

Identification of the Absence of Direct Path in ToA-Based Indoor Localization Systems

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Abstract Ultra-wideband (UWB) indoor positioning systems based on time of arrival (ToA) techniques are considered to be the high precision alternatives to those employing received signal strength (RSS) or angle of arrival (AoA) due to their superior time-domain resolution. However, the performance of such systems may easily be degraded by the blockage of the direct path (DP) and occurrence of undetected direct path (UDP) condition. By erroneous detection of the other multipath components (MPCs) as DP, which is the indicator of the true distance between the transmitter and the receiver, substantial localization errors will be introduced into the system. Hence, detection of DP categorizes the receiver locations into two main classes of detected direct path (DDP) and undetected direct path (UDP). The real challenge is to be able to identify the class of the receiver location; therefore, to remedy the ranging measurement in UDP condition. In this paper we propose a methodology to identify and mitigate the UDP conditions, which can substantially improve the overall indoor positioning accuracy.

Keywords ToA-based indoor localization · UWB communication · NLoS identification and mitigation · Hypothesis testing

1 Introduction

Localization using radio signals has recently attracted increasing attention in the fields of telecommunication and navigation. The very first program to address this problem on a worldwide scale resulted in launching a series of satellites for the global positioning system (GPS) [1]. Although GPS is widely used for personal and commercial outdoor applications in open areas, it is known that it does not perform satisfactorily in indoor environments due to heavy signal attenuation and multipath and hence needs further improvements.

As expected, the new indoor localization concept has given rise to a multitude of applications in commercial, health care, public safety, and military domains. In the commercial domain, localization has many potential uses in warehousing and in supply-chain management. In the health care domain, there are important uses for tracking/locating patients, medications, and instruments in hospitals, as well as tracking people with special needs such as elderly individuals and individuals with vision and hearing disabilities. In the public safety and military domains, precise localization can be utilized to assist fire-fighters and military personnel in accomplishing their missions [2].

Time of arrival (ToA) based localization techniques are one of the most popular techniques in indoor localization due to their accurate range estimation. Estimating the location of an individual or an object in an indoor environment using ToA can be a difficult task, often producing ambiguous results due to the harsh wireless propagation. The performance of ToA-based localization systems depends on the availability of the direct path (DP) signal [3, 4]. Indeed in its presence, such as short distance line-of-sight (LoS) conditions, accurate ToA estimates are feasible. The challenge, however, is ranging in indoor non-LoS

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(NLoS) conditions which can be characterized as dense multipath environments [3, 4]. These environments introduce several challenges to ToA-based ranging. At first, indoor environment corrupts the ToA estimates due to the multipath components (MPC), which are delayed and attenuated replicas of the original signal, arriving and combining at the receiver shifting the estimate. The second is the propagation delay caused by the signal traveling through obstacles which adds a positive bias to the ToA estimates. The third is the absence of the DP due to blockage, also referred to as undetected direct path (UDP) in [4, 5]. The ranging error is usually defined as the difference between the actual and the measured ToA. It is therefore possible to categorize the propagation channels into two main classes: detected direct path (DDP) and UDP. As a result the statistical occurrence of UDP in an indoor environment is our subsequent concern since the bias imposed by this type of error is usually much larger than in DDP and has a significant probability of occurrence due to metallic cabinets, elevator shafts, or metallic doors that are usually cluttering the indoor environment. Furthermore, mitigation of this problem through increasing the system bandwidth alone has its limitations [5].

Previous studies for identification of class of receiver location (NLoS identification) in cellular domain has been carried out in [6, 7] where they focused on rural and suburban scenarios. In indoor environment, however, the problem of modeling the channel and its propagation parameters becomes more challenging [8]. Research studies for NLoS identification report successful identification of such scenarios [9, 10]. They also propose ranging error mitigation algorithms to improve the accuracy of the localization algorithm [10, 11]. Their research efforts, however, is focused on the problem of NLoS rather than UDP identification and they utilize channel models rather than real-time channel profile obtained from measurement.

Recently, potential technologies emerged to deal with these indoor challenges which include ultra-wideband (UWB) systems [12, 13] and wireless sensor networks (WSNs) [5]. In the former, enhancements in ranging accuracy through the availability of excess system bandwidth makes it possible to resolve the MPCs effectively, thus combating multipath error [14, 15]. The latter approach takes advantage of redundant range measurements between the sensor nodes to further improve the accuracy. Nevertheless, these technologies still suffer in the face of UDP condition which is the major restriction to accurate indoor localization.

In order to deal with these UDP limitations, it is necessary to develop channel identification and mitigation mechanisms. In such schemes, UDP corrupted ToA range measurements must be identified and mitigated before incorporation into the localization process. In literature, significant amount of work has been reported on NLoS

identification and mitigation in localization systems [7, 16]. However the focus is for cellular localization where unbiased range estimation is usually assumed which is clearly not the case in indoor environments. Recently [10, 11] proposed to analyze the statistics of the propagation channel to infer the ranging condition and mitigate it. Although they introduce a unique approach in tackling the problem, they do not focus on UDP conditions and the work is not based on empirical measurements.

In this paper we propose a novel UDP identification and mitigation technique that is based on analyzing the statistics of the propagation channel. Specifically, the technique examines the channel excess delay, power of the first path and the total signal power to infer whether the mobile terminal is ranging in DDP or UDP. Following the identification procedure the range estimate is mitigated through a priori knowledge of the ranging error statistics in both conditions. Results based on simulation and measurements show that localization error can be reduced substantially when our identification and mitigation technique is applied.

The paper is organized as follows; Sect. 2 introduces the fundamentals of ToA-based localization and describes the metrics being used for UDP identification. Section 3 describes the results of the binary likelihood ratio tests for UDP identification while Sect. 4 illustrates the simulation setup and results for a sample indoor environment. Finally, Sect. 5 concludes the paper.

2 Problem Formulation

In this section a brief introduction to the fundamentals of localization utilizing ToA metric is presented.

2.1 General Description

The rich multipath indoor channel environment is characterized as an impulse response

$$h(t, \theta) = \sum_{k=1}^{L_p} \alpha_k \delta(\tau - \tau_k, \theta - \theta_k) \quad (1)$$

where L_p is the number of MPCs, $\alpha_k = |\alpha_k|e^{j\phi_k}$ represents the amplitude and phase of the k th path, τ_k represents the propagation delay of the k th path and θ_k is the AoA of the k th path [17].

The basic concept of any positioning system is illustrated in Fig. 1. The location sensing devices measure the distance-related metrics, between the mobile client, i.e. receiver and a fixed RP, such as ToA, AoA, RSS, and TDoA. The positioning algorithm processes the reported metrics to estimate the location coordinates of the receiver. The display system exhibits the location of the mobile terminal to the user. The accuracy of location estimation is

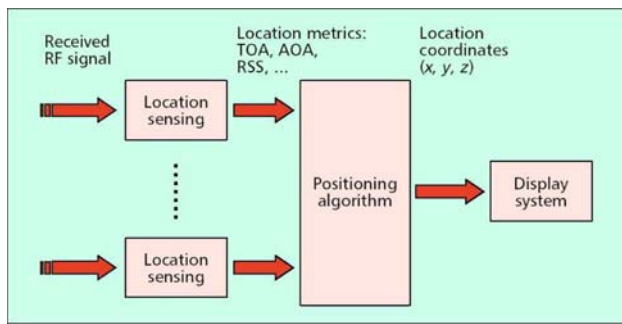


Fig. 1 Basic block diagram of a positioning system

a function of the accuracy of location metrics and the complexity of the positioning algorithm [5].

In ToA-based localization, ToA of the DP of the received signal is used to determine the time of flight, τ_{DP} , between the transmitter and the receiver and consequently the distance between the transmitter and the receiver [18]

$$d_{DP} = \tau_{DP} \times c \quad (2)$$

where d_{DP} represents the distance of the antenna pair, c represents the speed of electromagnetic waves in vacuum, and τ_{DP} represents the ToA of the DP.

The ideal channel impulse response (CIR) is usually referred to as the infinite-bandwidth channel profile since with infinite bandwidth the receiver could theoretically acquire every detectable path. In practice, however, the channel bandwidth is limited. Filtering the CIR with a limited bandwidth filter results in paths with pulse shapes. It can be shown that the sufficient bandwidth for accurate indoor localization based on the ToA metric is around 200 MHz [5] for the receiver to be able, relatively, to resolve the multipath and mitigate the ranging error associated with MPC.

Applying a peak detection algorithm to the filtered channel results in detecting first detected path (FDP) and its respective ToA. The ToA of FDP, τ_{FDP} , is then used to approximate the distance of the antenna pair

$$d_{FDP} = \tau_{FDP} \times c \quad (3)$$

where d_{FDP} is the estimate of the distance of the antenna pair and τ_{FDP} represents the estimate of the τ_{DP} . The erroneous detection of the DP component results in ranging error, ε , which can then be defined as

$$\varepsilon = d_{FDP} - d_{DP} \quad (4)$$

In the absence of multipath and presence of LoS conditions, the estimate of τ_{FDP} is very close to the true value, τ_{DP} , therefore, error is insignificant. However, in practice there are three main sources of ranging errors in indoor localization systems. The first source of error is multipath error which is the shift of FDP from DP due to a combination of bandwidth limitation and presence of rich multipath in indoor environments. The ranging error in the

presence of multipath is inversely proportional to the order of the bandwidth of the measurement system. Indeed in the presence of multipath and of course LoS conditions accurate UWB ToA estimates of the distance are feasible due to their high time-domain resolution [5] which allows the ToA-based localization systems to efficiently and properly function under such conditions. However, in the absence of LoS conditions it is possible for UWB systems to observe large errors depending on the availability of DP. It is worth mentioning that the absence of LoS condition does not necessarily imply that ranging error is bound to be large as discussed below.

The performance of ToA-based localization systems also depends on the availability of DP. Indeed, as mentioned before, in the presence of DP, even in rich multipath environment, accurate UWB ranging and localization is feasible. However, in non-LoS (NLoS) conditions accurate estimates of the distance of the antenna pair are difficult to obtain. The absence of DP (also referred to as UDP) due to blockage is the dominant source of error. The third source of error is associated with propagation delay and difference of the speed of the radio waves in different media.

Previous research relegates the receiver locations of a sample indoor environment into four main categories of DDP, natural-UDP (NUDP), shadowed-UDP (SUDP) and no coverage (NC) [5, 19, 20] which are best described in Fig. 2. In general, DDP and NUDP classes exhibit small ranging errors which makes their range estimate suitable to be used for localization purposes. On the other hand, SUDP class exhibits unexpectedly large ranging error; therefore its respective range estimate, if used for localization purposes, degrades the performance of the system drastically. Range estimate is assumed to be unavailable for NC class.

Detecting the DP component results in accurate ranging estimate of the distance of the antenna pair. On the other hand, the erroneous estimation of the distance of the

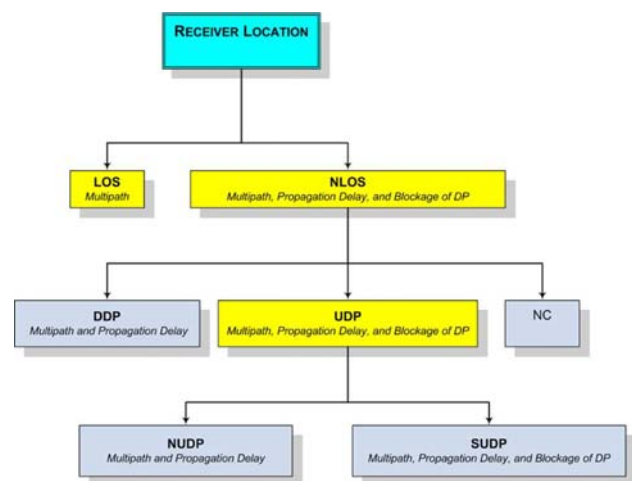


Fig. 2 Hierarchical illustration of the receiver locations classification

antenna pair results in large ranging error observed by the localization system and drastically degrades the performance of such systems. Therefore, we face two hypotheses

$$\begin{cases} H_0 : DDP \mid d_{FDP} \approx d_{DP}, \varepsilon \approx 0 \\ H_1 : UDP \mid d_{FDP} \gg d_{DP}, \varepsilon \gg 0 \end{cases} \quad (5)$$

where H_0 denotes the DDP hypothesis, which indicates that the channel profile can effectively be used for localization, and H_1 denotes the UDP hypothesis, which indicates that the channel profile is not appropriate for being used for localization purposes. d_{DP} , d_{FDP} , and ε are defined in (2) through (4).

In this paper, we propose a methodology to distinguish between the DDP and UDP conditions by investigating the statistics of the specific metric of the channel profile. For the purpose of simulation we formed a grid of receiver locations on the third floor of the Atwater Kent Laboratories building (AK Labs) at Worcester Polytechnic Institute (WPI). We, then, generated the respective CIR of each receiver location for different transmitter locations, for a total of 40,000 CIRs. In order to simulate the real-time channel profile of the CIR, a finite bandwidth raised-cosine filter is used to extract the channel profile. Post processing peak detection algorithm is used to extract the desired metrics, range estimate, τ_{FDP} , and subsequently we can estimate d_{DP} .

There are two types of metrics being extracted from channel profile which can be utilized in identification of UDP conditions. The first class of metrics, is the time delay characteristics of the channel profile, while the second class deals with power characteristics of the channel profile. We

can also utilize a hybrid metric, consists of time and power, in order to classify the receiver location.

2.2 Time Metrics

The time characteristics of channel profiles have been used in literature for variety of applications in communication field [21–23]. RMS delay spread and mean excess delay are being used to determine the data-rate of the communication systems in indoor and outdoor environment. Here, we utilize the time characteristic to identify UDP condition.

2.2.1 Mean Excess Delay

Delay information encrypted in the channel profile is our first time metric to investigate. Amongst all of the delay metrics the mean excess delay of the channel profile is the easiest to find and perhaps the most effective metric, relatively, to efficiently identify the UDP conditions. Mean excess delay is defined as the

$$\tau_m = \frac{\sum_{i=1}^{L_{dp}} \hat{\tau}_i |\alpha_i|^2}{\sum_{i=1}^{L_{dp}} |\alpha_i|^2} \quad (6)$$

where $\hat{\tau}_i$ and α_i represent the ToA and complex amplitude of the i^{th} detected path, respectively, and L_{dp} represents the number of detected peaks.

Conceptually, it can be observed that profiles with higher mean excess delay are more likely to be UDP

Fig. 3 Normality of τ_m for DDP and UDP profiles

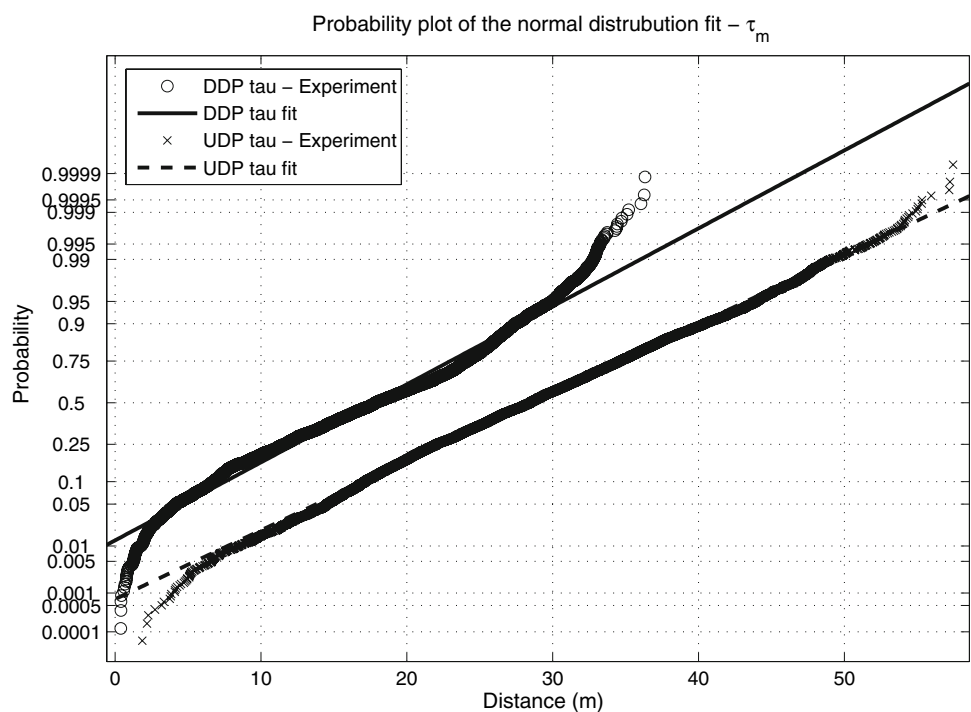


Table 1 The mean and standard deviation of the normal distribution for the τ_m

Channel profile	μ_τ	σ_τ	$K-S_\tau$ (%)	χ^2_τ (%)
DDP	17.65	7.90	94.02	55.61
UDP	28.54	8.95	98.31	59.72

conditions as it is illustrated in Fig. 3 in which the τ_m values are converted to distances. The probability plots of the distribution of DDP and UDP clearly indicates that they can be best modeled with normal distribution and their separation indicates that their normal distribution parameters are distinct.

In order to quantitatively determine the goodness-of-fit of the data to the normal distribution we apply the Kolmogorov–Smirnov (K–S) and χ^2 hypothesis tests. The results of the normal distribution parameters, K–S test and χ^2 test are summarized in Table 1.

It can be observed that normal distribution passes the assumption of normality for both DDP and UDP classes. It is worth mentioning that the other measures of time delay characteristics of channel profile are not found to be as effective for our classification.

2.3 Power Metrics

The other class of metrics that can be extracted from the channel profile are power characteristics. There is hidden information regarding the DDP/UDP classification in the

respective power characteristics. Amongst the useful power metrics, total power and FDP power are the most useful ones.

2.3.1 Total Power

RSS is a simple metric that can be measured easily and it is measured and reported by most wireless devices. For example, the MAC layer of IEEE 802.11 WLAN standard provides RSS information from all active access points (APs) in a quasi-periodic beacon signal that can be used as a metric for localization [18]

$$P_{tot} = r = 10 \log_{10} \left(\sum_{i=1}^{L_p} |\alpha_i|^2 \right) \quad (7)$$

For identification, we used $-P_{tot}$ which is referred to as power loss. It can be observed that profiles with higher power loss are more likely to be UDP conditions. This is best illustrated in Fig. 4 in which their respective probability plots with their Weibull fits are sketched. The separation of the curves illustrates the difference of the $P_{tot} = r$ behavior for different DDP/UDP conditions.

Again, in order to quantitatively determine the goodness-of-fit of the Weibull distribution to the data we apply the Kolmogorov–Smirnov (K–S) and χ^2 hypothesis tests. The results of the Weibull distribution parameters, K–S test and χ^2 test are summarized in Table 2.

It can be observed that Weibull distribution passes the K–S and χ^2 hypothesis tests.

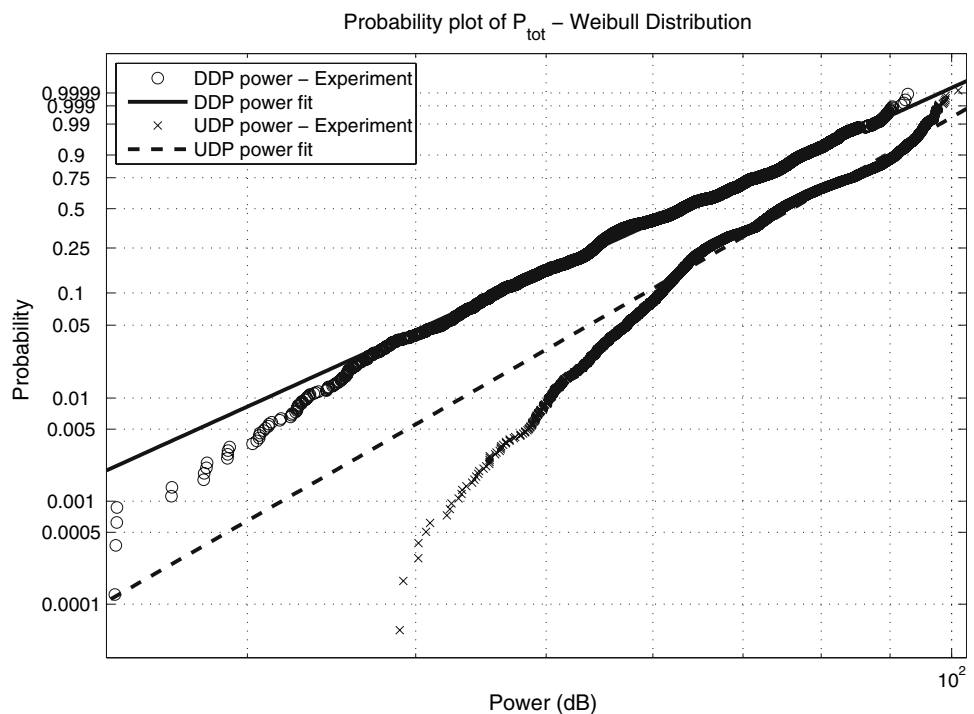
Fig. 4 Weibull distribution modeling of total power

Table 2 The a and b parameters of the Weibull distribution for the P_{tot}

Channel profile	a_P	b_P	$K-S_P$ (%)	χ^2_P (%)
DDP	67.38	5.92	95.11	55.97
UDP	79.94	7.49	94.78	46.51

2.4 Hybrid Time/Power metric

Although, each time or power metric can be used individually to identify the class of receiver locations, but one can form a hybrid metric to achieve better results in identification of the UDP conditions. Here, we propose to use a hybrid metric consisting of ToA of DP component and its respective power as the metric to identify the UDP conditions. Mathematically

$$\xi_{hyb} = -P_{FDP} \times \tau_{FDP} \quad (8)$$

where ξ_{hyb} represents the metric being extracted. It can be shown that the desired metric can be best modeled with Weibull distribution. Figure 5 represents the separation of the fits and proves that the proposed metric can efficiently be used in UDP condition identification.

The results of K-S and χ^2 tests for goodness-of-fit show close agreement for the assumption of the Weibull distribution. The results of the Weibull distribution parameters, K-S test and χ^2 test are summarized in Table 3.

Table 3 The a and b parameters of the Weibull distribution for the ξ_{hyb}

Channel profile	a_m	b_m	$K-S_m$ (%)	χ^2_m (%)
DDP	1056.89	1.50	94.58	56.69
UDP	2236.32	2.08	97.46	55.19

3 Binary Hypothesis Testing for UDP Identification

Knowledge of the statistics of τ_{rms} , P_{tot} , and ξ_{hyb} enables us to identify the UDP conditions. In order to do so binary likelihood ratio tests can be performed to select the most probable hypothesis. For this purpose, we picked a random profile and extracted its respective metrics. The likelihood function of observed RMS delay spread, τ_{rms_i} , for DDP condition can then be described as

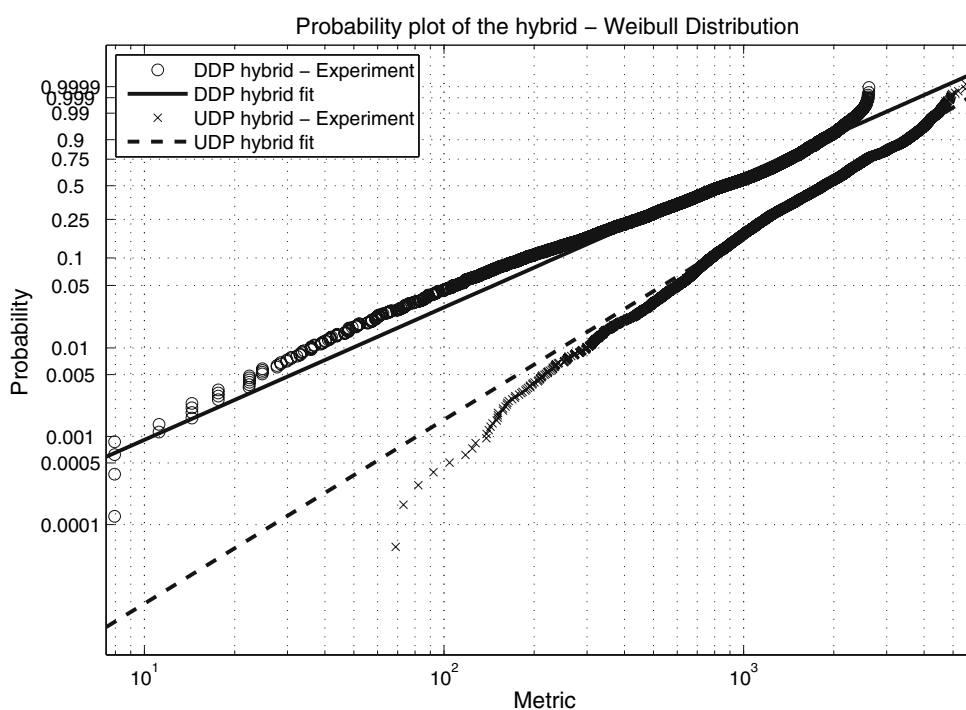
$$L(H_0|\tau_{rms_i}) = p(\tau_{rms_i}|H_0) \quad (9)$$

Similarly, the likelihood function of observed RMS delay spread, τ_{rms_i} , for UDP condition can then be described as

$$L(H_1|\tau_{rms_i}) = p(\tau_{rms_i}|H_1) = p(\tau_u)|_{\tau_u=\tau_{rms_i}} \quad (10)$$

The likelihood ratio function of τ_{rms} can then be determined as

$$A(\tau_{rms_i}) = \frac{\sup\{L(H_0|\tau_{rms_i})\}}{\sup\{L(H_1|\tau_{rms_i})\}} \quad (11)$$

Fig. 5 Weibull distribution modeling of hybrid metric

The defined likelihood ratio functions are the simplified Bayesian alternative to the traditional hypothesis testing. The outcome of the likelihood ratio functions can be compared to a certain threshold, i.e. unity for binary hypothesis testing, to make a decision

$$A(\tau_{rms_i}) > \frac{H_0}{H_1} r_{less} \eta_{rms} \quad (12)$$

Similarly, we can define the likelihood functions for P_{tot} and ξ_{hyb} as

$$A(r_i) = \frac{\sup\{L(H_0|r_i)\}}{\sup\{L(H_1|r_i)\}} \quad (13)$$

$$A(\xi_i) = \frac{\sup\{L(H_0|\xi_i)\}}{\sup\{L(H_1|\xi_i)\}} \quad (14)$$

which leads us to the corresponding hypothesis tests as

$$A(r_i) > \frac{H_0}{H_1} r_{less} \eta_r \quad (15)$$

$$A(\xi_i) > \frac{H_0}{H_1} r_{less} \eta_\xi \quad (16)$$

Each of the above likelihood ratio tests can individually be applied for UDP identification of an observed channel profile. The outcome of the likelihood ratio test being greater than unity indicates that the receiver location is more likely to be a DDP condition and can appropriately be used in localization algorithm while the outcome less than unity indicates that the profile is, indeed, more likely to belong to UDP class of receive location; hence, the estimated τ_{FDP} has to be mitigated before being used in the localization algorithm.

To use the likelihood functions more effectively, we can combine the functions and form a joint likelihood function. Assumption of the independence of the likelihood functions along with combining them leads to a suboptimal likelihood function defined as

$$\begin{aligned} \delta(\tau_m, P_{tot}, \xi_m) &= A(\tau_m, P_{tot}, \xi_{hyb}) \\ &= A(\tau_m) \times A(P_{tot}) \times A(\xi_{hyb}) \end{aligned} \quad (17)$$

which can be compared to a certain threshold for decision making, i.e. $A(\tau_m, P_{tot}, \xi_{hyb}) \underset{H_1}{\overset{H_0}{\geq}} \eta_\delta$. The results of the accuracy of the likelihood hypothesis tests, individually and as a joint distribution, are summarized in Table 4.

Table 4 Accuracy of the Likelihood Hypothesis Test

Likelihood ratio	Correct decision (%)
τ_m	70.85
P_{tot}	67.06
ξ_{hyb}	69.73
δ	89.29

It can be observed that the accuracy of using individual metrics for identification of UDP conditions is about 70% while combining the metrics for UDP identification can achieve 90% of accuracy.

4 Simulations and Results of Localization Using ToA Measurements

In two-dimensional localization, knowledge of three accurate distance measurements from three known reference points (RPs) will be sufficient to accurately locate the mobile terminal with the help of trilateration. Increasing the number of RPs will enhance the accuracy of the system as it increases the likelihood of observing three or more precise ranging measurements from RPs. In such scenarios, one approach to mitigate the UDP problem is to simply discard the profiles suspected to be UDP. In practice, however, those scenarios are rare and positioning systems often have access to only three RPs. In these cases, we have to mitigate the ranging error of the ToA measurement system. In practice, harsh indoor wireless environment introduces erroneous estimates of distance which degrades the performance of the localization algorithm.

One approach to the localization problem is to use least-squares (LS) method to solve the trilateration equations of the form

$$\begin{cases} (x_r - x_1)^2 + (y_r - y_1)^2 = d_{DP_1}^2 \\ (x_r - x_2)^2 + (y_r - y_2)^2 = d_{DP_2}^2 \\ (x_r - x_3)^2 + (y_r - y_3)^2 = d_{DP_3}^2 \end{cases} \quad (18)$$

in which d_{DP_i} represents the distance of the transmitter and the receiver. However, erroneous detection of DP and approximating d_{DP_i} with d_{DP_i} degrades the performance of the localization algorithm. The particular instance of the LS algorithm that has been used for our evaluations is the one by Davidon [24], which attempts to minimize the objective function

$$f(\mathbf{x}) = \sum_{k=1}^N \left(d_k - \sqrt{(x_r - x_k)^2 + (y_r - y_k)^2} \right)^2 \quad (19)$$

$$\mathbf{x} = [x_r \quad y_r]$$

in an iterative manner using the following relation

$$\mathbf{x}_{k+1} = \mathbf{x}_k - \mathbf{H}_k \mathbf{g}(\mathbf{x}_k) \quad (20)$$

where $\mathbf{H}_k$ represents an approximation to the inverse of the Hessian of $f(\mathbf{x})$, $\mathbf{G}(\mathbf{x})$, which is defined as

$$\mathbf{G}(\mathbf{x}) = \begin{pmatrix} \frac{\partial^2 f}{\partial x^2} & \frac{\partial^2 f}{\partial x \partial y} \\ \frac{\partial^2 f}{\partial y \partial x} & \frac{\partial^2 f}{\partial y^2} \end{pmatrix} \quad (21)$$

and $\mathbf{g}(\mathbf{x})$ is the gradient of $f(\mathbf{x})$, defined as

$$\mathbf{g}(\mathbf{x}) = \nabla f(\mathbf{x}) \quad (22)$$

The following relation defines when the computations will be terminated

$$\rho_k = (\mathbf{g}(\mathbf{x}_{k+1}))^T \mathbf{H}_k(\mathbf{g}(\mathbf{x}_{k+1})) \quad (23)$$

so that the iterations will stop when $\rho_k \leq \varepsilon$, where ε is a small tolerance value.

4.1 Simulations

For simulations, an internally developed ray tracing software has been used [25] and the output of this software has been processed by Matlab[®] by using Davidon's least squares algorithm [24]. The floorplan chosen for the simulations is the third floor of AK Labs at WPI. The transmitters have been placed as shown in Fig. 6 indicated by triangles. The metallic chamber and the elevator shaft, shown as black shaded boxes, block the DP for a certain portion of the receiver's pathway (indicated by blue dots) and hence leads to large localization errors (indicated by black dotted estimates). The RMSE value of localization error in this case is found to be 3.12 m.

Next we examine the UDP identification and range estimate mitigation associated with it. Identifying the UDP scenarios with the above method gives us an edge to mitigate the ranging estimate associated with the profile. Since the exact value of the error is not known, the best is to use the statistics of the error [26] and subtract that value from the observed estimated ranging and

$$\begin{aligned} \tau_{DP} &\simeq \tau_{FDP} - \varepsilon_\tau \\ d_{DP_i} &\simeq d_{FDP_i} - \varepsilon_d \end{aligned} \quad (24)$$

Mitigating the distance measurement of the antenna pair and employing the idea on the previous scenario results in enhanced localization error observed by each receiver location and greatly improves the accuracy of the

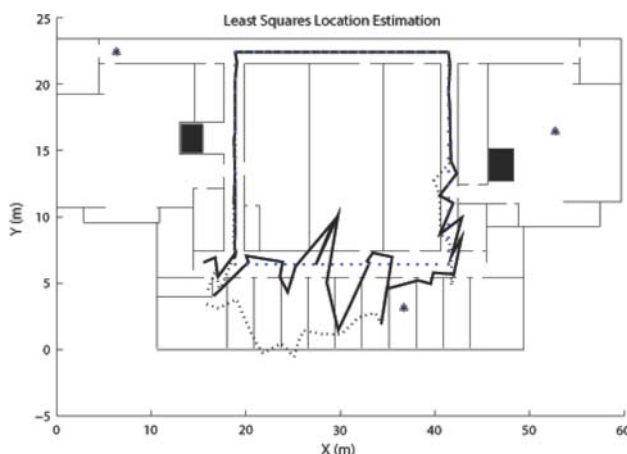


Fig. 6 Localization error in sample indoor environment—simulation

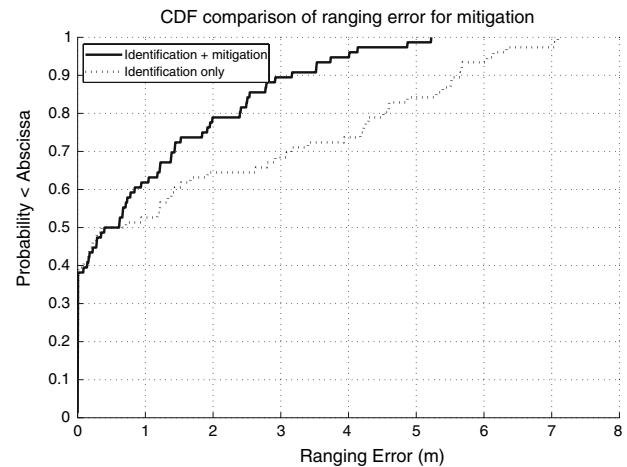


Fig. 7 CDF of localization error for sample indoor environment—simulation

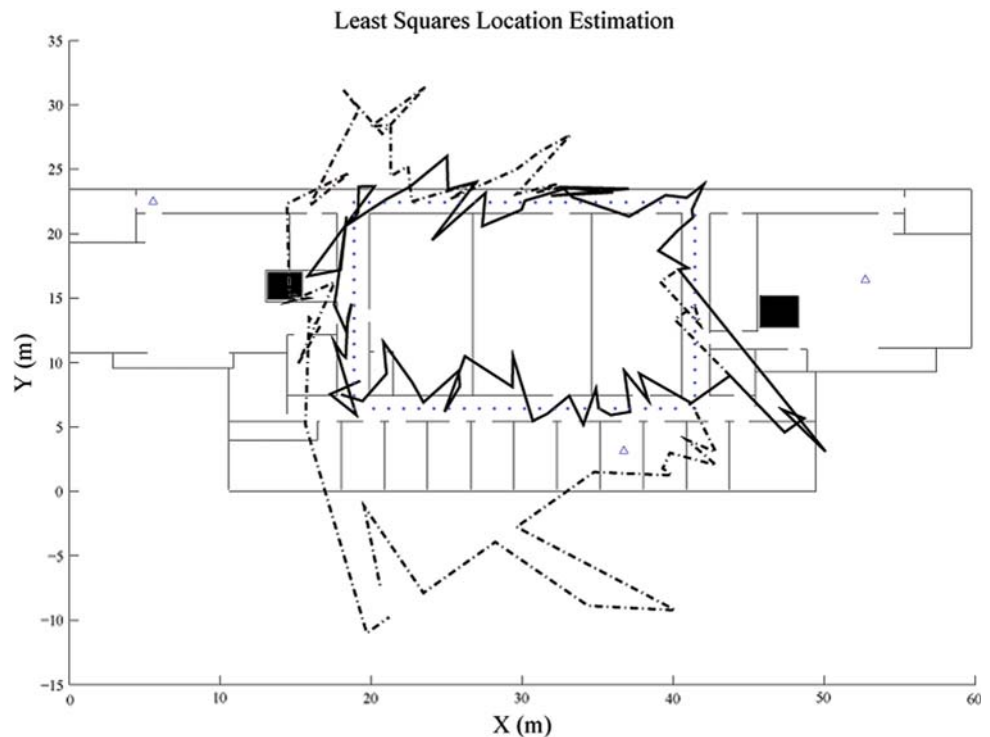
localization system. Figure 6 illustrates the estimation results in black solid line. It can be observed that identifying the UDP condition and mitigating the ranging error associated with such receiver locations, greatly improves the localization error observed in UDP receiver locations.

The RMSE value of the localization error has also improved by 50% and has dropped to 1.56 m. Obviously, the identification method is not absolute for all the receiver locations and it may identify some DDP profiles as UDP and by mistake subtract a correction value from their estimated ToA which will result in accuracy degradation at some receiver locations. However, as Fig. 6 illustrates, the identification and mitigation together can enhance the accuracy of the localization algorithm. Figure 7 compares the CDF of localization error associated with each scenario. It can be observed that even though localization error has increased at certain receiver locations, it has helped the algorithm to identify the UDP conditions and mitigate their ranging measurement to a more accurate location estimation on average.

4.2 Measurements

For the purpose of validating our approach in real world scenarios, we conducted UWB frequency domain measurements on the grid of receiver locations on the third floor of the AK Labs WPI. The measurement system consisted of vector network analyzer (VNA), monopole quarter wave antenna, low-noise amplifier and power amplifier. Measurements were taken from 750 MHz to 1.25 GHz, centered around 1 GHz, to provide enough bandwidth to resolve the MPCs. The results of the frequency domain measurements were then post-processed in Matlab[®] to obtain the time domain response using chirp-z

Fig. 8 Localization error in sample indoor environment—measurements



method along with raised-cosine filter. A Peak detection algorithm was then used to extract the MPCs, τ_{FDP} , and other desired metrics. τ_{FDP} is then used to approximate the spacing of the antenna pair.

To emphasize on the importance and significance of identification of UDP condition, Fig. 8 describes localization with only three known RPs in the presence of multipath and blockage (black dotted line). The RMSE value of localization error is found to be 8.42 m. The main reason for increased RMSE as compared to ray tracing is that in the real world scenario there are several micro metallic objects such as metallic shelves, doors, and cabinets which block the DP component from the transmitter to receiver; therefore, the channel profile exhibits an erroneous range estimate. In ray tracing only major walls and large metallic obstructions are considered.

When we applied UDP identification and error mitigation as described earlier, we observed that the RMSE value of the localization error has also improved by 60% and has dropped to 3.53 m.

Figure 9 compares the CDF of localization error associated with each scenario. Similar to the simulation case, it can be observed that, although localization error has increased at certain receiver locations, on average it has helped the algorithm to identify the UDP conditions and mitigate their ranging measurement for a more accurate location estimation.

Comparing the results of measurement with simulation reveals that for indoor environments the presence of

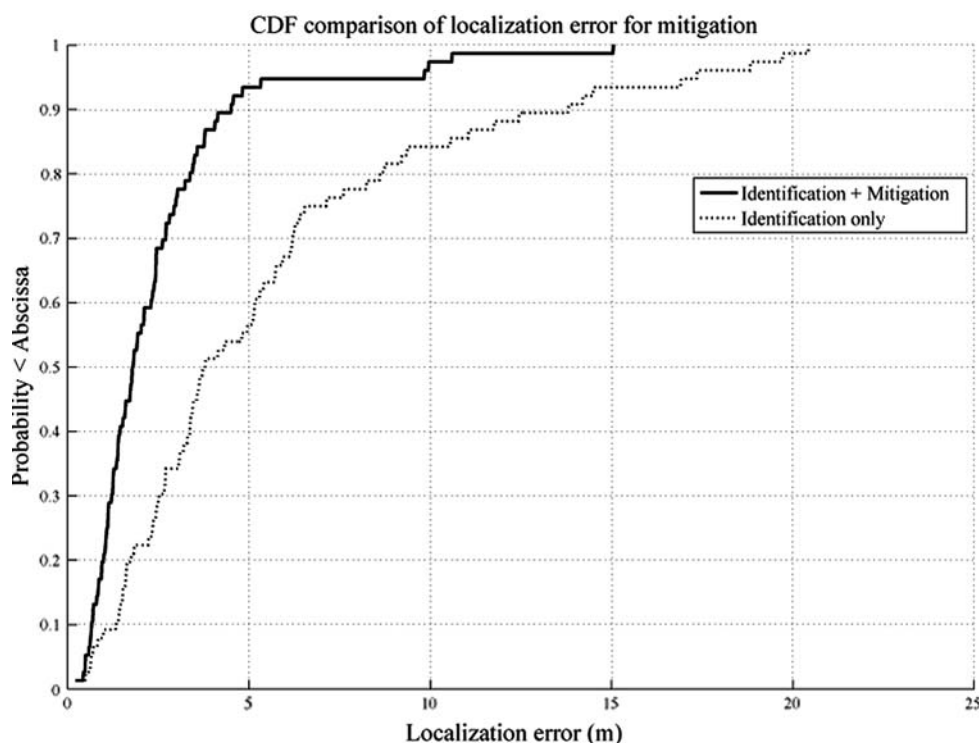
metallic objects degrades the accuracy of the range estimate. In simulations, due to limitations of the setup, it was not possible to include all the details and hence we can observe profiles with no ranging error. However, in a more realistic situation, which measurements are used for range estimate, all the channel profile exhibit range errors and hence localization becomes more challenging. This results in larger localization error as can be observed from Fig. 6 compared to results of localization using real-time measurement range estimates presented in Fig. 8.

It can also be observed that in both cases, and especially in more realistic scenarios, employing the idea of UDP identification and mitigation of range estimate helps the localization system to achieve better localization accuracy, as it can be observed from Figs. 7 and 9.

5 Conclusion

In this paper we have introduced a methodology to identify the UDP conditions and mitigate the large errors caused by it. We have proposed the use of power and time metrics for the received channel profile to obtain the likelihood functions for binary hypothesis testing. Comparing the outcome of the hypothesis tests to a certain threshold determines if a receiver is in DDP or UDP condition. Once the condition is identified, the ranging error associated with it can be mitigated. The results of ray tracing are then validated with real-time measurements conducted in the same

Fig. 9 CDF of localization error for sample indoor environment—measurements



environment. We can observe that in both scenarios, simulations and real-time measurements, identification of the UDP conditions used along with limited primary knowledge of the ranging error for UDP conditions can significantly improve the accuracy of the localization system.

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