Abstract - In this paper, an adaptive learning algorithm is developed using particle swarm to identify and mitigate the non-line of sight (NLOS) signals in ranging measurements. Training data is generated using the IEEE 802.15.4a UWB channel model for different conditions. Multiple metrics derived from this data are fused to identify the NLOS signals. Specifically, kurtosis, mean excess delay and root mean square delay are used as metrics for fusion. The fusion strategy is derived using PSO, considering the correlation between multiple classifiers. We compare the fusion methodology achieved by PSO for the correlated data set to the likelihood ratio based fusion methodology assuming independence. Further, the paper presents an NLOS mitigation approach derived using PSO. A scalar called “error mitigation ratio (EMR)” is defined. The EMR transforms a NLOS measurement into an equivalent LOS measurement. The PSO identifies the EMR using the training data. Application of PSO generated EMR enhances the positioning accuracy and is demonstrated in this paper for indoor wireless channel. This mitigation approach enables us to arrive at a position for the unknown node even when one of the measurements is identified as NLOS. Finally, PSO is used for multilateration to combine measurements from three nodes. Comparisons are done with the linearized least square method.

I. INTRODUCTION

The market demand for location-aware sensor network is continuously growing. A wide range of applications such as object tracking, environmental monitoring, warehouse inventory tracking, vehicle networks, building security and health care systems all require accurate locationing systems. Many of these applications are indoor or in underground environments where GPS systems can not work. The design of such location-aware networks typically requires the capability of peer-to-peer range or distance measurements. Ultra-wideband (UWB) technology is a promising solution for precision ranging due to its fine time resolution to resolving multipath fading. The IEEE 802.15.4a Task Group has developed a UWB based physical layer standard for short-range networks with a precision ranging capability [1]-[3].

UWB based ranging systems usually estimate the transmitter-receiver distance by utilizing the time-of-arrival (TOA) of the received UWB pulses. TOA estimation algorithms have been extensively studied in radar and other applications [4]-[6]. In order to locate a node in 2-D space, at least three nodes whose locations are known are needed. Ranges from the location-unknown nodes to the location-known nodes are used to triangulate the unknown node’s location. Thus, estimating the distance between two peer nodes becomes a key procedure in a location-aware sensor network.

In a multipath channel which is typical for indoor and underground environments, TOA algorithms depend on the direct path (DP) component of the received signal to get the arrival time estimate. In line of sight (LOS) situations, as DP propagates through free-space, the ranges can be calculated by multiplying the speed of light with the signal’s time of flight. When the LOS path between two nodes is blocked, only reflections of the UWB pulse from scatterers reach the receiving node. This is called the non-line-of-sight (NLOS) path. Therefore, the delay of the first arriving pulse does not represent the true TOA. Since the pulse travels an extra distance, a positive bias is present in the measured time delay. In addition to introducing a positive bias, NLOS propagation may also cause a situation where the first arriving pulse is usually not the strongest pulse. Therefore, conventional TOA estimation methods that choose the strongest path would introduce another positive bias into the estimated TOA [7].

In UWB locationing systems, localization accuracies in the order of tens of centimeters have been demonstrated in LOS scenarios [8]. However, in the absence of any information about NLOS errors, accurate location estimation is impossible. Thus, NLOS identification and mitigation techniques for UWB location-aware sensor network become an interesting research topic. Sinan Gezici et. al. proposed a simple variance hypothesis test and a more complex non-parametric identification hypothesis test to distinguish between LOS and NLOS range information [9], [10] uses the root mean square delay spread of the channel impulse response to distinguish between NLOS and LOS. The conditional probability density function of RMS delay spread for NLOS and LOS is well separated. This makes the design of
decision boundary very easy. [11] utilizes three multipath statistics, kurtosis, mean excess delay spread, and RMS delay spread of the CIR is developed for LOS/NLOS identification in [11]. A likelihood ratio test, assuming independence, is utilized to set the decision boundary. However, correlation between these metrics significantly affects the performance. The pearson correlation coefficients between these statistics for different scenarios are presented in Table 1. In this paper, we develop a data fusion algorithm using Particle Swarm Optimization (PSO)[12] to fuse the correlated metrics such as kurtosis, mean excess and RMS delay spread from the IEEE 802.15.4a UWB channel models to help us better distinguish between LOS and NLOS signals.

After identifying NLOS UWB signals, we develop a novel particle swarm enabled learning technique for NLOS range error mitigation. Then we use the resultant range estimates to multilaterate the unknown nodes position. We use a PSO based multilateration algorithm for this. Simulation results show that using our PSO based NLOS error mitigation technique, we can do precise positioning even with NLOS range information. The PSO based multilateration algorithm also can increase the positioning accuracy while reducing computations.

The remainder of the paper is organized as follows. Section II describes the particle swarm optimization algorithm. Section III describes the ultra wideband channel. The channel statistics used as metrics for our hypothesis testing are also given in this section. Section IV provides the design of PSO fusion algorithm for identification of NLOS measurements. The results achieved by the PSO fusion algorithm are compared to likelihood ratio test method. Sections IV presents the NLOS mitigation approach design using PSO. Results achieved using the PSO based mitigation and multilateration are presented in this section. Finally, conclusions are presented in Section V.

II. PARTICLE SWARM OPTIMIZATION

The PSO formulae define each particle as a potential solution to a problem in a D-dimensional space. Hence the ith particle represented as \( X_q = (x_{q1}, x_{q2}, \ldots, x_{qD}) \), where ‘D’ is the dimension number. Each particle also maintains a memory (pbest) of its previous best position, \( P_i = (p_{i1}, p_{i2}, p_{i3}, \ldots, p_{iD}) \) and a velocity along each dimension represented as \( V_i = (v_{i1}, v_{i2}, v_{i3}, \ldots, v_{iD}) \). In each generation, the pbest vector of the particle with the best fitness in the local neighborhood, designated as gbest, and the pbest vector of the current particle are combined to adjust the velocity along each dimension given by

\[
V_{id}^{t+1} = \omega \times V_{id}^{t} + \psi_1 \times (p_{id} - X_{id}) + \psi_2 \times (p_{gd} - X_{id})
\]  

The portion of the adjustment to the velocity influenced by the individual’s own pbest position is considered as the cognition component, and the portion influenced by gbest is the social component. Constants \( \psi_1 \) and \( \psi_2 \) determine the relative influence of the social and the cognition components, and are often both set to the same value to give each component (the cognition and the social learning rates) equal weight. \( V_{max} \) is often used to limit the velocities of the particles and improve the resolution of the search space.

The velocity is then used to compute a new position for the particle. The position update for the continuous part of the particle is given by

\[
X_{id}^{t+1} = X_{id}^{t} + V_{id}^{t+1}
\]  

For position update of the binary component of the particle, first the velocity is transformed into a [0, 1] interval using the sigmoid function given by

\[
sig_{id} (V_{id}) = \frac{1}{1 + e^{-V_{id}}}
\]  

where \( V_{id} \) is the velocity of the ith particle's dth dimension. A random number is generated using a uniform distribution, which is compared to the value generated from the sigmoid function, and a decision is made about the \( X_{id} \) from

\[
X_{id} = u(sig_{id} - U[0,1])
\]  

where \( u \) is a unit step function. The decision regarding \( X_{id} \) is probabilistic.

Algorithm PSO:

\[
\text{For } i=1 \text{ to the max. bound of the number on generations,}
\]

\[
\text{For } d=1 \text{ to the population size,}
\]

Apply the velocity update equation:

\[
V_{id}^{t+1} = \omega \times V_{id}^{t} + \psi_1 \times (p_{id} - X_{id}) + \psi_2 \times (p_{gd} - X_{id})
\]

where \( p_i \) is the best position visited so far by \( X_i \) and \( p_g \) is the best position visited so far by any particle.

Limit magnitude:

\[
V_{id}^{t+1} = \min(V_{max}, \max( - (V_{max}, V_{id}^{t+1}))
\]

Update Position:

\[
X_{id}^{t+1} = \min(\text{Max}_{d} \max((-\text{Min}_{d} X_{id}^{t+1} + V_{id}^{t+1})))
\]

End for-d;

Compute fitness of \( X_i^{t+1} \);

If needed, update historical information regarding \( p_i \) and \( p_g \);

End-for-i;

Terminate if \( p_g \) meets problem requirements;

End-for-i;

End algorithm.

Figure 1. Pseudo Code of Particle Swarm Optimization Algorithm

Accurate localization problem in sensor networks involves multiple sub-problems of different complexity levels. There are no closed form solutions available for these problems. The particle swarm optimization with its simple
operators provides an elegant solution to a sequence of these problems. In this paper we solve a multitude of problems in a locationing system using particle swarm optimization.

III. UWB LOS/NLOS IDENTIFICATION

A. UWB Channel Model

The impulse response of IEEE 802.15.4a channel model can be represented as the sum of the contributions of the different multipath components (MPC):

$$h(t,\tau) = \sum_{i=1}^{N} a_i(t)\delta(\tau - \tau_i) = a_{dp}(t)\delta(\tau - \tau_{dp}) + \sum_{i=2}^{N} a_i(t)\delta(\tau - \tau_i)$$

where \(a_{dp}(t) = a_i(t), \tau_{dp} = \tau_i\) represent the amplitude and delay of the direct path MPC, \(N\) is the total number of the MPCs. \(h(t,\tau)\) can usually be simplified as \(h(t)\).

In this paper, we first collect 100,000 samples of CIR \(h(t)\) as training data by running IEEE 802.15.4a channel model. Then we extract different metrics from the received MPCs forming the training data. Then we learn from these metrics to design decision boundaries for NLOS and LOS signals. We choose kurtosis, mean excess delay and RMS delay as our LOS/NLOS identification metrics.

B. Multiple Identification Metrics

The first metric is the kurtosis of CIR. The kurtosis is defined as the ratio of the fourth order moment of the data to the square of the second order moment (i.e., the variance) of the data [11]. The kurtosis of a CIR \(h(t)\) can be written as:

$$\kappa = \frac{E[(h(t) - \mu_{h(t)})^4]}{E[(h(t) - \mu_{h(t)})^2]^2}$$

Since the kurtosis is the degree of peakness of a distribution and CIR of LOS channel tends to be less dispersive than NLOS channel, we can use the kurtosis as one classifier.

NLOS signals tend to have much higher values of delay-spread statistics [10]. The second and the third classifiers are the mean excess delay and the RMS delay spread. The mean excess delay of \(h(t)\) is defined as:

$$\tau_m = \frac{\int_{-\infty}^{\infty} t |h(t)|^2 dt}{\int_{-\infty}^{\infty} |h(t)|^2 dt}$$

and the RMS delay spread is defined as:

$$\tau_{rms} = \frac{\int_{-\infty}^{\infty} (t - \tau_m)^2 |h(t)|^2 dt}{\int_{-\infty}^{\infty} |h(t)|^2 dt}.$$
For example, if we want to use kurtosis to distinguish CM5 and CM6 as shown in Table III in [11], the identification rates are only 66.3% and 71.4%, respectively. In the following subsections we present a new fusion methodology that fuses the three classifiers to get better classification/identification performance.

TABLE I. CORRELATION BETWEEN DIFFERENT METRICS FOR DIFFERENT CHANNELS

<table>
<thead>
<tr>
<th>Channel</th>
<th>$\kappa$, $\tau_{rms}$</th>
<th>$\tau_{rms}$, $\tau_m$</th>
<th>$\kappa$, $\tau_m$</th>
</tr>
</thead>
<tbody>
<tr>
<td>CM 1 (Residential LOS)</td>
<td>-0.0859</td>
<td>0.6763</td>
<td>-0.446</td>
</tr>
<tr>
<td>CM 2 (Residential NLOS)</td>
<td>-0.20954</td>
<td>0.63955</td>
<td>-0.5281</td>
</tr>
<tr>
<td>CM 3 (Indoor LOS)</td>
<td>-0.0839</td>
<td>0.71932</td>
<td>-0.33084</td>
</tr>
<tr>
<td>CM 4 (Indoor NLOS)</td>
<td>0.067390</td>
<td>0.513283</td>
<td>-0.34728</td>
</tr>
<tr>
<td>CM 5 (Outdoor LOS)</td>
<td>-0.02282</td>
<td>0.5923</td>
<td>-0.37269</td>
</tr>
<tr>
<td>CM 6 (Outdoor NLOS)</td>
<td>0.0341</td>
<td>0.60434</td>
<td>-0.28427</td>
</tr>
</tbody>
</table>

IV. LOS/NLOS IDENTIFICATION USING PSO BASED FUSION OF CLASSIFIERS

The LOS/NLOS identification problem can be considered as a binary hypothesis-testing problem. The two hypotheses are:

$$H_0: \text{LOS channel} \quad (9)$$

$$H_1: \text{NLOS channel} \quad (10)$$

There are two errors in this hypothesis testing problem, known as probability of false LOS ($P_{FL}$) and probability of false NLOS ($P_{FN}$). The probability of false LOS is the detection of the LOS when actually NLOS is present. Similarly, probability of false NLOS is the detection of a LOS signal as a NLOS signal.

In order to formulate the problem, it is assumed that the prior probabilities of encountering a LOS signal or a NLOS signal are the same. Also, we define a cost for false LOS detection $C_{FL}$ and a cost for false NLOS detection $C_{FN}$. These are incorporated into a performance function for evaluating the fusion methodology. The Bayesian cost (error), which the paper intends to minimize, is

$$R = C_{FN} \times P(H_0) \times P_{FN} + C_{FL} \times P(H_1) \times P_{FL}, \quad (11)$$

where $C_{FL} + C_{FN} = c$ and $c$ is a constant. In this paper we assume $c=2$.

A. Likelihood Ratio Test (LRT) Assuming Independence

A likelihood ratio test can be applied to each metric determining the presence of LOS/NLOS. This method works the best if the likelihood probability density models are available for each of the models. In absence of such models, the models can be estimated using the training data. [11] estimates the conditional density models for each of the metric to the lognormal distribution. We employ the same procedure and estimate the parameters for the lognormal distribution for each of the channels data. The parameters for the lognormal distribution for each channel are not given this paper for the sake of brevity. The joint likelihood ratio test, given values $\kappa$, $\tau_{rms}$, $\tau_m$ for a particular observation of CIR, can be applied as in

Figure. 3. (a) IEEE 802.15.4a Outdoor Scenario: channel 3 vs. channel 4, (b) IEEE 802.15.4a Industrial Scenario: channel 7 vs. channel 8
Assuming independence for the three observations the LRT can be simplified [18], [11], as in

\[
P_{\text{LRT}} = \frac{C_{\text{FN}} \times P_{\text{LOS}}}{C_{\text{FN}} \times P_{\text{LOS}} + C_{\text{FP}} \times P_{\text{NLOS}}}
\]

(12)

Let us assume that the classifiers decision thresholds are fixed at \([\lambda_{\text{res}}, \lambda_{\text{los}}, \lambda_{\text{ind}}]\). Here, (17) and (18) require the calculation of joint probabilities. The number of combinations of individual classifier decisions \(n\) determines the number of joint probabilities \(l\) that need to be estimated:

\[
l = 2^n.
\]

(19)

The performance of decision level fusion depends on design of the thresholds and fusion rule. The optimal design of fusion rule and thresholds for each individual classifier is considered in [12]. A particle swarm optimization based (PSO) algorithm is designed in [12] to optimize the thresholds and fusion rule given the training data. A hybrid of binary and continuous PSO is used to achieve the fusion strategy. We employ this algorithm on the training data to achieve the thresholds and the fusion rule. The resultant configuration is applied to testing data.

### TABLE II. LOS/NLOS IDENTIFICATION RATE USING DATA LEVEL LIKELIHOOD RATIO TEST ASSUMING INDEPENDENCE

<table>
<thead>
<tr>
<th>Channel Model</th>
<th>Result on Testing Data</th>
<th>ERROR</th>
</tr>
</thead>
<tbody>
<tr>
<td>CM 1 (Residential LOS)</td>
<td>87.176</td>
<td>0.14793</td>
</tr>
<tr>
<td>CM 2 (Residential NLOS)</td>
<td>83.238</td>
<td>0.04783</td>
</tr>
<tr>
<td>CM 3 (Indoor LOS)</td>
<td>99.992</td>
<td>0.00073</td>
</tr>
<tr>
<td>CM 4 (Indoor NLOS)</td>
<td>99.892</td>
<td>0.0066</td>
</tr>
<tr>
<td>CM 5 (Outdoor LOS)</td>
<td>97.177</td>
<td>0.04783</td>
</tr>
<tr>
<td>CM 6 (Outdoor NLOS)</td>
<td>93.507</td>
<td>0.05066</td>
</tr>
</tbody>
</table>

The results are presented for the PSO based strategy for the three different scenarios in Table III. Error is calculated using (11). The LRT based approach is presented in Table II. Highest performance benefits are achieved in the residential scenario. From Figure 2 one can see that the overlap between the two channels is higher in the residential scenario. A better detection performance in this scenario is hard to achieve. We achieve close to 13% performance benefit by using a...
PSO based fusion strategy. Similar performance benefits are observed in other scenarios as well.

V. PSO BASED NLOS ERROR MITIGATION AND MULTILATERATION

The signals that go through LOS channels cause small random errors compared to the signals that go through NLOS channels, which have larger errors. We build an UWB ranging simulation system using Matlab and collect the range information for developing our NLOS mitigation technique and different positioning algorithms [15][16]. Naturally one expects an increase in the ranging error with the increase of distance between Tx (transmitter) and Rx (Receiver), so we modify the IEEE model according to empirical measurement results from [17].

A. UWB NLOS Range Error Modeling

Following the impulse response of IEEE 802.15.4a channel model in (1), the TOA of the received signal is given by:

\[
\begin{cases}
\tau_{\text{TOF}} = \tau_1 + \tau_s & \text{LOS} \\
\tau_{\text{TOF}} = \tau_1 + \tau_s + \tau_d & \text{NLOS}
\end{cases}
\]

(20)

where \( \tau_n \) is the measurement error caused by noise. Its value can be either positive or negative, modeled as Additive White Gaussian Noise (AWGN). \( \tau_c \) is the extra time that the first MPC takes to go through the NLOS channel, which is modeled in the IEEE 802.15.4a channel model report [15] as:

\[
\tau_c = \left( \frac{1}{2\Lambda} * r_n \right)^2 + \left( \frac{1}{2\Lambda} * r_d \right)^2
\]

(21)

where \( \Lambda \) is the cluster arrival rate. The report lists 4 types of NLOS channels, each has a unique value for \( \Lambda \). \( r_n \) is a random number between 0 and 1. Since \( \tau_n \) does not employ the measurement error’s dependence on Tx and Rx distance, we modify it according to [17] as below:

\[
\tau_c = \left[ \left( \frac{1}{2\Lambda} * r_n \right)^2 + \left( \frac{1}{\sqrt{2\Lambda}} * r_d \right)^2 \right] \log(1+c\tau_i)
\]

(22)

where \( c \) is speed of light, \( d = c\tau_c \) is the actual distance between Tx and Rx. \( \epsilon_{\text{NS}} = c\tau_c \) can be define as the NLOS ranging error, its value is always positive. After the modification to the channel model, the range estimates are more close to the real empirical measurement results. The NLOS ranges then can be described as:

\[
d_{\text{NLOS}} = d + \epsilon_{\text{NS}} + \epsilon_n
\]

(23)

where \( \epsilon_n \) is the ranging error caused by noise.

B. PSO enabled NLOS Error Mitigation Technique

There are a wide variety of algorithms that can used to calculate the position of an unknown location node from the range measurements between the target node and some known neighbor nodes. However, they all severely suffer from the NLOS range errors we mentioned above. After we identify the NLOS signals, there are two ways of using the NLOS ranges. One is to discard them. The other is to mitigate the NLOS errors first and use them in positioning algorithms. In absence of enough LOS ranges it becomes paramount to use the NLOS ranges as well.

The problem now reduces to mitigating the NLOS range \( d_{\text{NLOS}} \) and use it to estimate the real distance \( d \). Specifically the NLOS range measurement can be transformed into its equivalent LOS measurement. In absence of a closed form solution for this transformation, we learn this transformation from the training data. We define an “error mitigation ratio” (EMR) \( r' \) between the NLOS ranges \( d_{\text{NLOS}} \) and real distance as below:

\[
r_i = d_i / d_{\text{NLOS}}
\]

(24)

\[
r = \arg \min F(r_i)
\]

(25)

\[
F(r_i) = \sum_{i=1}^{N} (r_i \times d_{\text{NLOS}} - d_i)^2
\]

(26)

where \( N \) is the total number of data points. Thus NLOS mitigation problem becomes a minimization problem. We use PSO to find the “error mitigation ratio” \( r \) for different \( d_{\text{NLOS}} \) values. For our first set of experiments, we divide the data pertaining to different range bins between 4-16 (bins are formed in steps of 0.5). For each dataset we run PSO to minimize (26) and identify the \( r' \). The results in Figure 4 show that at different \( d_{\text{NLOS}} \) range, the optimized ratio (found by PSO) value \( r \) is different. As a comparison, we present the ratio achieved by averaging the values obtained by using (24) over all data points in each range bin. For our second set of experiments, we combine the entire data and use PSO to arrive at a single ‘\( r' \) across all ranges. This value is 0.8648. As a comparison, we present the ratio achieved by averaging the values obtained using (24) over all the data points. This value is 0.8492. The different empirical \( r \) values we get from our training data enables us to find the error mitigated \( d_m \) value for the \( d_{\text{NLOS}} \) results given by

\[
d_m = r \times d_{\text{NLOS}}
\]

(27)

In our positioning algorithm, we assume we have 2 LOS ranges and one NLOS range. \( d_m \) is used along with the 2 LOS ranges to locate the nodes in a 2-D space.

C. PSO Based Multilateration Positioning Algorithm

We use PSO based multilateration in our positioning procedure. Multilateration is a simple positioning technique, but the specific mathematics of its implementation vary widely. The idea of multilateration algorithm is to use the Cartesian positions of \( n \) known (beacons) nodes
and their measured ranges to the target node $d_i$ to determine the unknown position of the target node $s = (x, y)$.

If those ranges are absolutely precise, the true position of the target node should be at the intersection of all the spheres whose centers are the coordinates of the beacons and radius are the ranges between the beacons and the target node (as shown in Figure 5 ‘A’, ‘B’ and ‘C’ are nodes whose positions are known). However, since the accuracy of range estimation is affected by noise and the NLOS transmission channel, the spheres will not always give a conclusive single intersection point. The basic multilateration algorithm finds the best estimate of the true position $s(x, y)$ by minimizing the sum of the squared errors between each of the measured ranges and the predicted distance as:

$$s = \arg\min_s E(s)$$

$$E(s) = \sum_{i=1}^{n} \left\| s - b_i \right\| - d_i)^2$$

where $n$ is the number of beacons used for locationing. Particle swarm solves this problem efficiently. The fitness function for PSO is $E(s)$, in another form:

$$f(x, y) = \sum_{i=1}^{n} \left( \sqrt{(x_i - x)^2 + (y_i - y)^2} - d_i \right)^2$$

The swarm search space is the two dimensional position of the unknown node $s = (x, y)$ which has the least error $f(x, y)$. The $d_i$’s are the range measurements from each of the known nodes. When a measurement is identified as a signal coming from a NLOS path using the algorithm presented in Section 4, the range measurement is transformed using the error mitigation ratio. This process is illustrated in the Figure 6. It is the zoomed version of Figure 5 and shows that when NLOS error mitigated range (shown as “modified NLOS range”) in the figure is used in (30), the “location error” is greatly reduced.

In order to test the performance of the NLOS error mitigation technique and the PSO based multilateration method, we consider a room (Indoor scenario) of size 40m x 40m. The center of the room is assumed to be the origin and the target node is assumed to be at this position, i.e., at $[x, y] = (0, 0)$ m. The nodes whose positions are known are randomly scattered around the room, at distances of 4m to 10m from the target. The resultant measured NLOS ranges are distributed from 4m to 16m. We compare four different approaches. First, we use the “error mitigation ratio” value found by PSO and the PSO based multilateration approach (PSO MTLR, PSO-ratio). In the second approach a simple mean ratio value (calculated in each range bin) in the NLOS error mitigation procedure is adopted along with the PSO based multilateration (PSO MTLR, mean-ratio). The third approach and fourth approach employ linearized least square method with the two different ratios.

Figure. 4. Empirical $r$ values vs. measured NLOS distance

Figure. 5. NLOS error mitigation in multilateration positioning

Figure. 6. Positioning error comparison between w/o NLOS error mitigation

We ran a Monte Carlo simulation for 10000 cases. The results presented in Figure 7 show that using $r$ for NLOS error mitigation found by PSO, combined with our PSO based multilateration algorithm, the average location error drops significantly to a value less than 1 meter. Traditionally it is difficult to estimate the position of the unknown node with one NLOS and 2 LOS measurements. Usually on encountering an NLOS measurement, more measurements are collected causing delays and/or higher energy utilization. With the swarm based learning approaches presented in this

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paper we are able to achieve a accuracy of 1m by transforming the measurement. The linearized least square approach is highly sensitive to the ratio used. The ratio found by the PSO gives better results than the mean ratio in this case. This demonstrates the efficacy of the PSO algorithm.

Greater advantages are found for the ratio if LLS approach is used. A single step LLS is used to solve the multilateration problem. This is computationally less expensive than PSO based multilateration (which is iterative). The use of PSO defined ratio brings the performance of LLS closer to the PSO based multilateration approaches. Thus the PSO based ratio lets us use the computationally simple LLS technique.

We presented a novel ultrawideband positioning system design using particle swarm enabled learning techniques. First a classification strategy is developed using the particle swarm optimization technique. The classification strategy identifies the NLOS signals from the received signal set. Then a PSO based strategy is developed to mitigate the error due to the NLOS signal. Specifically a ratio is achieved using PSO that transforms the NLOS measurement into its equivalent LOS measurement. Finally, the PSO is used for the multilateration problem, which combines the measurements from three different nodes.

We have compared our strategies to traditionally applied techniques and achieved higher performance. Performance is measured in terms of the Bayesian risk function for the NLOS identification. For localization the performance is measured in terms of the positioning error, i.e. distance from the true position. We are able to achieve less than a meter error when PSO based strategies are used.

VI. CONCLUSIONS

We presented a novel ultrawideband positioning system design using particle swarm enabled learning techniques. First a classification strategy is developed using the particle swarm optimization technique. The classification strategy identifies the NLOS signals from the received signal set. Then a PSO based strategy is developed to mitigate the error due to the NLOS signal. Specifically a ratio is achieved using PSO that transforms the NLOS measurement into its equivalent LOS measurement. Finally, the PSO is used for the multilateration problem, which combines the measurements from three different nodes.

We have compared our strategies to traditionally applied techniques and achieved higher performance. Performance is measured in terms of the Bayesian risk function for the NLOS identification. For localization the performance is measured in terms of the positioning error, i.e. distance from the true position. We are able to achieve less than a meter error when PSO based strategies are used.

VII. REFERENCES