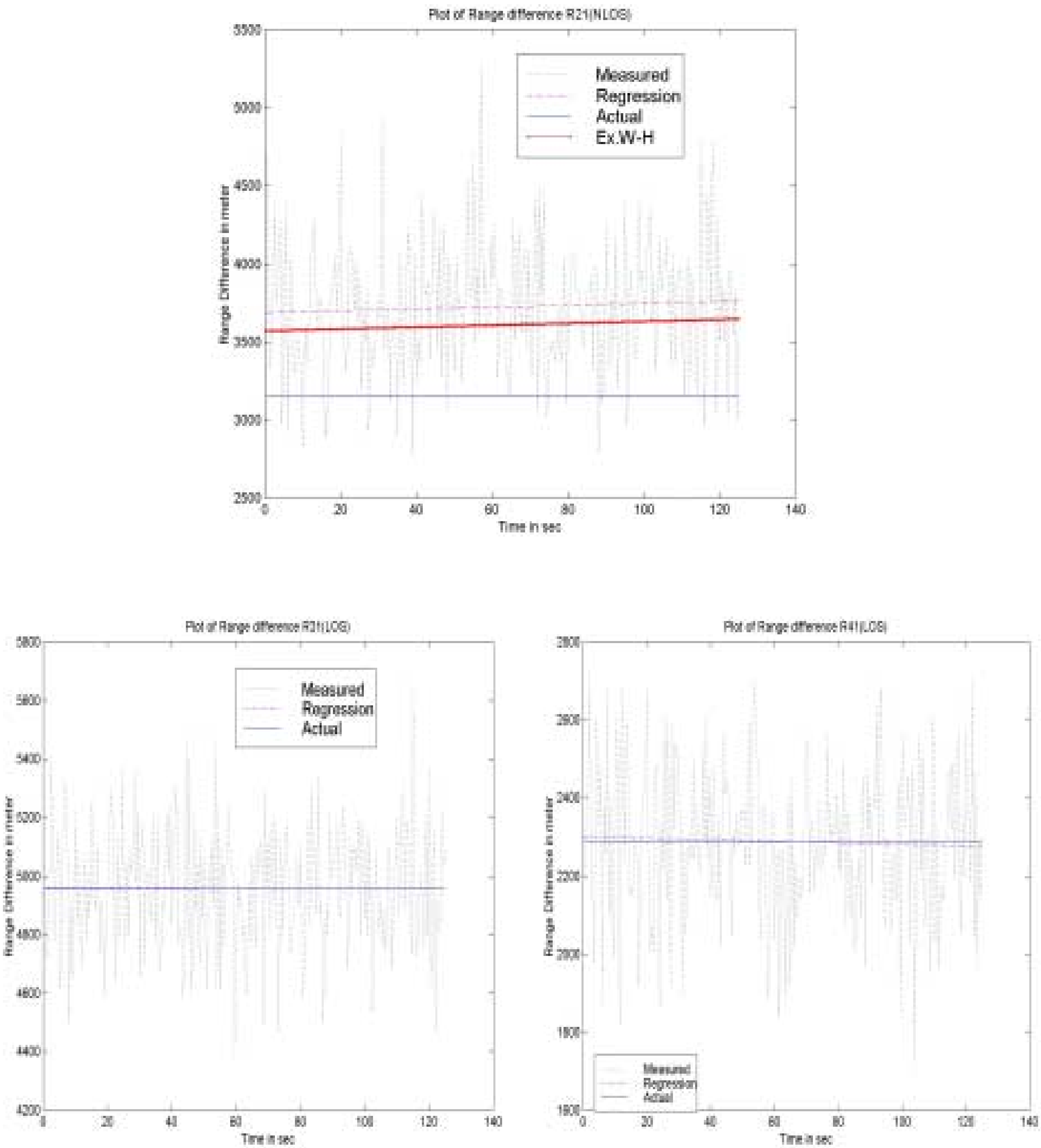

Figure 6.1: Plot of Range Differences vs. time (With Extended W-H Algorithm)

From the plot it is evident that the Wylie-Holtzman algorithm, applicable to the TOA measurements, is not directly applicable to the TDOA measurements. Therefore, in order to reduce the effect of NLOS noise in the TDOA measurements, we have to adopt a different kind of correction method. In the following section we are proposing a new correction method, which would provide better improvement compared to that obtained by the extended Wylie-Holtzman algorithm.

6.3.3 Proposed Correction Method

We are still assuming that the standard measurement noise has zero mean Gaussian distribution with standard deviation of 212.13 meters. Once again we should remind that we are still assuming that the controlling base station BS#1 has a complete LOS with the MS. Therefore if the MS has an NLOS with the I^{th} base station, the corresponding range differences will contain a single NLOS error. The NLOS error will have a single sided Gaussian distribution with mean of 513 meter and standard deviation of 409 meter. In the previous section, we have mentioned that the effect of an NLOS error is only to bias the measured range differences. Since the NLOS error has only positive support ranges, therefore the data will contain a positive bias. On the average, the measurement will have a positive bias almost equal to the mean of the NLOS error. Therefore we propose that, instead of using equation 6.9 for reducing the NLOS error bias in the TDOA ranges, we will shift the raw measurements downwards by the value equal to the mean of the error. Figure 6.2 shows the improvement of the range differences obtained by applying the proposed algorithm. As only the BS#2 has an NLOS with the MS, the range difference R_{21} contains the error bias, and therefore correction method is applied only to these measurements. From the figure it is also evident that, the averages of the measurements R_{31} and R_{41} lie close to the true values. We can also conclude from the figure that, the proposed algorithm can offer significant improvement in eliminating the bias in the TDOA data.

6.4 Validation of Correction Method Applied to TDOA Measurements

Figure 6.2 shows plot of estimated range of the MS from the BS#1 as a function of signal-to-noise ratio. From the figure we find that, for high SNR higher than 22 dB the estimates obtained from the GCC method is close to the estimates where TDOA range measurements are synthesized by the proposed model. For computational simplicity, we will use the model where the TDOA range measurements are synthesized by first determining the true range difference between the base stations using the Euclidian distance approach. We then have modeled the TDOA measurements according to the equation 6.3 described in Section 6.1.

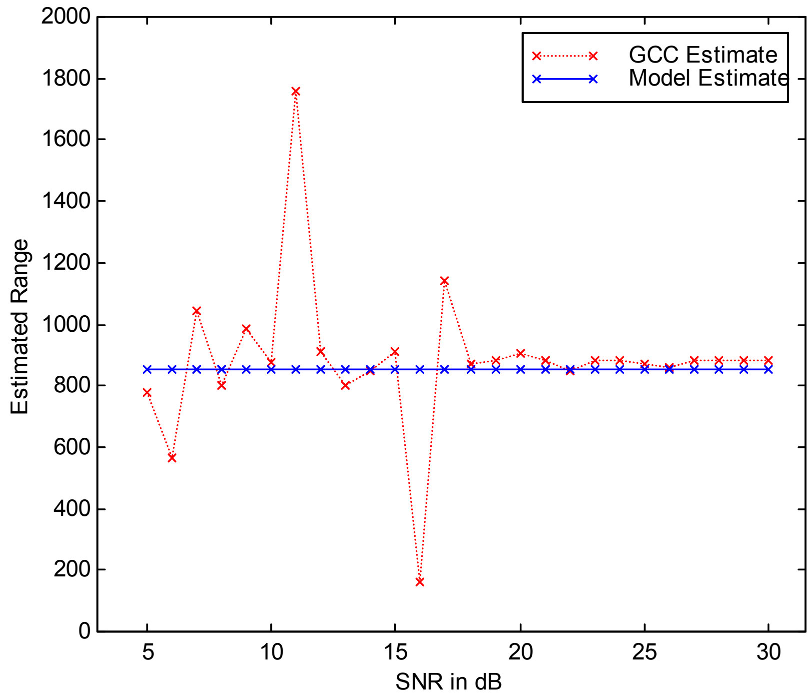

Figure 6.2: Plot of Estimated Range vs. Signal-to-Noise Ratio

At first we would perform the mobile trajectory estimation test and then we would set the velocity of the mobile to zero in order to evaluate the performance of the TDOA PL estimator when proposed correction method is applied to the measurements. The simulator determines the NLOS bias in the measurements by doing hypothesis test and then takes necessary actions to correct the errors. We would choose the position (600, 600) of the mobile as the starting point of the trajectory. The velocity of the mobile would be set to (v_x = 9.7 m/sec, v_y = 16.8 m/sec). The estimator estimates the mobile trajectory from a series of measurements taken at different times.

6.4.1 Mobile Trajectory Estimation

We would estimate the trajectory of the MS, which would move along a straight line. 250 time samples taken at a sampling rate of 2 samples/sec would be considered for the trajectory estimation. The mean and the standard deviation of the standard noise are taken to be zero and 212.13 meters respectively. The values used for an NLOS error are the ones mentioned in the section 6.3.2. Since BS#1 is the controlling base station, all the range differences are calculated with respect to the range of the mobile from the BS#1. In this simulation we have assumed that the BS#1 has a full LOS whereas the BS#2 has an NLOS. Therefore the range difference R_{21} would contain the NLOS error bias and the proposed correction method would be applied to the R_{21} measurements to reduce the bias introduced by the error. Due to the NLOS error, the standard deviation of the R_{21} measurements would be much higher than the standard deviation of the R_{31} and R_{41} measurements. The table 6.1 shows the standard deviation of the range measurements with the above mentioned base station configuration. These standard deviations of the range differences are used for hypothesis testing in determining the presence of an NLOS error in the measured TDOA ranges. The threshold value for hypothesis testing is taken to be 350 meter. From the table, it is evident that the TDOA simulator is able to detect the presence of the NLOS bias in the range measurements R_{21} and would therefore take necessary steps to reduce the effect of the bias in the measurements. The figure 6.3 shows the output of the TDOA PL estimator with different kind of inputs. The dashed line indicates the real mobile trajectory; the dotted line shows the estimated mobile trajectory when the biased raw TDOA data is fed as the input to the estimator. The solid line represents the estimated trajectory with proposed correction method applied to the TDOA measurements. The dotted line represents this trajectory. From the figure we can conclude that our proposed correction method indeed provides significant improvement in determining the MS position location in the Non-Line-Of-Sight environment.

6.4.2 TDOA PL Estimator's Performance with Corrected TDOA Measurements

We will assume that the mobile is stationary in order to evaluate the estimator's performance with corrected TDOA ranges. Therefore, for the simulation results of this section, we will set the velocity of the mobile to zero. Table 6.2 shows the simulator's performance at different MS location. The estimator estimates the x-coordinate and the y-coordinate of the mobile with 250 samples at each location. The 250 estimates are used to determine the mean and variance of the estimator output. The CRLB is included in the table to compare the range standard deviation to the theoretical limit. The uncorrected results are presented, assuming that the BS#2 has NLOS with the MS. The range bias in the table indicates the remarkable improvement obtained by the proposed correction method. We will now see the application of the simulator to the data fusion architecture.

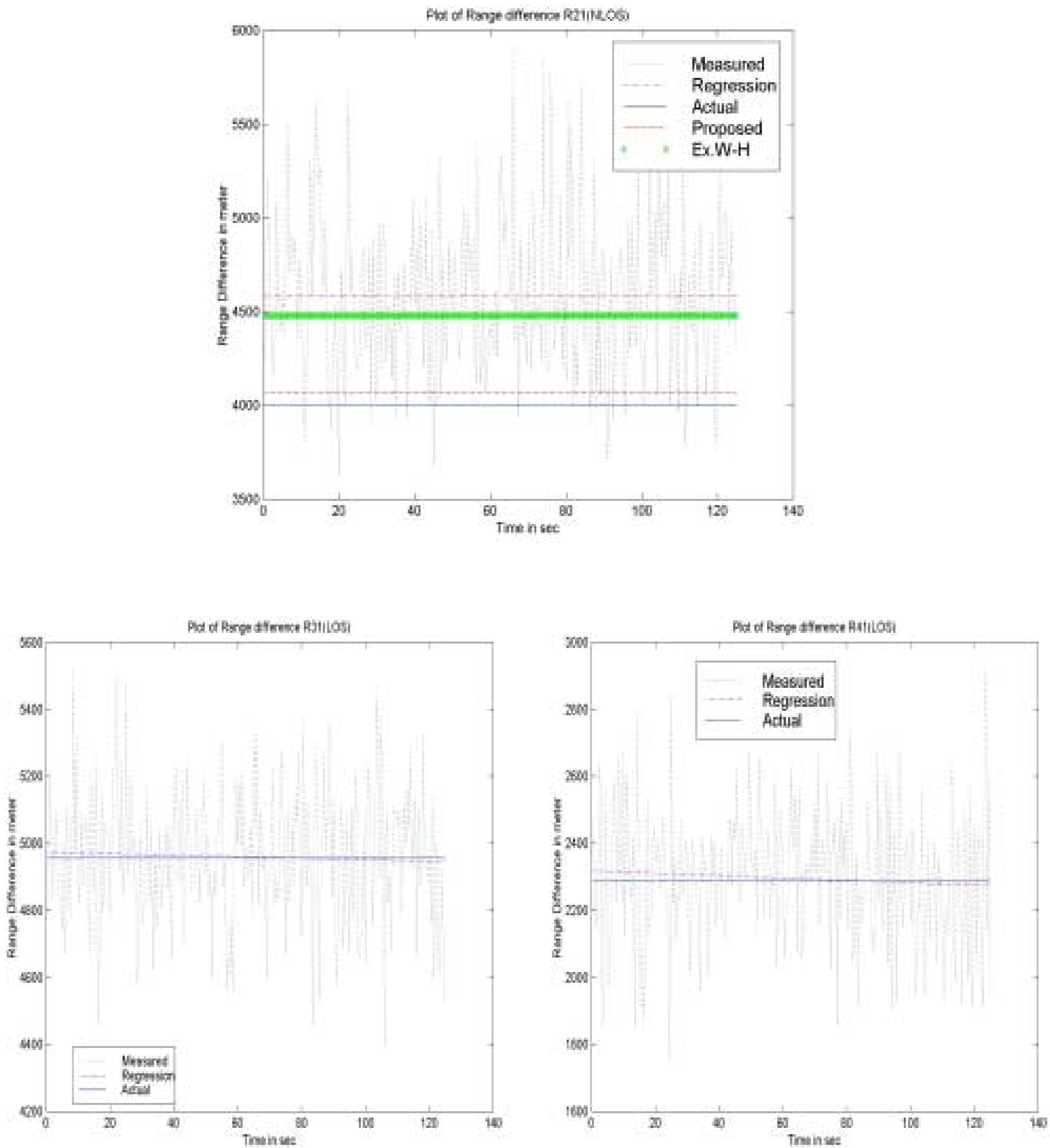

Figure 6.2: Plot of Range Differences vs. time (With Proposed Correction)

Table 6.1: Standard Deviation of TDOA Range Measurements from Smoothed Curve

BS#I	NLOS	$\hat{\sigma}_{i1}$ of R_{i1}
1	No	-
2	Yes	429
3	No	184
4	No	227

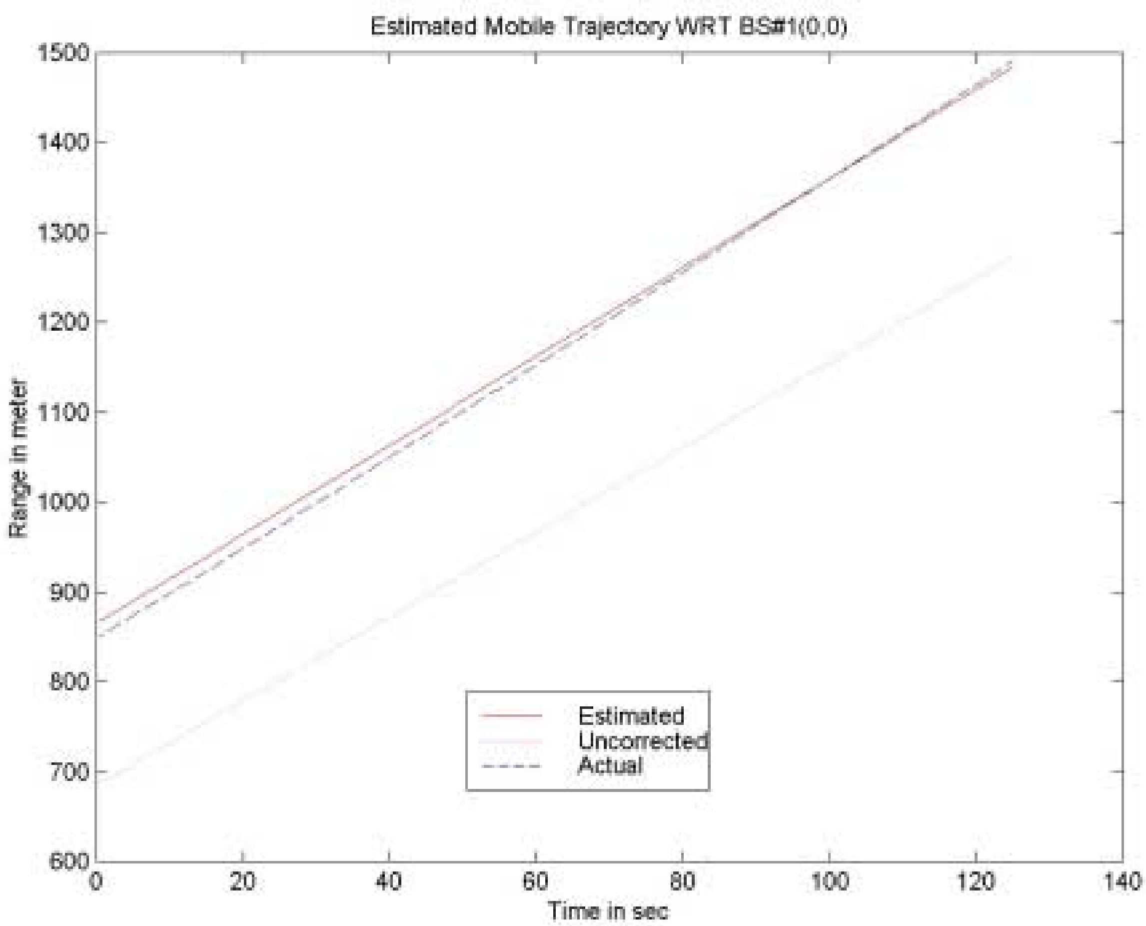

Figure 6.3: Plot of Estimated Trajectory vs. time

Table 6.2: TDOA Estimator Performance at Different Mobile Location

		MS Location	MS Location (MS Far From All BS)	MS Location (MS at the edge of the cell)
Real Position $\left(x_0, y_0\right)$		600, 900	2000, 2000	600, 2500
Estimator Mean $\left(\hat{x}, \hat{y}\right)$	**Corrected**	569, 896	1951, 2015	571, 2533
	Uncorrected	299, 937	1548, 2045	318, 2524
Estimator Standard Deviation $\left(\sigma_x, \sigma_y\right)$	**Corrected**	276, 133	344, 138	313, 142
	Uncorrected	228, 116	327, 128	267, 146
Range Bias, R	**Corrected**	31	52	43
	Uncorrected	303	454	283
Range Standard Deviation, σ_r	**Corrected**	306	371	344
	Uncorrected	256	351	304
$\sqrt{CRLB}$	**Corrected**	333	367	348
	Uncorrected	328	361	348

6.5 Data Fusion Architecture with Corrected TDOA Measurements

The data fusion model for position location problem has already been discussed in Chapter 3. In section 5.4 we have also discussed how this model has been simulated using MATLAB codes. We will discuss briefly the simulation model used to present the results in this section.

The TOA measurements have been synthesized by using equation 2.1. The true distance between the base station and the MS is determined by the Euclidian distance method. The TDOA measurements have been simulated using equation 6.3. The Euclidian distance is used to determine the true range differences. For the TOA PL estimator, the smoothed measurements are used as the input to the estimator. However, for the TDOA PL estimator, the raw measurements are used as the input to the estimator. At the first level fusion, the TOA measurements are used to derive another set of the TDOA measurements. In that case, we used the raw TOA measurements to convert it to the TDOA ranges. The means of the TOA and the TDOA PL estimator are combined at the second level of the architecture. The level-four process determines the best estimate among all the four estimates. The decision is made according to the criterion mentioned in the reference number 23. We should once again remind that, according to the reference number 23, the level-four process decides which of the position estimates is the best one. The decision is mainly based on the approximate position estimate of the TOA estimator and the estimators' variances. If the TOA mean estimate indicates that the MS is within 500 meters radius of the controlling base station, disregard the TDOA estimate; and of the remaining estimates, choose the one with the lowest variance as the best estimate. If the TOA mean estimate implies that the MS is outside the 500 meters disk, choose the TDOA estimates as the best ones, irrespective of the magnitude of the range standard deviation.

The results shown in the Tables 6.3, 6.4 and 6.5 indicate that the TDOA estimator indeed performs best when the MS is located outside the 500 meters disk of the controlling base station. This eventually conforms to the decision criterion mentioned in the reference number 23. Another important observation is that, the performance of the second level data fusion is very close to that of the single TOA estimator. This is mainly because the second level fusion combines the mean from the TOA estimator with the mean from the TDOA estimator. The means are weighted according to the TOA and TDOA estimator variances. The combined estimate originates from the Bayesian inference. The TOA estimate is regarded as the best estimate, and it is updated with the additional TDOA estimate. The higher the variance of the TDOA estimates, the lesser it will be weighted. It is evident from the results that, the TDOA estimator variance is several times higher than the TOA estimator variance. As a result, the TDOA estimates are always weighted much lower than the TOA estimates, and the performance of the second level fusion becomes closer to that of the TOA estimator.

Table 6.3: Estimators' Output in Data Fusion Architecture at MS (600, 900)

		TOA Estimator	TDOA Estimator	TOA/TDOA 1st level fusion	TOA/TDOA 2nd level fusion
Actual Position (x_0, y_0)		(600, 900)	(600, 900)	(600, 900)	(600, 900)
Estimator mean $(\hat{x}, \hat{y})$	**Corrected**	509, 970	580, 873	543, 912	508, 969
	Uncorrected	-	271, 928	435, 921	528, 943
Standard Deviation (σ_x, σ_y)	**Corrected**	6.73, 3.93	258.1, 132.8	177.2, 83.7	6.72, 3.9
	Uncorrected	-	251.6, 113.3	177.4, 89.3	22.2, 29.6
Range bias R	**Corrected**	114.6	33.9	58	114.5
	Uncorrected	-	329.8	166.3	117.3
Range Standard Deviation σ_r	**Corrected**	7.79	290.3	196	7.8
	Uncorrected	-	275.9	198.6	37.6
Choice	**Corrected**		•		
	Uncorrected		•		

Table 6.4: Estimators' Output in Data Fusion Architecture at MS (2000, 2000)

		TOA Estimator	TDOA Estimator	TOA/TDOA 1st level fusion	TOA/TDOA 2nd level fusion
Actual Position (x_0, y_0)		(2000, 2000)	(2000, 2000)	(2000, 2000)	(2000, 2000)
Estimator mean $(\hat{x}, \hat{y})$	**Corrected**	1940, 2082	1967, 2003	1901, 2015	1940, 2081
	Uncorrected	-	1544, 2035	1685, 2030	1927, 2080
Standard Deviation (σ_x, σ_y)	**Corrected**	9.5, 12.1	345.3, 136.9	237.2, 94.2	9.51, 12
	Uncorrected	-	321.4, 124	230, 85.6	10.3, 7
Range bias R	**Corrected**	101.6	31.6	100.4	101.1
	Uncorrected	-	457.3	316.5	108.1
Range Standard Deviation σ_r	**Corrected**	15.39	371.4	255.2	15.38
	Uncorrected	-	344.5	245.4	12.5
Choice	**Corrected**		•		
	Uncorrected		•		

Table 6.5: Estimators' Output in Data Fusion Architecture at MS (600, 2500)

		TOA Estimator	TDOA Estimator	TOA/TDOA 1st level fusion	TOA/TDOA 2nd level fusion
Actual Position (x_0, y_0)		(600, 2500)	(600, 2500)	(600, 2500)	(600, 2500)
Estimator mean $(\hat{x}, \hat{y})$	**Corrected**	526, 2523	571, 2490	553, 2492	525, 2522
	Uncorrected	-	346, 2490	411, 2505	489, 2537
Standard Deviation (σ_x, σ_y)	**Corrected**	14.9, 1.25	337.4, 113.4	202.6, 75.4	14.91, 1.26
	Uncorrected	-	309, 113.1	217, 74	23.6, 5
Range bias R	**Corrected**	77.7	30.7	47.7	77.65
	Uncorrected	-	254	188.6	116.9
Range Standard Deviation σ_r	**Corrected**	15	355.9	216.2	14.95
	Uncorrected	-	329	229.2	24.1
Choice	**Corrected**		•		
	Uncorrected		•		

Table 6.6: Estimators' Output in Data Fusion Architecture at MS (50, 50)

	TOA Estimator	**TDOA Estimator**	**TOA/TDOA 1st level fusion**	**TOA/TDOA 2nd level fusion**
Actual Position (x_0, y_0)	(50, 50)	(50, 50)	(50, 50)	(50, 50)
Estimator mean $(\hat{x}, \hat{y})$	8, 78	466, 532	46, 53	46, 79
Standard Deviation (σ_x, σ_y)	6, 1	21, 20	62, 93	6, 1
Range bias R	51	637	5	29
Range Standard Deviation σ_r	7	29	112	6
Choice				•

Table 6.7: Estimators' Output in Data Fusion Architecture at MS (150, 150)

	TOA Estimator	**TDOA Estimator**	**TOA/TDOA 1st level fusion**	**TOA/TDOA 2nd level fusion**
Actual Position (x_0, y_0)	(150, 150)	(150, 150)	(150, 150)	(150, 150)
Estimator mean $(\hat{x}, \hat{y})$	52, 246	29, 363	105, 175	51, 287
Standard Deviation (σ_x, σ_y)	1, 7	32, 10	52, 122	1, 6
Range bias R	138	245	51	169
Range Standard Deviation σ_r	8	34	133	7
Choice				•

The results in the Tables 6.3 to 6.7 are based on the assumption that only the BS#2 has an NLOS, and all other base stations have complete LOS with the MS. Now we will present the data fusion estimator output with the base station configuration that all the participating BS's have NLOS with the MS. The results will represent the estimators' performance under an extreme harsh environmental condition.

Table 6.8: Data Fusion Architecture Performance at MS (600, 900) with all BS having NLOS

		TOA Estimator	**TDOA Estimator**	**TOA/TDOA 1st level fusion**	**TOA/TDOA 2nd level fusion**
Actual Position (x_0, y_0)		(600, 900)	(600, 900)	(600, 900)	(600, 900)
Estimator mean $(\hat{x}, \hat{y})$	**Corrected**	537, 922	543, 841	500, 846	537, 921
	Uncorrected	-	355, 916	449, 915	651, 992
Standard Deviation (σ_x, σ_y)	**Corrected**	9.4, 15.2	310.5, 245.6	219.5, 168	9.36, 15.18
	Uncorrected	-	264.5, 116.4	194.9, 82.8	17.6, 19.8
Range bias R	**Corrected**	66.5	82.3	113.5	66.4
	Uncorrected	-	246	151.4	105.6
Range Standard Deviation σ_r	**Corrected**	17.86	395.9	276.4	17.8
	Uncorrected	-	289	211.8	26.7
Choice	**Corrected**		●		
	Uncorrected		●		

Table 6.9: Data Fusion Architecture Performance at MS (2000,2000) with all BS having NLOS

		TOA Estimator	**TDOA Estimator**	**TOA/TDOA 1st level fusion**	**TOA/TDOA 2nd level fusion**
Actual Position (x_0, y_0)		(2000,2000)	(2000,2000)	(2000,2000)	(2000,2000)
Estimator mean $(\hat{x}, \hat{y})$	**Corrected**	21163, 2072	1922, 2006	1883, 1946	2115, 2072
	Uncorrected	-	1538, 1667	1739, 1777	2147, 2061
Standard Deviation (σ_x, σ_y)	**Corrected**	30.9, 12.94	377, 280.7	248.8, 192	30.8, 12.93
	Uncorrected	-	317.3, 243.2	241.1, 190.3	6.42, 15.7
Range bias R	**Corrected**	136.7	78.7	128.8	135.5
	Uncorrected	-	569.3	343.8	159.1
Range Standard Deviation σ_r	**Corrected**	33.52	470	314.3	33.44
	Uncorrected	-	399.8	307.12	16.9
Choice	**Corrected**		●		
	Uncorrected		●		

Table 6.10: Data Fusion Architecture Performance at MS (600,2500) with all BS having NLOS

		TOA Estimator	TDOA Estimator	TOA/TDOA 1st level fusion	TOA/TDOA 2nd level fusion
Actual Position (x_0, y_0)		(600,2500)	(600,2500)	(600,2500)	(600,2500)
Estimator mean $(\hat{x}, \hat{y})$	**Corrected**	512, 2542	583, 2448	473, 2445	513, 2543
	Uncorrected	-	463, 2147	557, 2247	716, 2506
Standard Deviation (σ_x, σ_y)	**Corrected**	20.3, 8.1	408.2, 226.7	295.4, 152.8	20.27, 8.11
	Uncorrected	-	299.7, 213.9	247.8, 149.2	23.3, 3.7
Range bias R	**Corrected**	97	54.4	138.2	96.8
	Uncorrected	-	378.7	256.8	116.3
Range Standard Deviation σ_r	**Corrected**	21.9	467	332.6	21.8
	Uncorrected	-	368.2	289.3	23.7
Choice	**Corrected**		●		
	Uncorrected		●		

The results once again indicate the amount of improvement obtained by the proposed correction method even under a harsh environmental condition. Although in most cases when the MS is located outside the 500 meters disk of the controlling base station, the TDOA estimator performs best, there are some cases when we found that first level data fusion performs best. One of such cases is shown in the table 6.8. We find that although the range bias of the second level data fusion is minimum, yet the output of the TDOA estimator is selected to be best estimator since the MS is located outside the 500 meters disk of the controlling base station. This once again indicates that attention must be given to decide optimum estimate in the data fusion architecture. In this research work we did not focus on finding an optimum estimate in the data fusion architecture. Further research should be carried along this avenue.

Tables 6.11 to 6.13 represents data fusion architecture performance where the TDOA data are generated using the GCC method. The channel models described in sections 4.2 and 4.3 are used in these simulation results. In CDMA system, automatic power control is used. The automatic power control causes the MS transmitter to transmit at the higher power when the MS is far from the controlling base station. As a result, the received signal power is stronger at the base stations far away from the MS. This is one of the reasons why TDOA estimator performance improves in the CDMA networks as the MS moves away from the controlling base station. The results indicate to another fact, that the data fusion architecture for PL promises to show better performance in the CDMA system.

Table 6.11: Data Fusion Architecture Performance at MS (600,2500) in GCC with 25 dB SNR

	TOA Estimator	TDOA Estimator	TOA/TDOA 1st level fusion	TOA/TDOA 2nd level fusion
Actual Position (x_0, y_0)	(600, 900)	(600, 900)	(600, 900)	(600, 900)
Estimator mean $(\hat{x}, \hat{y})$	641, 833	588, 843	602, 838	641, 833
Standard Deviation (σ_x, σ_y)	14, 19.3	160, 244	94, 173	14, 19.27
Range bias R	78	58	61	78
Range Standard Deviation σ_r	23.9	292.4	197.1	23.8
Choice		●		

Table 6.12: Data Fusion Architecture Performance at MS (600,2500) in GCC with 25 dB SNR

	TOA Estimator	TDOA Estimator	TOA/TDOA 1st level fusion	TOA/TDOA 2nd level fusion
Actual Position (x_0, y_0)	(2000,2000)	(2000,2000)	(2000,2000)	(2000,2000)
Estimator mean $(\hat{x}, \hat{y})$	2085,1924	1999, 1964	1993, 1911	2084, 1924
Standard Deviation (σ_x, σ_y)	24.8, 21.8	197, 275	121, 191	24.6, 21.7
Range bias R	114	36	90	113
Range Standard Deviation σ_r	33	339.4	226.5	32.8
Choice		●		

Table 6.13: Data Fusion Architecture Performance at MS (600,2500) in GCC with 25 dB SNR

	TOA Estimator	TDOA Estimator	TOA/TDOA 1^{st} level fusion	TOA/TDOA 2^{nd} level fusion
Actual Position (x_0, y_0)	(600,2500)	(600,2500)	(600,2500)	(600,2500)
Estimator mean $(\hat{x}, \hat{y})$	953, 2539	604, 2515	636, 2518	932, 2539
Standard Deviation (σ_x, σ_y)	52.9, 18	197, 247.2	109, 188	51, 18
Range bias R	354	16	40	334
Range Standard Deviation σ_r	55.85	316	218	55
Choice		●		

Chapter 7

Conclusions

Position estimation of the mobile users in the cellular phone networks is becoming an important issue as the deadline for meeting the FCC requirements approaches. A precise position estimation capability will allow the service providers not only to satisfy the FCC requirements but also to offer new services to stay competitive. The RF based techniques are found to be practically viable for the cellular system. This research work provides an overview of different RF based position location techniques, Data Fusion for PL and evaluates the suitability of these structures for E-911 service. In the revised standards for the Phase-II location accuracy and reliability, the FCC regulates that for network-based solutions, all the carriers must be able to locate a mobile with an accuracy of 100 meters in 67 percent of all the calls and 300 meters for 95 percent of all the calls. The main objective of this research is to develop enhanced techniques for reaching these goals.

7.1 Summary of Results

In Chapter 1, we briefly discussed the background of the E-911 service, presenting an overview of modified handset techniques and unmodified handset techniques. Unmodified handset based TOA and TDOA techniques are found to be the most attractive solutions, since these methods can be implemented with minimal changes in the network hardware and software.

Chapter 2 discussed the system independent algorithms of TOA and TDOA based PL techniques. The core part of this research work is based on the results of the examinations conducted by Silventoinen and Rantalainen [4]. According to the work of [4], the Non-Line-Of-Sight propagation is the prime source of error for the TOA measurements. The NLOS error adds a positive bias to the measurements and needs to be removed in order to get an acceptable PL accuracy. The Wylie-Holtzman algorithm suggests a method to eliminate the NLOS bias from the measurements. The chapter includes a discussion on the basic principle of the Wylie-Holtzman algorithm as well. Once the presence of the NLOS bias in the TOA measurements is determined, the Wylie-Holtzman algorithm is applied to eliminate the bias, and then the corrected measurements are used as the input to the TOA estimator. The Taylor-Series Least Square method is used for both the TOA and the TDOA estimator to estimate the position location of the mobile. The Taylor-

Series is used to linearize the non-linear range equations results from the GCC range measurement. The least square error method is used to solve the resulting set of linear equations locally, and therefore the composite method is called the Taylor Series Least Square method. In practice, the TDOA range measurements are calculated using the GCC method. Two base stations receive signals from the MS and the received signals are correlated to determine the TDOA of the signal relative to one base station. The location of the first peak at the correlator output gives an approximate TDOA of the signal. The Circular Error Probability describes the figure of merit of the position estimate. The estimator's performance largely depends on the geometrical configuration of the base station and the mobile unit. The TDOA estimator suffers from a large GDOP when the MS is located close to the BS. In order to measure the accuracy of the position estimator, the RMS position error of the estimator is compared to the CRLB, which is the theoretical limit for the unbiased estimator. The CRLB actually indicates how optimally the estimation process is working.

In Chapter 3, we discussed about the general JDL data fusion architecture and its application to the PL solution. The JDL data fusion architecture is a conceptual model that identifies and categorizes the process, functions, and techniques applicable to data fusion. When same source data is gathered by using multiple independent sensors, the data would have statistical gain over single source data. The main feature of the data fusion architecture is that, decisions are made at different hierarchical levels. One thing should be clearly understood that, the levels are classified according to the type of data used as the input to the decision processor; a higher numbered level does not indicate better decision stage. In general, the source-of-information, human-computer interaction, source processing, level-1 processing, level-2 processing, level-3 processing, and level-4 processing conceptualize the JDL model. Information may be a sensor data or *a priori* information from the database. The data fusion process must work with the data that is most pertinent to the existing condition and at the same time deduce the processing load. Level-1 operates on the raw data and performs multiple functions. We briefly discussed the hybrid model proposed by Hall [14] that combines level one and level two fusion based on the JDL model. The chapter also discussed the data fusion model for position location estimation proposed by Kleine-Ostmann and Bell [23]. The model combines the raw TOA and TDOA data at the first level data fusion. Since only the similar kind of data can be fused, the TOA data are converted to the corresponding TDOA data before fusing at the first level. The control process, which is the second level fusion, makes the final choice about the best estimate. The second level data fusion utilizes the Bayesian Inferences to improve an estimate with known statistics once new data is available. The probability distribution of the old estimate is updated depending on the probability distribution of the new data and the amount of data available.

Chapter 4 included a discussion on the received signal models, path loss models and the additive white Gaussian noise channel. The range measurements between the base station and the mobile unit are linearly proportional to the TOA measurements. When there is a complete LOS between the BS and the MS, only the standard measurement noise affects the true range measurements. Otherwise, the NLOS error has the predominant effect on the range measurements. The path loss model used indicates the average received signal power that decreases logarithmically with the distance. The near-field effects otherwise may alter the reference path loss.

Chapter-5 presents the results for the TOA estimator, the TDOA estimator and the data fusion approach. The TOA data was modeled according to the measurement statistics presented in the reference number [4]. Basically, the chapter presents simulation results that validate the performance of the TOA and the TDOA estimator. The chapter also includes the results to indicate the performance of the data fusion simulator with corrected TOA and uncorrected TDOA measurements. The results are useful to compare the improvement obtained by the proposed TDOA correction method presented in Chapter 6.

Finally, Chapter 6 presents the results of the basic contribution of this research work. In this chapter we have shown how a data model for the TDOA range measurements can be derived from the TOA range models presented in the reference number [4]. The chapter includes a discussion on how the NLOS error bias incorporated in the TDOA range measurements can be reduced to get acceptable location identification accuracy under the non-line-of-sight environmental condition.

7.2 Contributions of this Research Work

The basic contributions of this research work are as follows:

- The new data model for the TDOA range measurements
- Development of the algorithm to reduce the NLOS error bias in the TDOA range measurements
- Evaluation of the Data Fusion Architecture of PL proposed in the reference number [23]

The data model presented in this research is derived from the knowledge of the measurements obtained by Silventoinen and Rantalainen [4]. The model can be used to synthesize the TDOA range measurements, even under non-line-of-sight conditions. The range difference between base stations with respect to the controlling base station is given by the equation 2.2. The standard measurement noise has a zero mean Gaussian distribution with standard deviation of 212 meter. In an LOS environment, the base station measures range difference in the presence of the standard system measurement noise. Depending on the base stations configuration, the mean and standard deviation of the NLOS error will vary. We have derived the equations under the assumption that the controlling base station has a complete LOS with the MS all the time. Under such conditions, the mean and variance of the NLOS error is found to be 513 meter and 436 meter respectively. The NLOS error tends to be the key source of error in the measurements, and therefore needs to be eliminated in order to get acceptable accuracy from the TDOA measurements.

The proposed correction method requires that, at first the NLOS error bias have to be detected in the TDOA data. The bias in the measurements can be identified if we have the *a priori* knowledge of the standard deviation of the standard measurement noise. In the presence of the NLOS error, the measured range differences would deviate from the smoothed curves so that the standard deviation is much greater than the standard deviation of the standard measurement noise.

The proposed correction method is based on the fact that the effect of NLOS error is to positively bias the measured range differences. Since the standard measurement noise has zero mean Gaussian distribution, hence on the average the measurements will have a positive bias equal to the mean of the NLOS error. So to reduce the effect of the bias, the raw measurements need to be shifted downward by the value equal to the mean of the NLOS error. The results shown the Table 6.2 indicates significant improvement obtained by the new correction method applied to the TDOA data in the NLOS environment. We have also applied the proposed data model and the correction method to the data fusion architecture for PL proposed by Kleine-Ostmann and Bell [23]. The performance of the architecture indicates that the model is potential to meet the FCC requirements with improved accuracy. The simulation results show that, the TDOA estimate is usually better than the TOA estimate, but deteriorates faster under an unfavorable geometric configuration of the base stations and the MS. The data fusion architecture for PL is capable of coping with the geometric dilution of precision. The unique property of the model is that, it evaluates two types of input data and tries to achieve better estimate than a single estimate. The best choice of the estimates is made at the level four of the architecture. According to Kleine-Ostmann and Bell [23], the decision is based on the approximate position estimate of the TOA method and the estimator variance. The estimate that is regarded to be the best is the final data fusion process output. If the TOA mean estimate indicates that the MS is in a radius of 500 meter around the controlling base station, the

TDOA estimate is discarded. Under such circumstances, the one with the lowest variance is taken as the final estimate. If the TOA estimate indicates that the MS is located outside the 500 meters radius circle around the controlling base station, then the TDOA estimate is considered to be the best solution. Although most of the simulation results of DF architecture in this research conform to this decision criterion, results of some instances contradict the criterion. For example, in Table 6.6, we find that, although the range bias of the first level fusion is minimum among all the range biases, the second level output is still chosen as the best estimate. Therefore we conclude that the data fusion architecture for PL is indeed suitable for providing solution to the E-911 PL problem with improved accuracy, but the decision criterion is not optimum, and thus requires some modifications.

7.3 Directions for Future Research

The simulation results have shown that both the TOA and the TDOA techniques are eligible for the E-911 PL solution. However, the algorithms have to be tested under real world conditions. The TOA and TDOA data need to be recorded in different terrains so that the statistics can be evaluated properly. The correction algorithms largely depend on the statistical parameters, configured at different environmental conditions.

The work done in this research can be extended in different ways. We have derived the TDOA data model assuming that the controlling base has a complete line-of-sight with the MS. The model needs to be tuned when the controlling base station and the participating base stations have an NLOS with the MS. Analysis should be carried out to find the mean and variance of the NLOS error under such circumstance. Testing is required to verify the proposed correction method with the real TDOA measurements obtained from the GCC method. We have simulated the data fusion model with an ideal base station configuration, and with a simple channel model. It will be interesting to see how the proposed DF model performs with a non-ideal base station arrangement, since cellular layout in the real situations seldom follow the ideal hexagonal layout. In all the simulations we have assumed that the mobile is stationary at a particular location. Investigation can be pursued to see the estimators' perform in the fading channel.

Another avenue of progress would be to delve into the decision criterion used in the control process of the data fusion architecture. Finding an optimum decision criterion in the DF architecture would be a research topic alone.

One of the interesting observations made in this research was the divergence problem of the TDOA estimator. Although it is more of a mathematical problem rather than an engineering problem, yet it will be interesting to find out at what condition the Taylor Series Least Square estimator suffers from the convergence problem.

The position location algorithms require participation of at least three base stations in the process. The requirements of the network for position determination exceed the requirements for communications. The practical cells are laid in a fashion such that it is unfavorable for the position determination algorithm. However, according to Silventoinen and Rantalainen, the accessibility is only a problem in the rural environment. If the decision is made to implement the TOA and the TDOA solutions, the requirements for location estimation must be taken into account in the network planning. Once the hardware of the base stations is modified to implement the position estimation, then from an application standpoint, it is important to know exactly at which layer of the processing stack this process is executed, and how much additional processing load would it require for the switching.

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Vita

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