CHAPTER 4
HYBRID TOA/RSSI BASED PL SYSTEM

4.1. Introduction

The use of cell phones has risen exponentially in the recent past, compelling wireless service providers to scrounge everyday for new technologies to accommodate the enormous population and to provide superior wireless location-based services. However, the biggest challenge the wireless industry faces today is to provide such supreme services, while the user is within an indoor environment. A popular technology used to locate a mobile user in an indoor location is the radio location system that measures the location metrics of radio signals between the Mobile Station (MS)/target and a set of Base Stations (BSs)/receivers. The location metrics of this class, which is with respect to the handset or the network, depends on the magnitude of the received signal strength (RSS), time difference of arrival (TDOA), angle of arrival (AOA), and time of arrival (TOA) as described in [106] and [56]. Before the assessment of location metric, one needs to understand the parameters that play a vital role in altering location metric in indoor conditions. One such parameter is the line of sight between the mobile station and the base stations. When there is an LOS, the quality of the location metrics is precise and this makes the error computation simple. However, in an indoor condition, it is not possible to have an LOS, as there are several obstacles which may either deflect the radio wave or absorb it, causing errors due to excess length, noise or a weak signal. The condition where one does not have an LOS is coined as NON LINE OF SIGHT (NLOS). Thus, the error due to NLOS, which gives rise to a dense multipath of signals, influences the location metrics heavily [107].

Assuming that an ensemble of MS is mainly located in an indoor condition, in this present study, a hybrid TOA/RSSI is used with unconstrained nonlinear optimization
technique adapting UWB radio link. The combination of the two was chosen for the following reasons:

1. The UWB technology has high inherent delay resolution and ability to penetrate obstacles, thus allowing high accurate ranging in the most unsuitable environment for range based localization [85, 86].

2. The UWB facilitates low power, high speed and indoor wireless communication.

3. The knowledge of LOS/NLOS condition is unnecessary as the algorithm uses a previously established path loss model [108, 109] and RSS to distinguish between the NLOS/LOS conditions to establish a geometrically objective function between the BSs and TOA range circles.

Thus, the algorithm using only three TOA measurements using GCC caters to the needs of accurate measurement and ranging of the location metrics in a dense environment. Accurate measurement and ranging of the target location estimation in a complex environment is described in [110, 111] and are prone to errors when used with any other wireless technology. The present study concentrates on accurate location of the target, which depends on weight factors. Assignment of weight factors is based on the results obtained from the hypothesis testing. These factors could be used to give more weightage to the TOA range measurements. Further it will influence the objective function, during the process of target location estimation. Estimation of target position is performed using MATLAB. Simulations were carried out to study the performance of the proposed technique for different scenarios of the NLOS errors.

The forthcoming sections discuss Hybrid TOA/RSSI wireless location algorithm, nonlinear objective function, path loss model, LOS/NLOS BS identification and simulation results along with the conclusions drawn.
4.2. Hybrid TOA/RSSI wireless location algorithm

In this present study, a Hybrid TOA using GCC/RSSI indoor wireless location using unconstrained nonlinear optimization technique is proposed for the UWB radio. The Flow chart of Hybrid GCC based TOA/RSSI wireless location algorithm [112] is shown in Fig.4.1.

![Flow chart of Hybrid TOA/RSSI wireless location algorithm](image)

Fig.4.1 Flow chart of Hybrid TOA/RSSI wireless location algorithm [112]

The TOA which is also popularly known as the spherical PL system is the intersection of multiple spheres, produced by multiple range measurements from multiple base stations. This provides an approximate estimate of the user. The algorithm in this chapter uses only three such spheres whose centre is the BS and radius is the product of TOA measurement and speed of the electromagnetic wave.
Assuming $t_i$ to be the time of arrival at each BS calculated using GCC described in [57], the estimated range $R_i$ corresponding to $i^{th}$ BS can mathematically be represented as

$$R_i = c \times t_i$$  \hspace{1cm} (4.1)

Fig.4.2 Geometry of TOA based localization and MS lies in the overlapped region

If there is no NLOS error and measurement noise, the intersection of three TOA range circles will be the true MS/target position. The NLOS error causes the measured ranges to be greater than the true ranges. The problem with NLOS is that the three TOA range circles do not intersect at a single point. Either they may not intersect at all or they might intersect in a region. The latter case is shown in Fig.4.2. The UWB target can be present anywhere in the region of intersection indicated by the points U, V and W. To find the actual position of the user with a good degree of accuracy, this chapter makes use of optimization algorithm in the following sections.

4.2.1. Nonlinear objective function

The actual ranges between the MS and the $i^{th}$ BS can be mathematically represented as

$$D = \sqrt{(x - x_i)^2 + (y - y_i)^2}$$ \hspace{1cm} (4.2)
where, \((x, y)\) is the true position of MS and \((x_i, y_i)\) is the location of \(i^{th}\) BS.

Let \(P_i\) be the power measurement of received signal from the MS to the \(i^{th}\) BS and \(R_i\) be the TOA measurements. The objective function, in the presence of NLOS error, can be established as the sum of weighted square errors.

\[
F(x) = \alpha_1^2 \mid x - x_u \mid^2 + \alpha_2^2 \mid x - x_v \mid^2 + \alpha_3^2 \mid x - x_w \mid^2
\]

where, \(x_L = (x, y)^T\) is the estimated MS location vector, \(x_u, x_v\) and \(x_w\) represent the position of points \(u, v\) and \(w\) respectively and the reliability of the signals are represented by the weights \(\alpha_i\). The corresponding range measurements in general are more reliable if the weights are smaller. Therefore, by adjusting the weight that correlates each intersection, the location error can be reduced by minimizing the objective function.

### 4.2.2. Selected path loss model

To determine the value of weight factors, the relationship between RSSI and distance is utilized. For a given RSSI and predefined path loss model [108, 109] in a wireless transmission network, the distances from the Mobile Station (MS) to all Base Stations (BSs) can be determined. These parameters i.e. the path loss model and RSSI are also utilized for estimating the transmitter-receiver separations, which are further used in LOS/NLOS identification. The flow chart of the Hybrid TOA/RSSI wireless location algorithm is depicted in Fig.4.1. Indoor environment is simulated by fixing the UWB receivers at the location \((0, 0), (20, 0)\) and \((10, 0)\). To locate the target in 2D plane, this algorithm utilizes three TOA range measurements. It does not require the knowledge of LOS/NLOS situations. The algorithm yields the objective function from the geometrical relationships of the BSs and TOA range circles. It makes use of the RSSI and pre-established path loss model. It approximates the propagation conditions and also discriminates between LOS or NLOS range measurements. Mainly accuracy of the IPS depends on propagation conditions. The
performance of IPS is highly affected if the parameters of the path loss are not exactly known. By using TOA range measurement, hypothesis testing is performed. The result of this testing assigns the weight factors to the objective function. These factors are taken for the objective function during the process of the target’s location estimation. Finally the target position is optimized by unconstrained nonlinear optimization scheme.

A general path loss expression that accounts for the reflection, diffraction and scattering for both LOS and NLOS paths can be expressed as

$$PL(d) = PL_0 + 10^{\gamma} \log_{10}(d/d_0) + S$$  \hspace{1cm} (4.4)

where, $PL_0$ is the mean path loss at the reference distance $d_0 = 1$ m. $\gamma$ is the path loss exponent that depends on the structure of the indoor environment. $S$ denotes lognormal shadow fading in dB. $S$ has an rms value of $\sigma$ (also in dB). For indoor environment, $PL_0$ and $\gamma$ must be properly chosen so that $\sigma$ is minimised. This can be written as

$$S = y\sigma$$  \hspace{1cm} (4.5)

where, $y$ is the zero mean unit variance Gaussian random variable. The spatial variation of random variable $S$ is usually referred to as shadowing and it captures the path loss deviation from its median value. Equation 4.4 defines a statistical path loss model with a fixed intercept point $PL_0$, treating $\gamma$ and $\sigma$ as random variables over buildings [109]. The Gaussian distribution is completely defined by its first and second moments:

$$\gamma = \mu_\gamma + \sigma_\gamma^*x_1$$

$$\sigma = \mu_\sigma + \sigma_\sigma^*x_2$$  \hspace{1cm} (4.6)

where, $x_1$ and $x_2$ are independent and identically distributed zero mean, unit variance Gaussian random variables which vary from building to building. Finally, the complete statistical path loss model is defined as described in [108]. It is given by

$$PL(d) = PL_0 + 10^{\mu_\gamma} \log_{10}(d/1m) + 10^{\sigma_\gamma} \log_{10}(d) + y^{\mu_\sigma} + y^{\sigma_\sigma} \sigma_\sigma$$  \hspace{1cm} (4.7)

where median path loss is $PL_0 + 10^{\mu_\gamma} \log_{10}(d/1m)$ and deviation from median path loss is $10^{\sigma_\gamma} \log_{10}(d) + y^{\mu_\sigma} + y^{\sigma_\sigma} \sigma_\sigma$
The deviation from the average path loss is a combination of effects from the two zero mean, unit variance Gaussian variables $x_1$ and $x_2$ and the zero mean, unit variance Gaussian random spatial variable $y$. The median pathloss for LOS and NLOS condition is defined as

For LOS: $PL(d) = 47.2 + 10 \times 1.82 \times \log_{10}(d/1m)$

For NLOS: $PL(d) = 50.4 + 10 \times 3.34 \times \log_{10}(d/1m)$

where 47.2 and 50.4 denote mean pathloss at the reference distance and 1.82 and 3.34 are the pathloss exponent for LOS and NLOS conditions respectively [109].

**4.2.3. LOS/NLOS BS Identification**

The shadowing effect can be reduced by data smoothening [109]. For this, let $P_i$ be the received mean path loss at $i^{th}$ BS. The $R_{LOSi}$ and $R_{NLOSi}$ are the estimated propagation distances under LOS and NLOS environments respectively and written as:

LOS: $R_{LOSi} = 10^{(P_i-47)/10n_{LOS}}$ (m)

NLOS: $R_{NLOSi} = 10^{(P_i-50.5)/10n_{NLOS}}$ (m)

where $n_{LOS}$ and $n_{NLOS}$ are pathloss exponent for LOS and NLOS condition respectively. The LOS/NLOS decision boundaries yield the value of $R_{Ti}$, which is the threshold values shown in Fig.4.6.

By using the TOA range measurement $R_i$, a testing is performed to discriminate LOS and NLOS conditions:

$H_1$ (LOS): $R_i \geq R_{Ti}$

$H_0$ (NLOS): $R_i < R_{Ti}$

As the result of this testing, the weight factors are assigned by the following rules:

$H_1$ (LOS): $\alpha_i = \frac{|R_{LOSi} - R_i|}{R_i}; R_i \geq R_{LOSi}$

$\frac{|R_{LOSi} - R_i|}{R_{LOSi}}; R_i < R_{LOSi}$

$H_0$ (NLOS): $\alpha_i = \frac{|R_{NLOSi} - R_i|}{R_i}; R_i \geq R_{NLOSi}$

$\frac{|R_{NLOSi} - R_i|}{R_{NLOSi}}; R_i < R_{NLOSi}$

(4.11)
The weight factors from the three BSs describe the credibility of TOA range measurements. The algorithm can be summarized as non-linear unconstrained optimisation approach, and is represented as

\[
(X_{\text{mobile station}}, Y_{\text{mobile station}}) = \text{arg min}\ {F(X)}
\]  

(4.12)

and can be solved by MATLAB unconstrained nonlinear minimization function fminunc.

4.3. Results and Conclusion of the Hybrid TOA/RSSI based PL system

The performance of the location estimation algorithm is examined with the BSs – MS configuration, with true MS location (6, 5) and the coordinates of the BSs are BS1 (0, 0), BS2 (20, 0) and BS3 (10, 10). All the numerical quantities are expressed in metre. Assume one BS is an NLOS measurement and the other two are LOS BSs.

Fig.4.3 shows the output from GCC. The first curve shows the transmitted signal by the MS. The second curve shows the delayed signal received by the BS. The third signal shows the cross correlated output of the first two signals, and gives the time delay of the signal received by BS. This is used for range measurement using TOA.
Fig. 4.3 Generalized Cross correlator output.

Fig. 4.4 shows the effect of weight factors on Average Location Error (ALE) in the TOA algorithm in which NLOS/LOS case is simulated. It indicates that ALE remains constant, if equal weights are selected. Smaller weights mean more precise location estimate.
of the user. These smaller weights exhibit LOS condition between target and the fixed UWB receivers. Smallest weight has been used in this study. The accuracy improvement of location estimation is obtained when any two BSs are of LOS (smaller weights are used) and one BS (larger weight is used) is of NLOS with the target.

Fig. 4.5 shows the estimated mean path loss and its variance of LOS and NLOS data as a function of T-R separation. By using the mean path loss and its variance, decision boundary that separates the path loss under LOS and NLOS conditions can be derived with the help of equation (4.9).

![Fig. 4.5 Estimated mean path loss and its variance](image)

The values $R_{Ti}$ are the threshold values obtained by the LOS/NLOS decision boundary as shown in Fig.4.6.
Let the true position of the target be \((x, y)\) and its estimated value using Hybrid TOA/RSSI based positioning system is \((x_i, y_i)\). Then MSE is

\[
MSE = (x - x_i)^2 + (y - y_i)^2
\]  

(4.13)

From MATLAB simulation, the estimated position of the MS is \((6.078, 5.09)\), whereas the true position of MS is \((6, 5)\). Substituting these values in equation (4.13) gives MSE as 0.0142. Thus it can be seen that for the error model considered, the proposed Hybrid TOA/RSSI location algorithm gives a Mean Square Error of 0.0142. The results are due to the LOS/NLOS identification and the selection of weight factors, which reduce the location error for the proposed algorithm. The NLOS error not only depends on the environment and BSs/receivers – MS/transmitter deployment but also on the performance of different location algorithms. Thus, it can be concluded that this algorithm provides a pragmatic solution to accurate position location in an indoor environment even under grave NLOS conditions.

Recently there is a significant attraction in estimating the position of the mobile target in both indoor and outdoor environments. Chapter 5 discusses the combined indoor-outdoor positioning of the target using UWB and GPS technologies.