ISSN No:-2456-2165

A Survey of Hybrid Wireless Localization Techniques in Non-Line-of-Sight

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Abstract:- Wireless localization plays a key role in enabling location-based services in commercial, healthcare, public safety, and military applications. Thus, an increasing number of localization techniques have been proposed based on motion or location dependent parameter (MLDP) including time-of-arrival (TOA), time-difference-of-arrival (TDOA), received signal strength (RSS), angle-of-arrival (AOA), angle-of-departure (AOD), Doppler-shift (DS), etc. Recently, the expansion, heterogeneity, and coexistence of wireless networks stimulate new research efforts in developing novel hybrid localization techniques, which utilize combinations of two or more MLDP types. However, the accuracy of these localization techniques highly depends on complex electromagnetic spectrum, e.g., multi-user interference, multipath effects, and non-line-of-sight (NLOS) propagation. The latter issue has been known as a major source of localization errors in wireless systems. Therefore, developing robust localizing algorithms for coping with NLOS propagation is of great importance. The aim of this paper is to survey the key characteristics and technical challenges of hybrid wireless localization techniques in NLOS environments, to provide comprehensive performance analysis and finally to identify possible new research directions and further improvements.

Keywords:- *Hybrid Localization Techniques, Non-Line-of-Sight (NLOS) Identification, NLOS Mitigation, Wireless Localization, Positioning.*

I. INTRODUCTION

The proliferation of mobile devices, decreasing deployment costs, and rapid advancements in wireless technologies have fostered a growing interest in location-aware services. Satellite based global positioning system (GPS) is by far the most popular localizing technology in use today, which can provide high precision and real-time localization only if the GPS receiver is covered by at least four satellites. However, this condition is not always satisfied for indoor, dense urban and underwater environments, where satellite signals can either be largely attenuated or even get completely blocked by various solid and dense objects. In order to offer accurate and ubiquitous localization solutions, wireless localization techniques have been developed in which the location of unknown nodes can be inferred with help from nodes with knowledge of their location, called anchor nodes, by means of the intersection of range measurements from anchor nodes. Hence, wireless localization techniques serve as a complement or replacement of the GPS when the latter is not reliable or operational.

Over the past years, there has been an increasing demand for wireless localization techniques in many applications. For instance, precise indoor positioning system can support elderly living alone, children and people with special needs who may be out of visual supervision. In smart buildings, localization is needed for optimizing energy management systems based on occupancy levels, access control, and security. In hospitals, accurately localizing the in-demand portable equipment, assets, and staff can help in lowering operational cost and increasing efficiency. In public safety and military operations, real-time localization capability enables navigation and coordination of police officers, firefighters, or soldiers to complete their mission inside buildings, reduce risks in rescue operations, and locate victims faster. In addition, accurate wireless localization will play a key role in other important applications such as location-sensitive billing, intelligent transportation, fraud protection, mobile yellow pages, and animal tracking.

Localization of wireless nodes can be commonly realized by measuring motion or location dependent parameter (MLDP) such as received signal strength indicator (RSSI), time of arrival (TOA), and time difference of arrival (TDOA), Doppler-shift (DS) from anchor nodes at known location. Consequently, distances between an unknown node and anchor nodes are calculated from these MLDPs and then passed to the estimation techniques such as least-squares, maximum likelihood estimation, and convex optimization to determine location of the unknown node. A large number of non-hybrid techniques, which employs one type of MLDP, have been extensively studied for location estimation, each with its own advantages and limitations. Driven by the diversity of applications, widespread implementation of heterogeneous wireless networks, and the ease of obtaining a variety of localization metrics, the hybrid localization techniques, which utilize combination of MLDP types, have attracted significant research interest. One of the main advantages of hybrid techniques is to overcome the limitations of non-hybrid techniques by exploiting their complementary behavior. Moreover, fusion of different MLDP types can compensate some inaccurate measurements, and hence increase accuracy of the localization performance. Hybrid localization techniques are also useful in weak mobile hearability conditions or low base stations (BS) density. In

ISSN No:-2456-2165

particular, hearability is the ability to simultaneously receive signals with sufficient power from neighboring BSs, and low hearability conditions can adversely affect the performance of the deployed localization technique. More[1]over, the accuracy of the location estimation highly depends on the propagation conditions of the wireless channels. High accuracy can be achieved when the line-of-sight (LOS) paths between the unknown node and anchor nodes are present. However, harsh radio propagation environments such as through tunnels, under bridges, tree canopies, or other enclosed areas commonly cause non-line-of-sight (NLOS) propagation conditions, in which the LOS path between a transmitter and a receiver is either completely blocked or only partially blocked with the signal still penetrating through obstacles such as walls and windows. NLOS propagation tends to incur significant errors in MLDPs and increase uncertainties in the location estimate, which seriously affects the localization performance. Therefore, it is of the utmost importance to analyze the impact of NLOS conditions on the localization techniques and to develop mitigation methods.

There are two classes of method to deal with NLOS conditions, i.e., identification and mitigation. The former class is to distinguish between LOS and NLOS conditions, and then eliminate the NLOS corrupted measurements. The later class is to minimize the errors introduced by NLOS links. There are several survey papers for NLOS mitigation and non-hybrid localization techniques. However, to our best knowledge, a detailed survey of hybrid localization methods in NLOS environments is not available in the literature. In order to inspire new research efforts in this field, there is still a need of better understanding of state-of-the-art hybrid localization techniques. Thus, this paper is an attempt to serve for this purpose. We provide a unified overview of different hybrid localization methods under NLOS conditions, and analyze the investigated techniques in terms of accuracy, complexity, and robustness.

The paper is organized as follows: Section II provides an overview of NLOS propagation. In Section III, a performance analysis of hybrid localization techniques with NLOS links is presented. Section IV discusses possible new research directions and further improvements.

II. NLOS PROPAGATION

In this section, we give a brief overview of NLOS propagation. Direct link between a transmitter and receiver (i.e., line-of-sight (LOS) link) rarely exists in dense urban and indoor environment. Instead, the transmitted signal experiences reflection, diffraction, and scattering, as illustrated Fig 1, through its propagation. Hence, the received signal might consist of multi path components (MPC). Single bounce model is commonly used by many researchers due to its simplicity. In this model, each MPC of the received signal is assumed to bounce only once from each scatterer, which forms a one-to-one correspondence between a scatterer and an MPC. Besides single bounce model, pathless propagation model and shadowing is widely considered in hybrid localization approaches. Path loss represents the level of signal attenuation while shadowing characterizes variations of the mean received power. Cost is one of the standard channel models for path loss propagation [1], and shadowing is modeled by a normal distribution with zero mean and certain standard deviation (SD). The impact of multipath is simply discarded during estimation of the location of the target by averaging the measurements.

Due to the lack of LOS link, the measured distance is generally much larger than the true path. As a result, measurements might face a deviation error from the corresponding true values. Therefore, NLOS error statistics are modeled and incorporated into the estimation to improve the accuracy. More specifically, the NLOS bearing error is uniformly distributed while the NLOS range error component in UWB indoor environment is modeled as exponential distribution, i.e.,

$$p(\epsilon_{NLOS}) = \begin{cases} \lambda e^{-\lambda \epsilon_{NLOS}} & \epsilon_{NLOS} \geq 0 \\ 0 & \epsilon_{NLOS} < 0 \end{cases} \tag{1}$$

Above, $1/\lambda$ denotes the mean. In the presence of strictly NLOS links where LOS blockage occurs, AOA measurements denoted by $\hat{\theta}$ are modeled as uniform distribution in the following [2]:

$$P_{block}(\hat{\theta}) = \frac{1}{\pi} \quad \text{where} \quad \hat{\theta} \in [-\frac{\pi}{2}, \frac{\pi}{2}] \tag{2}$$

When both LOS and NLOS paths exist, AOA measurements are modeled based on a linear combination of Gaussian and blockage probability as follows [2]:

$$P(\hat{\theta}) = \alpha_{block} P_{block}(\hat{\theta}) + (1 - \alpha_{block}) P_{LOS}(\hat{\theta}) \tag{3}$$

where α_{block} represents the probability of blockage.

$$P_{LOS}(\hat{\theta}) = \frac{1}{\sqrt{2\pi\sigma_{ls}^2}} e^{-\frac{(\hat{\theta}-\theta)^2}{2\sigma_{ls}^2}} \tag{4}$$

Above, σ^2_{ls} is the standard deviation of local scattering.

This paper contains results and findings of a research project that was funded by King Abdulaziz City for Science and Technology (KACST) Grant No. LGP-36-155.

III. HYBRID LOCALIZATION TECHNIQUES

In this section, we analyze various hybrid localization techniques proposed for NLOS propagation. Two tables that summarize the key characteristics of the investigated techniques is provided.

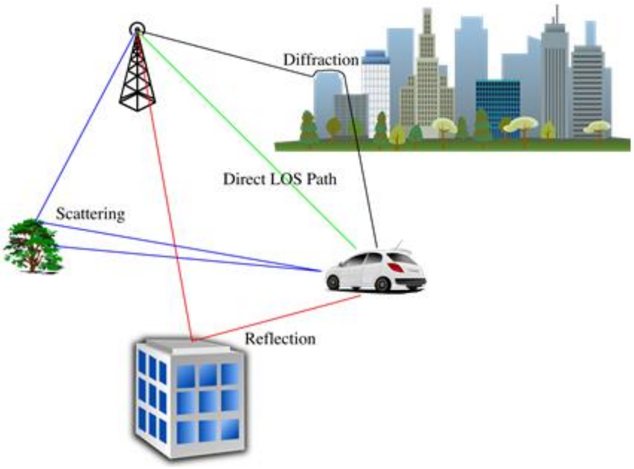

Fig 1:- NLOS signal propagation and scattering

A. TOA/RSSI

Unconstrained nonlinear optimization technique is utilized to process hybrid TOA and RSSI measurements for wireless localization [3]. First, the distances between the target and all BSs are determined using the path loss model for given RSSI values. Then, the estimated distances are employed in identifying the LOS and NLOS BSs in a binary hypothesis testing. Based on the result of the hypothesis testing, weight factors indicating the reliability of the measurements are assigned for the objective function, which consists of the sum of the weighted square errors.

In another work [4], the maximum likelihood (ML) estimation of the time delay is introduced exploiting path loss information whereas the exact ML and maximum correlation estimators are derived in [5]. Since the time delay includes a sufficient relation to both position vector and positive delay distance due to NLOS, the resulting estimate is transformed to the mobile position vector using proposed least square, weighted least square and ML estimators. It is shown that identifying NLOS measurements a priori, removing them in the estimation and using only LOS time delay is sufficient to achieve optimal performance in terms of estimation error variance [5].

One of the drawbacks of the proposed methods is the clock synchronization requirement between the target and BS, which is prone to timing errors in NLOS environment. Also, the methods need a priori knowledge of path loss model. However, the indoor environment has a different path loss exponent changing as function of carrier frequency, environment, and the degree of obstructions (e.g., wall material, furniture etc.).

B. TOA/Fingerprinting

In Fingerprinting (FP) method or pattern matching method, a database is constructed by location signatures (i.e., fingerprints) based on channel impulse response (CIR) of different fixed locations in a region. Consequently, target location is estimated by correlating CIR collected from the target with the stored fingerprints in database. The recent work [6] combines FP method and an iterative-TOA estimation for wireless localization in ultra-wide-band (UWB) signaling systems. More specifically, the target location is first estimated by matching its CIR pattern of with all available CIR patterns in the database. Then, the resulting estimate is given as an initial position for iterative-TOA method. Hence, the proposed hybrid method plays an important role to reduce NLOS errors in the final location estimation. Although the FP method can be employed in NLOS environment, its high computational complexity can be a major challenge for practical systems.

C. TDOA/Fingerprinting

Also, it should be noted that TOA-based approaches require a tight clock synchronization between BS and MS whereas TDOA-based methods do not have this limitation. However, their accuracy is greatly affected by the relative location of the BSs. In TDOA based distance estimation, the signal may reflect through scatterers in the multipath environment before reaching the MS, which potentially introduces a ranging error. Fingerprinting method is used to correct this error [7]. Following, LS approach is used to estimate the position of MS.

D. TOA/AOD/DS

The Viterbi algorithm, forward-backward algorithm and online Bayesian recursive filter are used to estimate the position of a mobile station (MS) using TOA, AOD and Doppler-shift observations [8]. The Doppler-shift observations depend on the speed and direction of movement of the MS. Therefore, the proposed algorithms give satisfactory estimation performance if the MS has a high probability of transition. On the other hand, if the MS is stationary, TOA and AOD measurements are not sufficient to estimate its position. The computational complexity of the proposed algorithms is quite high since the complexity grows exponentially with the number of scatterers.

The joint estimation of the position and speed of the MS has been proposed in [9] where the location of scatterers are estimated using AOD observations and then DS, TOA, and AOD observations are combined to estimate the position of the MS. The scatterers' locations and the distances between the scatterers and the MT are estimated using least-squares (LS) technique. The algorithm is suboptimal since the least-squares technique is applied to a nonlinear estimation problem.

The MS location, MS speed and excess time delay of the first arriving ray are determined simultaneously [10] by solving a set of non-linear equations obtained from angle of arrival (AOA), time of arrival (TOA) with respect to first arriving ray, and Doppler shift measurements from each arriving ray. Simplex method is used to solve the equations. The unique solution exists for the number of scatterers being greater than or equal to 6. The above works considered single bounce model for NLOS propagation, created a mapping between the LMDP of the multipath component and the MT coordinates, and estimated the latter. It is shown that increasing the number of multipath components, i.e., rich scattering environments leads to better estimation accuracy.

Another approach is to solve constrained non-linear least squares optimization, which explicitly attempts to reduce the impact of NLOS links by using bounds on the range and angle errors inferred from the geometrical relationships among the BSs, the scatterers and the unknown MS based on single bounce Gaussian scatter density model [11]. The optimization is solved using a novel grid search, which is computationally expensive. In this setting, a unique solution exists when the number of BSs is greater than or equal to 4.

E. TOA/AOA/RSS

User cooperation has been exploited in wireless localization problem. In particular, when the BS receives a location information request from a MS, it constructs a cluster in the surroundings of that MS [12]. The neighbors of that MS are assigned as cluster-members (CM). The BSs take TOA and AoA observations for each BS-CM link while each CM takes RSS observations for each CM-CM link. First location estimate for each CM is obtained by a data fusion method. For each corresponding initial location estimate, the BSs in NLOS are identified and the NLOS mean error for TOA estimates is calculated. The calculated NLOS mean error is subtracted, which compensates NLOS errors in the measurements. The final location estimate is obtained by solving NLLS minimization with initial location estimates, TOA, AOA and RSS measurements.

In the optimization, the long and short-range measurements are weighted appropriately to reflect the reliability of the measurements for each BS-CM link and CM-CM link, respectively. For instance, the link quality among CMs is likely to be better than of between BS and CM. Therefore, higher weight is selected for these links in the objective function, which geometrically constrains the final solution and hence reduces its location error.

In the case of non-cooperation, three BSs are generally required to obtain an accurate location estimation. However, when the MS is closer to one BS than the other BSs, the signal-to-noise ratio (SNR) of the received MS signal at the neighboring BSs can be low and might be interpreted as interference. Therefore, the location estimation is actually performed with less than 3 BSs. This case is known as hearability problem, which deteriorates the estimation accuracy. In the case of restricted hearability conditions, the MS should either communicate with a local Wi-Fi hotspot or perform cooperation with the other known MS with known location. In this regard, the recent work [13] considered hybrid localization by applying Unscented Kalman filter (UKF) to long-range measurements (i.e., TOA, AOA and RSS measurements) obtained by one BS and short range measurements obtained by Wi-Fi hotspot. The estimation performance is improved by assuming knowledge of the NLOS errors statistics (i.e., NLOS error is assumed to follow an exponential distribution in TOA based distance estimation) and reducing ambiguities with available AoA information.

F. TOA/AOA/AOD

Given AoD, AoA and ToA measurements, the authors [14] introduced a three dimensional LS approach for jointly estimating the positions of the MS and scatterers under the assumption of single bounce reflection model for NLOS propagation.

G. TDOA/AOA

The AOA and TDOA information are used by EKF for estimating the position of MS [15]. For each BS, hypothesis testing is performed periodically to discriminate NLOS and LOS links. If the NLOS link is detected, a biased Kalman filter is utilized to mitigate the NLOS TOA error. On the other hand, AOA measurements from NLOS BSs are discarded and only AOA measurements from LOS BSs are used in the estimation. In contrast, the work [1] processed all measurements obtained from mixed LOS/NLOS propagation. In particular, the authors introduced lower and upper bounds on the NLOS bias based on geometrical considerations into the filtering step of the EKF equations. Since KF cannot effectively mitigate the impact of the NLOS bias, at least one LOS range measurement is assumed to be available.

H. AOA/RSSI

TOA based approaches require at least 3 BSs. AOA based localization techniques are robust to shadowing and uncertainty in the values of environmental parameters. On the other hand, RSSI based localization methods are robust to low resolution in estimating the direction of target and local scattering. Consequently, combination of AOA and RSSI based methods provide more robust and accurate estimates in the presence of localization errors due to NLOS propagation. Also, they eliminate the need of at least 3 BSs.

The aforementioned works adopted LS and KF approaches for positioning. However, the localization in NLOS propagation has multi-modal and non-Gaussian nature. Motivated by this fact, the authors [17] applied particle filter by exploiting RSSI and AOA measurements from 2 BSs. When both the transmit power and location of the MS is not known, RSSI difference between two points on the path are considered in order to eliminate the need for estimating the transmit power. The computational complexity of the particle filters grows exponentially with the size of the state vector, thus it is less suitable for practical applications. To reduce the complexity, particle filter is replaced by multi-step extended Kalman filter (EKF) and UKF [18]. RSSI difference between two points on the path determines the linearization point for EKF, and initial mean and sigma points for UKF. Then, the AOA measurements are incorporated to improve the estimation accuracy. Although equivalent estimation performance is achieved, EKF and UKF still suffer from high computational cost. In addition, EKF is very sensitive to the linearization point to model a non-Gaussian process such as localization in NLOS. Also, the accuracy of UKF is highly dependent on positive definite property of the covariance matrix. This condition may not be guaranteed due to numerical errors. This problem can be alleviated using decomposition methods for covariance matrix update.

The position of MS is found as the intersections of three circles and a line obtained by three highest RSS measurements and the AOA information at the serving BS, respectively without identifying NLOS/LOS links [19]. The impact of NLOS is mitigated by combining a weighting procedure with the geometrical feature of cell layout. Different from the work [19], the authors [20] estimated the location of MS using two highest RSS measurements and the AOA information. In this approach, the proper weights are assigned to reduce the impact of the NLOS-corrupted measurements, and the angular bounds inferred from the statistics of the AOA distribution are used to minimize the NLOS contribution to the estimation accuracy.

Another approach to minimize the effects of NLOS propagation is joint estimation of scatterers' orientations, the target location and its transmission power [21]. Since the optimization problem is highly nonlinear and non-convex, the authors apply the relaxation of the non-convex equality constraint to obtain a convex approximation and relax the problem to a semi-definite programming problem.

Instead of using all available measurements (i.e., both LOS and NLOS), a hybrid hypothesis test is proposed to identify the most probable two LOS BSs by incorporating both RSS and AOA measurements [22]. If two LOS BSs are identified, then localization is performed. Otherwise, the hypothesis testing returns the two least probable NLOS BSs and a weighting approach is employed to reduce the effect of NLOS propagation, which in turn improves the location accuracy.

I. TDOA/RSS

The approach in [23] benefits from both TDOA and RSS measurements to derive best linear unbiased estimator (BLUE). The estimated ranges based on TDOA observations are chosen for the estimator if RSS is greater than a predetermined threshold. Hence, good SNR and high ranging accuracy is achieved. On the other hand, RSS is below a threshold, the estimated ranges by RSS are all chosen for location estimation. One of the limitations of BLUE is to include matrix inversion, which is computationally complex for online applications.

J. TOA/AOS

In TOA based approaches, location estimate is found by determining the points of intersection of circles whose centers are located at the BSs. By incorporating AoA measurements, the area of the possible positions of the MS is reduced, which consequently improves estimation accuracy. Different kinds of estimators proposed to solve the nonlinear TDOA/AOA location equations, i.e., minimax estimator [24], Wiener estimator [25], two-step LS estimator [26] for low-to-moderate NLOS effects. However, when there exits considerable NLOS errors, the estimation accuracy is deteriorated. In order to overcome this issue, the authors incorporated geometric information from the cell layout into the formulation of the two-step LS estimation [27]. Consequently, more accurate location estimates are obtained in the presence of severe NLOS environments. The authors [28] alternatively utilized non-linear constrained optimization for positioning subject to bounds on the range and angle errors inferred from geometry.

The measured ranges and AOAs depend on the location of scatterers. Hence, by considering the locations of scatterers and geometrical relationships among the MS, scatterers and the base stations (BSs), the location estimates are less sensitive to NLOS errors. The locations of the dominant scatterers are unknown in practice. Therefore, their location together with the location of MS are estimated jointly by means of a nonlinear optimization approach based TOA and AOA measurements subject to nonlinear geometrical constraints [29]. A grid search-based technique is also proposed to solve this problem [30].

The aforementioned hybrid TOA/AOA localization techniques assumed single bounce channel model. The recent work [31] analyzed multiple-bound paths (i.e., 2 paths) and proposed nonlinear programming localization algorithm for severe NLOS propagation conditions. Instead of utilizing all LOS/NLOS measurements, authors [32] developed an iterative minimum residual scheme to sequentially detect and eliminate NLOS BSs. Hence, the estimation is performed with only LOS BSs. However, this algorithm does not provide efficient location estimates in strictly NLOS environments.

IV. FUTURE RESEARCH DIRECTIONS

In this paper, we present a detailed survey of hybrid localization techniques in the presence of NLOS errors. In Table 1 and Table 2, we provide a brief summary of different techniques including main assumptions, limitations and NLOS mitigation approaches adopted. As discussed, many proposed techniques suffer from high computational complexity. Therefore, further research efforts should be spent to develop practical and efficient localization approaches that can deal with NLOS propagation. Therefore, we believe that this survey will serve as a valuable resource for shedding a light on tradeoffs among the existing hybrid techniques. It is interesting to note that machine learning based techniques are not exploited in the literature for identification of NLOS links and mitigating NLOS range biases in localization. Robust logistics regression may be effective to classify links as LOS and NLOS. Artificial feed-forward neural networks that exploit signals from an existing communication infrastructure such as Wi-Fi and Bluetooth may mitigate impacts of NLOS links. We plan to research these two topics as part of our future work.

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MLDP	# of BSs involved	LOS/NLOS Assumption	Channel Model	NLOS localization strategy	Limitations
TOA, RSSI [3]	At least 3	At least one BS in LOS/all NLOS	Simplified pathloss model with shadowing. Target and BSs are stationary	LOS/NLOS identification and weight factor assignment in the objective function	A priori knowledge of pathloss model is required
TOA, SS [5]	At least 3	At least two BSs in LOS and one BS in NLOS	Simplified pathloss model. Target and BSs are stationary	LOS/NLOS identification, and removing NLOS measurements in the estimation	A priori knowledge of pathloss model is required
TOA, FP [6]	Large number of fixed stations used for training phase in FP	All NLOS	UWB channel model by IEEE802.15 for WPAN	Estimating the target position using pre-calculated location database and giving it as an initial estimate to iterative TOA estimation	Computational complexity is high for FP training database (i.e., 2000 CI per location point)
TDOA, FP [7]	Ten access points	Mixed LOS/NLOS	5G band	Finding the shortest NLOS paths using location database and removing the multipath components	High computational complexity for FP training
TOA, AOD DS [8]	One BS, one MS stationary scatterers	Strictly NLOS	Single bounce model Markov mobility model for MS motion	Introducing a NLOS propagation model creating a mapping between the MLDP of the MPC and the MS coordinates and estimating the latter	High computational complexity of the proposed algorithm
TOA, AOD DS [9]	One BS, one MS stationary scatterers	Strictly NLOS	Single bounce model Linear mobility model for MS motion	Introducing a NLOS propagation model creating a mapping between the MLDP of the MPC and the MS coordinates and estimating the latter	The algorithm is suboptimal
TOA, AOD DS [10]	One BS, one MS stationary scatterers	Mixed LOS/NLOS	Single bounce model Linear mobility model for MS motion	Introducing a NLOS propagation model creating a mapping between the MLDP of the MPC and the MS coordinates and estimating the latter	Number of scatterers to be greater than or to 6, otherwise unique solution does not exist
TOA, AOD DS [11]	One BS, one MS stationary scatterers	Mixed LOS/NLOS	Single bounce model Linear mobility model for MS motion	Reduce the effect of NLOS by using bounds on the range and angle errors inferred from the geometry.	Grid search is computationally expensive
TOA, AOA RSSI [12]	One BS, one MS multiple CMs	Mixed LOS/NLOS	Statistical channel model based ray tracing	Identify and remove NLOS measurements for each CM	Accurate clock synchronization between the BS and CM needed
TOA, AOA RSSI [13]	One BS one Wi-Fi hotspot one MS	Mixed LOS/NLOS	Simplified pathloss channel model	Reduce the effect of NLOS by using bounds on the range and angle errors inferred from the geometry	UKF has high computational cost
AOA, RSSI [17]	One UAV one MS	Mixed LOS/NLOS	Pathloss model with local scattering probability of blockage, shadowing	Reduce the effect of NLOS by using bounds on the range and angle errors inferred from the geometry	UAV needs to have multiple antenna
AOA, RSSI [18]	One UAV one MS	Mixed LOS/NLOS	Pathloss model with local scattering probability of blockage, shadowing	Introducing a NLOS propagation model and apply filtering	UKF, EKF have high computational complexity

Table 1:- Hybrid Localization Techniques with NLOS Mitigation.

MLDP	# of BSs involved	LOS/NLOS Assumption	Channel Model	NLOS localization strategy	Limitations
TDOA, RSSI [23]	4 BSs, one MS	Mixed LOS/NLOS	Pathloss model with shadowing	Linear LS optimization which intrinsically mitigates the effect of NLOS errors	The proposed estimator includes matrix inversion, which is computa-tionally complex for online applications..
AOD, AOA TOA [14]	One BS, one MS stationary scatterers	Mixed LOS/NLOS	Single bounce model	Linear LS optimization which intrinsically mitigates the effect of NLOS errors	The proposed algo-rithm is suboptimal
TDOA, AOA [15]	3 BSs, one MS	Mixed LOS/NLOS	Standard UWB channel model	NLOS/LOS identification remove NLOS measurements	EKF has high computational cost
TDOA, AOA [16]	4 BSs, one MS	Mixed LOS/NLOS	Pathloss channel model	Introduce bound constraints on the NLOS bias based on geometry in the optimization	EKF has high computational cost
AOA, RSS [19]	3 BSs, one MS	Mixed LOS/NLOS	Pathloss channel model with shadowing	Apply proper weights to reduce the impact of NLOS propagation	A priori knowledge pathloss model is required
AOA, RSS [20]	2 BSs, one MS	Mixed LOS/NLOS	Pathloss channel model with shadowing	Introduce variable LOS/NLOS weighting coefficients, and angular bounds inferred from the statistics of the AOA distribution	A priori knowledge pathloss model and statistics of the AOA distribution is required
AOA, RSS [21]	6 sensor nodes one MS	Strictly NLOS	Single bounce model with shadowing	Jointly estimate orientations of the scatterers and target	Algorithm converge issue
AOA, RSS [22]	At least 2 LOS BSs, one MS	Mixed LOS/NLOS	Pathloss channel model with shadowing	Identify LOS BSs apply proper weights to reduce the impact of NLOS propagation	A priori knowledge pathloss model is required
TOA, AOA [27]	At least 2 BSs one MS	Mixed LOS/NLOS	Single ounce model	Incorporate the geometric constraints into the optimization	Different geometric layouts possible
TOA, AOA [28]	3 BSs one MS	Mixed LOS/NLOS	Single bounce model	Reduce the effect of NLOS by using bounds on the range and angle errors inferred from the geometry	A priori scattering model is required
TOA, AOA [30]	3 BSs one MS	Severe NLOS	Single bounce model	Incorporate geometrical relation-ships among MS, scatterers and BSs	Grid search is computationally complex
TOA, AOA [32]	Less than 2 NLOS BSs one MS	Mixed LOS/NLOS	Single bounce model	Detect and discard NLOS measurements	Low accuracy for strictly NLOS environments

Table 2:- Hybrid Localization Techniques with NLOS Mitigation