Non-line-of-sight localization in multipath environments

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NON-LINE-OF-SIGHT LOCALIZATION IN MULTIPATH ENVIRONMENTS

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University

in fulfillment of the requirement for the degree of
Doctor of Philosophy

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Statement of Originality

I hereby certify that the work embodied in this thesis is the result of original research done by me and has not been submitted for a higher degree to any other University or Institute.

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Date

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Abstract

Wireless localization is a major challenge for accurately estimating the position of devices that operate in multipath environments. In indoor environments, non-line-of-sight (NLOS) propagation has a significantly negative impact on the performance of conventional localization schemes. These schemes can be divided into two categories. The first is known as the fingerprinting scheme. Under this scheme, localization begins with a training process to construct a database of the features of a predetermined location before the device is used in that location. When a user with the unknown mobile device (MD) sends a positioning query, the localization scheme searches the database and returns the corresponding fingerprints and locations. Fingerprinting can handle the NLOS problem. Doing so requires the pre-calibration of signal characteristics between each Reference Device (RD) and the MD. In addition, the scheme is sensitive to changes in the environment. The second localization scheme is called the geometric scheme and makes use of position-related parameters, such as the angle of arrival (AOA), the time of arrival (TOA), and received signal strength (RSS), to construct the geometric position of possible MDs under the line-of-sight (LOS) assumption. In two-dimensional localization, at least two or three RDs are required for the AOA and TOA localization schemes respectively. However, the geometric approach faces a serious challenge when a signal is disturbed by the multipath effect. Therefore, much research effort has been devoted to tackling the NLOS problem to improve localization. These efforts

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have focused either on NLOS identification or NLOS mitigation. NLOS identification distinguishes LOS/NLOS range measurement information and uses the LOS information in the conventional methodology to find the estimated location. NLOS mitigation reduces the impact of NLOS paths on localization accuracy by assigning lower weights to longer propagation paths. However, these schemes have not been satisfactory in heavy multipath environments. Other proposed schemes include the use of NLOS paths for localization without the need for mitigation schemes. The schemes work by first constructing the lines of possible MD locations, referred to as the line of possible mobile device (LPMDs), on the LOS or NLOS paths based on pairs of TOA and AOA measurements at both the RD and the MD. The MD's location can be determined at the intersection points of the LPMDs, causing this technique to be known as line intersection methodology. It is worth noting that line intersection methodology does not work well in a dense multipath environment, especially when the angle between LPMDs is small.

This thesis focuses on novel and robust geometrical-based localization schemes in a multipath environment by using just one RD and without the need for any identification and mitigation schemes. Firstly, a robust localization scheme is proposed based on a Gaussian weighting function and proximate points. This scheme uses all measurement data (TOA and AOA) and either LOS or NLOS propagation information to formulate a Gaussian weighting function and proximate points to find the MD's location without any identification and mitigation schemes. To further improve localization accuracy, an area-based localization scheme which does not require any weighting factor was designed

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to estimate the MD's location. To perform a robust localization to handle multiple reflections and diffractions in the dense multipath environment, virtual RD-based and elliptical Lagrange-based NLOS localization schemes are proposed to determine the MD's location by using one RD and one signal path which undergoes one or more reflections or diffractions. Finally, experiments are conducted to verify the localization accuracy of the virtual RD-based and elliptical Lagrange-based NLOS localization schemes in a heavy multipath environment.

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List of Abbreviations

Acronyms

2D	Two-Dimensional
ALE	Average Location Error
AML	Average Maximum Likelihood
AOA	Angle of Arrival
AP	Access Point
APMD	Area of Possible Mobile Device
CDF	Cumulative Distribution Function
CRLB	Cramer Rao Lower Bound
EM	Expectation Maximization
ESPRIT	Estimation of Signal Parameter via Rotational Invariance
GNSS	Global Navigation Satellite System
GPS	Global Positioning System
IMM	Interacting Multiple Model
INS	Inertial Navigation System
LOS	Line-Of-Sight
LPMD	Line of Possible Mobile Device
LS	Least Square
MD	Mobile Device
MDS	Multidimensional Scaling
ML	Maximum Likelihood
MSE	Mean Square Error

List of Abbreviations

MUSIC	Multiple Signal Classification
NLOS	Non-Line-Of-Sight
PDF	Probability Distribution Function
RD	Reference Device
RFID	Radio-Frequency Identification
RMS	Root Mean Square
RSS	Received Signal Strength
RTT	Round Trip Time
SAGE	Space Alternating Generalized Expectation
SDP	Semidefinite Programming
SNR	Signal to Noise Ratio
TDOA	Time Difference of Arrival
TOA	Time of Arrival
UWB	Ultra-Wideband
VNA	Vector Network Analyzer
WLAN	Wireless Local Area Network

Chapter 1

Introduction

1.1 Motivation

Wireless systems that collect information on the accurate position of people and objects have been receiving greater attention recently, as these technologies develop quickly and there is increasing demand for such services [1]-[5]. Wireless systems have become an integral part of our lives. One example of this is the growing numbers of drivers who use satellite navigation units in their cars to avoid getting lost. These units update route information continuously and guide drivers to their destinations by using digital maps.

Today, the most common wireless localization systems are Global Navigation Satellite Systems (GNSS) which receive signals from satellites to provide real-time global location information [6]. Examples of GNSSs include the Global Positioning System (GPS), GLONASS, BEIDOU and Galileo. The architecture of a GNSS receiver consists of four modules: the front-end, acquisition, tracking and navigation. In the first module, the signal goes through the filter

and the amplifier and is converted to a digital signal. The acquisition module then detects the satellites that are visible to the receiver and determines the code delay and Doppler shift. Once the code delay and Doppler shift have been estimated, the system continues to track and refine them to ensure that the receivers are accurately synchronized. At the last stage, the navigation module determines the user's location by estimating the time delay estimation of at least four visible line of sight (LOS) satellites. To date, GPS is the only fully functional GNSS system.

In outdoor environments, GPS can provide a high level of positioning accuracy. However, when a GPS receiver is used indoors, its accuracy worsens dramatically as the signal will lose its LOS path and is severely attenuated because of the building structure [7]. This challenge has led to research in positioning in indoor environments. Recently, the ability to provide accurate and reliable localization has become increasingly important in emergency services and sensor network applications such as personnel tracking and surveillance indoor environments [8]-[11]. For example, the infrastructure-based indoor tracking system has been used in complex environments such as hospitals and multi-storey shopping malls to guide people to their destinations. For infrastructure-less indoor tracking scenarios, such as civil defense search and rescue operations, a group of rescue responders need to be localized. As a result, a myriad of indoor localization schemes have been developed. Some of these schemes use various types of wireless infrastructure such as RFID [8]-[10], wireless local area networks (WLAN) [11]-[13] and ultra-wideband (UWB) [14]-[16], while others, such as the inertial navigation system (INS)

[17]-[20] and a Non-line-of-Sight (NLOS) localization system using one reference device (RD) or node to node localization without the need of any external device [100], are termed “infrastructure-less”. This is because they can be used as an infrastructure-based localization application as one of the nodes can be a reference device. However, in infrastructure-less scenarios such as civil defense search and rescue operation, pre-installing the reference nodes is not feasible and only the relative position between nodes is required. Hence, for ease of discussion, one of the two nodes is called the reference device (RD) and the other is called mobile device (MD), regardless of the localization scenario in use: infrastructure-based or infrastructure-less.

Infrastructure-based localization schemes can be further divided into statistical and geometrical approaches. The traditional statistical methodology use signal strength (RSS) fingerprinting [21]-[24] and requires a training process to construct a database of features in advance at the predetermined location. Thus, when the unknown mobile device (MD) sends a positioning query, the localization scheme will search the database and return the corresponding fingerprints and locations. However, this methodology is very sensitive to the changes in the environment. The database needs to be updated when environmental conditions change significantly. In addition, this methodology also requires the pre-calibration of signal characteristics at each RD facility.

The geometric approach uses measurement data, such as time of arrival (TOA) [26]-[36], time difference of arrival (TDOA) [37]-[45], angle of arrival (AOA) [46]-[63] and received signal strength (RSS) [64]-[73] to find the location of

the MD based on the relationship between the geometric characteristics of the RD and the MD. The TOA scheme provides localization based on the precise clock synchronization between the MD and the RD. The TDOA method removes the need for synchronization between the MD and the RD but requires all RDs to be synchronized. The AOA method needs an antenna array structure or directional antenna to estimate the angle and do not require any synchronization. The RSS method utilizes the propagation model to extract the distance information to perform localization.

In conventional localization schemes, AOA, TOA, TDOA and RSS information are used to perform localization. At least two and three RDs are required for AOA and TOA based localization schemes, respectively. These algorithms can achieve high location accuracy only when a LOS path exists between each RD and MD. However, the geometric approach faces a serious challenge when the signal undergoes the multipath effect. In indoor environments, the LOS path may not be detectable and thus measurement data TOA/AOA represents the information for multipath propagation. Furthermore, the channel parameters used in signal strength-based localization schemes is different from dynamic multipath environments. This weakens the performance of this localization system.

Therefore, many research efforts have been devoted to tackling the NLOS problem and find a better localization solution [70]-[95]. These algorithms can be classified as either NLOS identification or NLOS mitigation. NLOS identification differentiates between LOS and NLOS range measurement

information and uses LOS information by a conventional methodology to find the location estimation. The others use both LOS and NLOS measurements to reduce the impact of NLOS range errors on the accuracy of location estimation using weighting factors.

The infrastructure-less-based localization scheme, such as the inertial navigation system (INS), has become a rapidly growing location-based service domain. For example, smart phones can have a high rate of penetration because they use the INS to provide positioning information for subscribers, especially for indoor situations.

Figure 1.1 Strapdown inertial navigation algorithm [17]

Figure 1.1 illustrates the inertial navigation system. It contains an accelerometer and gyroscope and utilizes the strapdown algorithm to combine orientation and speed data to find a device's location without the need of infrastructure. First, the measured angular velocity from the gyroscope is used to obtain the orientation of the device. The acceleration caused by gravity on the accelerometer is subtracted as it will lead to a large error when calculating the device's position. Then, the remaining measurement data is projected onto the global frame and two time integrations are produced to obtain the device's

current position. An error correction mechanism has also been included in the strapdown algorithm to reduce any error in the motion of the device. However, it needs a reference node to provide accurate initial location information. Also, it suffers from position drift, with this error greatly increasing over time.

Another infrastructure-less-based localization scheme which allows wireless node to node localization without the need of external references is proposed by Miao et al. [98] and Seow and Tan [100]. This scheme directly uses NLOS paths to provide robust localization in multipath environment without the need for any mitigation schemes. In [98] and [100], TOA and AOA are measured at both the RD and the MD locations. The schemes in [98] and [100] explore the measured TOA and AOA of one bounce reflection path to estimate the location of the MD by using the least squares solution. However, in a heavy multipath environment, the multiple bounce reflection paths become dominant. If these paths are mistakenly used for localization, location accuracy will be dramatically decreased. As a result, Seow and Tan [100] construct weighting factors and use the threshold value to identify LOS, single and multiple bounce signal paths by using the proximity relation among the multipath signals. Finally, the location of the MD can be determined through the intersection points of the LPMDs from LOS and single bounce reflection paths.

However, the proposed localization scheme in [100] does not work well in a dense multipath environment, especially when the angle between LPMDs is small. Any slight perturbation of AOA and TOA measurements due to the parametric estimation of these values will result in large errors. For example, in

Figure 1.2, the solid lines represent the noise-free LPMDs. Noise-free LPMD₁ and LPMD₂ are due to one bounce reflection path by obstacle 1 and obstacle 2 respectively. The true angle between the LPMDs β^0 is 22° . The dashed lines represent LPMD under small AOA and TOA perturbations of 2° and 0.5m respectively for path 2 at RD and MD. Such a minor change leads β^0 to become β' which is 18° . As shown, small perturbations in AOA and TOA estimation result in large drift in the position from MD to MD'. In addition, the intersections of LPMD lines will fail to find the location of the MD if the pair of LPMD lines is parallel to each other. Moreover, in dense multipath environments where there is only one dominant single bounce reflection path, it may not be possible to find two single bounce reflection paths between an RD MD pair. Hence, the line intersection method is not possible in this scenario. Even if two single bounce paths exist between an RD MD pair, the weaker single bounce path will have larger TOA and AOA noise variance [25] since the accuracy of parameter estimation is proportional to its signal to noise ratio (SNR). This in turn results in the noisy LPMD construction and poor estimation of the MD's location. Last but not least, the multipath identification scheme in [100] requires weighting factors and threshold value that are arbitrarily chosen. Since these values depend on the environment, it is difficult to estimate the appropriate values to be used.

Figure 1.2 Reference and mobile devices are shown with two one-bounce scattering paths and their corresponding LPMDs.

1.2 Objective and Contributions of the Thesis

The objective of this research is to develop novel and robust localization schemes in both LOS and NLOS scenarios using just one RD without any identification and mitigation schemes. The simulations are conducted in different kinds of environments to illustrate the robustness of our developed localization schemes. Additionally, we also set up an experiment in a real multipath environment to test and verify our designed localization schemes.

The main contributions of the thesis are:

1. Propose a LPMD-based localization scheme to improve mobile device (MD) location accuracy in multipath environments. This scheme uses TOA and AOA measurements, which may be LOS or NLOS propagation information, to formulate a Gaussian weighting function to find the MD's location without the need of identification and mitigation schemes.
2. Develop an APMD-based localization scheme which only requires one reference device (RD) to estimate the MD's location. This localization scheme only makes use of one dominant propagation path and does not require any weighting factor at all.
3. Design a NLOS localization scheme based on the concept of a virtual RD for the NLOS propagation path between RD and MD in the dense multipath environment. With the position of a virtual RD, the proposed NLOS localization scheme only relies on one RD and one signal path which undergoes one or more reflections to determine the MD's location. The position of the virtual RD can be determined when the initial MD's location is found or when the MD transits from the LOS to NLOS condition.
4. Develop an indoor localization scheme to track the MD's trajectory and condition in an indoor environment by seeking some continuity information between each pair of adjacent points. The proposed localization scheme uses measured TOA and AOA data of the NLOS path, which is subject to reflection or diffraction to give a robust performance in a severe multipath environment.

1.3 Organization of the Thesis

The rest of the thesis is organized as follows:

Chapter 2 is a literature review of conventional localization algorithm such as TOA, TDOA, AOA and RSS which are employed for geolocation. In addition, identification and mitigation methodologies to overcome the NLOS problem will also be discussed in detail.

Chapter 3 presents a LPMD based localization scheme for indoor environment based on the Gaussian weighting function and proximate point. A Gaussian weighting function is constructed based on the calculated variance and the weighting factor is assigned to the intersection points based on how close these points are to the intersection point of interest. The proposed Gaussian weighting process improves the localization robustness by using measured TOA and AOA data at both sides without any selection scheme and threshold value. The performance of the localization scheme is analyzed through simulations in the indoor environment and by comparing it with the existing localization schemes.

Chapter 4 presents a novel area of possible mobile device (APMD)-based localization algorithm by employing only one dominant path to estimate MD location without any weighting factor. The proposed scheme uses the measured TOA and AOA at both the RD and MD and the characteristics of the probability distribution for measurement data to form an intersection area to

estimate the MD's location. The analytical error variance is derived, and the performance is analyzed in different multipath environments.

In a heavy multipath environment, the NLOS path will dominate. Thus, the proposed scheme in Chapter 4 cannot perform well and location accuracy will greatly deteriorate. In Chapter 5, a virtual RD-based localization scheme is proposed to overcome the abovementioned limitation without any prior knowledge of the whole environment. The location of the virtual RD can be determined when the initial MD's location is estimated or when the MD transits from the LOS region to the NLOS region. With the help of the location information of the virtual RD, the proposed NLOS localization scheme requires only one signal path which can even undergo multiple bounce reflection. The weighted least-squares solution of the virtual RD's location is formulated based on the measured TOA and AOA of one bounce reflection path. Simulation results and experimental data obtained from an experiment in an indoor environment, the Internet of Things (IoT) laboratory at the School of EEE, Nanyang Technological University, are used to assess the performance of our proposed localization scheme.

Chapter 5 proposes an NLOS localization scheme that makes good use of a virtual RD of the reflection path. However, when the NLOS signal changes from the reflection to the diffraction region, the performance of the proposed localization in Chapter 5 is seriously impaired. In Chapter 6, an indoor tracking localization scheme is proposed to overcome the above problem. The proposed tracking algorithm exploits the reflection point of the one bounce scattering

Chapter 1 Introduction

path to track the MD's trajectory and condition. A constrained function is constructed to estimate the locations of reflection points. The performance of the proposed tracking localization scheme is evaluated based on simulation and experimental results from the School of EEE, Nanyang Technological University, together with the derivation of the Cramer Rao lower bound (CRLB).

Finally, we conclude the thesis and suggest future work in Chapter 7.

Chapter 2

Literature Review

This chapter reviews the literature on existing localization schemes according to conventional LOS and existing NLOS schemes. The conventional localization schemes are discussed in Section 2.1. These schemes use estimated signal parameters to determine the MD's location and do well under the LOS assumption. Section 2.2 presents the existing NLOS localization schemes under the two different systems, either with or without prior information. These schemes use NLOS information and provide robust location estimates by mitigating NLOS error.

2.1 Conventional LOS Localization Schemes

2.1.1 Time of Arrival (TOA)

The TOA algorithm is based on a combination of the TOA estimates of the signals received from at least three RDs. The TOA measurement multiplies the speed of the signal to obtain a measurement of the range between the RDs and

the MD. For two-dimensional localization, this provides a circle centered at the RD on which all possible positions of the MD must lie. At least three RDs are used to solve the ambiguities that result from the multiple crossings of the lines, and the MD is located at the intersection of the circles as shown in Figure 2.1. Even with LOS TOA measurements, the intersection of multiple TOA circles may not produce a single point because of measurement error. The result is usually a small enclosed area.

Figure 2.1 Combining TOA measurements from three RDs.

A constrained weighted LS location estimator [26] is derived by minimizing the constrained least squares function including the weighting matrix based on the Lagrange multiplier. This approach allows us to attain the Cramer Rao lower bound (CRLB) under small noise perturbation. A best linear unbiased estimator algorithm [27] is formulated to eliminate the intermediate variable by combining all linear equations, and then producing a weighted LS solution. In [28], a range-based positioning method with low computational complexity is introduced to employ a quadratic equation that links the extra variable with the

estimated position of the MD. This approach greatly decreased computational complexity while approximating the LS solution. In [29] and [30], an optimization method is proposed to formulate the localization problem into the convex function to improve the accuracy of the location. In [31]-[34], a multidimensional scaling (MDS) scheme [35] and [36] is used to provide robust localization capabilities in the presence of high levels of measurement noise. This is done by applying eigenstructure analysis to the scalar product matrix. The scheme in [34] also shows that the proposed weighted MDS can obtain the CRLB when the measurement error is very small. To obtain accurate location estimation, the TOA algorithm requires all RDs and MD to precisely synchronize.

2.1.2 Time Difference of Arrival (TDOA)

The TOA positioning algorithm requires accurate timing synchronization between the RD and MD, as any drift in the clock can generate an error in the location estimate. Such clock synchronization errors can be prevented by the TDOA localization. It only needs the synchronization among all RDs.

In the TDOA method, the differences in the arrival times of the MD's signal are measured at multi-pairs of RDs. Each TDOA measurement can be transformed into a range difference that defines a hyperbola on which the MD is located with the RD as the focus [37]. The position of the MD is estimated from the intersection of hyperbolas derived by solving a set of nonlinear equations. The method in [37] uses the relationship between the MD's range and the MD's

location to improve the accuracy of location by exploiting a constrained least squares method. Chan and Ho [38] presents a two-step least squares (LS) scheme for localization using the TDOA metric. In the first step, a weighted LS estimator is calculated to yield an initial location. Then, leveraging the relationship between the extra variable and the estimated location, the second weighted LS is applied to further improve the estimation. In [39], [40], a recursive method is formulated to refine the estimated location by using an initial guess position. In the sensor network, Yang et al. [41] presents a robust localization method by employing the maximum likelihood formulation and provides efficient solution for the optimization problem. However, the approach is sensitive to the error in sensor locations. Several schemes [42]-[46] have been proposed to overcome this problem and alleviate sensor error in localization. These schemes take statistical knowledge of positional error into account [43], [45] or use a calibration emitter with an exactly known position [44], [46] to reduce the error and improve the accuracy of the location.

2.1.3 Angle of Arrival (AOA)

The AOA method requires the RD to measure the angle of the arriving signal. To estimate the AOA, antenna arrays need to be installed on the RD. The AOA estimation schemes consist of the beamforming scheme, and the subspace estimation and deterministic estimation methods. The beamforming scheme serves to determine the direction that produces the maximum power [47]-[49]. It is sensitive to the signal-to-noise ratio (SNR), fails to solve the multipath component and provides low resolution. Subspace estimation methods, such as

multiple signal classification (MUSIC), root MUSIC and estimation of signal parameters via rotational invariance techniques (ESPRIT) [50]-[54], have been introduced to enhance directivity. They do so by using eigenstructure analysis. However, they are unable to resolve the issue of obtaining a coherent signal in multipath environments. Thus, a deterministic approach is proposed for handling the multipath effect. Such an approach is used to iteratively detect estimation direction by using the space-alternating generalized expectation maximization (SAGE) and expectation maximization (EM) algorithms [55]-[58].

To find the MD's position, AOA measurements need be conducted from at least two RDs in two dimensions. This results in multiple lines of position for the MD. The MD's location is determined by combining all of the AOA measurement data to provide a least squares (LS) solution [37], [59]. The maximum likelihood (ML) estimator in [60], [61] is applied to solve the self-localization problem as an asymptotically unbiased estimator. However, the ML method requires an initial guess about the location and suffers from the problem of divergence. A semidefinite programming (SDP) method described in [62], [63] estimates the locations of the sensor networks based on the measured AOA between each node and anchor pair. Thus a high level of connectivity is required among all the anchors and nodes. The advantage of the AOA algorithm is that it does not necessitate RD or MD clock synchronization. However, the disadvantage is that antenna array elements or directional antennas are needed to estimate the angle of arrival, which may increase the system's cost. Also, in the multipath environment, the constructive and

destructive interference of the signals gives rise to fluctuations in the received signal phase. This can cause errors in the estimation of the AOA.

2.1.4 Received Signal Strength (RSS)

The RSS approach measures the path loss from the MD to the RDs and uses a geometric scheme to estimate the position of the MD. Compared to the TOA and AOA methods, RSS measurements are relatively inexpensive and simple to carry out in hardware.

The main RSS based localization methods are the fingerprint method and the signal propagation modeling method. The fingerprint scheme has been widely adopted for indoor localization purposes. Training locations are first chosen within a target area. The access points (APs) measure the RSS values for each training location and this data is stored in the database as prior information. The MD's location is then calculated by matching the actual RSS values with the values in the database. The main limitations of this method are that it requires a stable environment for mapping the initial phase as well as accurate measurements for creating the database. The scheme in [64] applies Kalman filtering to the fingerprint location scheme because the Kalman filtering method can incorporate additional information about the MD's motion to improve the location estimate. Jin et al. [65] uses the channel impulse response to increase the dimensions of the fingerprint vector and to distinguish the location over a large area. A small number of APs are deployed at the same time to provide communication coverage within the larger area. Figuera et al.[66], [67] reduce

the cost of the fingerprinting process by analyzing and providing the optimum value of the time space sampling period. In [68]-[70], the mean RSS value is recorded in the database. In the localization phase, the location is estimated by comparing the observed RSS information with the collected mean RSS values. These approaches can work well with a large number of collected samples. Indoor location estimation [71] is proposed to make use of the labeled and unlabeled samples to reduce the offline calibration. A small number of labeled samples are first employed to construct the initial model of the RSS measurement metrics and survey location. Then, the unlabeled samples are exploited to refine the model. Localization is carried out based on the model and labeled data as this provides a high degree of location accuracy.

RSS-based localization through the use of signal propagation modeling consists of estimating the ranges from RSS measurements and then computing the MD's position. In an indoor environment, the RSS is unreliable as the signal suffers from the multipath and shadowing effects. To overcome this problem, Barsocchi et al. [72] employs a calibration mechanism to automatically calibrate the parameters of the propagation model and select and weight RSS values according to their strength. The calibration works in two phases: the global virtual calibration and the per-wall virtual calibration. The former is done to assign the same parameter to every wall, based on all the RSS measured from any pair of anchors. The latter uses an attenuation factor for the walls that only affects communication between exact pairs of RDs. Laaraiedh et al. [73] puts forward two schemes to find the MD's location: the direct scheme and the indirect scheme. The former finds the MD's location by using the weighted LS

method based on the log normal distribution. The latter maximizes the joint probability distribution function.

2.2 Existing NLOS Localization Scheme

The methods mentioned in section 2.1 can obtain a high level of accuracy under the assumption of LOS propagation. However, in dense multipath environments, such as the one shown in Figure 2.2, NLOS error has been thought as a key issue for precise localization, since they induces large and unpredictable deviations in measurements. Therefore, some methods have been developed to tackle the NLOS problem. Generally, these methods can be divided into methods with and without a prior information scheme.

Figure 2.2 Multipath propagation shows reflection, diffraction and scattering paths.

2.2.1 NLOS Localization without Prior Information

The methods can be further separated into NLOS identification and NLOS mitigation [74]-[77]. The former differentiates between LOS and NLOS information, and only LOS measurements are utilized for localization. The latter finds the location by taking into account all NLOS and LOS measurements. A decision frame for NLOS identification is proposed in [78]. It uses the fact that the errors of NLOS measurements are more dominant to formulate the problem as a hypothesis test based on the Gaussian model. The scheme in [79] also uses a hypothesis test to determine whether the MD is LOS or NLOS by comparing the MSE of the propagation distance measurements with the variance of the LOS distance estimations. Compared with [78], the scheme in [79] also handles the case where there are fewer than three LOS RDs, by employing the statistics of the arrangement of circular traces to improve position estimation.

Ma et al. [80] uses a hypothesis test performed on the cost function to mitigate an NLOS error for the TDOA location system. The procedure to detect NLOS error is as follows. First, use all TDOA measurements in LOS/NLOS to find the intersection. The intersection's distribution is then constructed and the intermediate location of the MD is derived by seeking the maximum intersection distribution. Second, the cost function is formed to identify NLOS to further improve location accuracy. The shortcoming of hypothesis

identification is that prior variance statistics need to be observed and recorded which is not feasible in ad hoc wireless networks.

A residual testing algorithm is presented in [81]. The principle, based on the residuals which are the squared differences of the estimates and the true values, is that if all measurements are in an LOS scenario and the location solution is attained by approximate maximum likelihood (AML), the residuals will follow a central χ^2 distribution. Otherwise, the distribution is noncentral χ^2 . The decision as to whether the measurements are in an LOS scenario is made by counting the number of residuals for a noncentral χ^2 distribution and checking if they exceed what a central χ^2 distribution should have. If the number is larger than that, NLOS errors exist. In this method, all possible combinations of the RDs should be tried out to discover NLOS situations. Since this method is computationally intensive and time-consuming, Lei et al. [82] proposes a low computational residual test. This optimized process examines only an intermediate set of measurements that has the highest probability of not having any NLOS errors and then judges whether this set is in LOS propagation. A simpler method that uses LS estimation instead of AML is used in the identification process. In indoor environments, a situation may arise where only NLOS ranges are available while estimating the MD's location.

Maximum likelihood (ML) detection is applied to the NLOS problem on the basis of redundant TOA measurements [83]. There are two steps: first, the ML estimation position is calculated by using the RDs that are assumed under LOS.

Second, the theoretical variance is compared to the variance of the estimated position. The final position is the one that minimizes the value of η .

A novel method based on multipath channel statistics instead of range measurements is presented in [84]. It separates LOS from NLOS by using the amplitude and delay statistics of UWB channels. The amplitude is described by kurtosis, which is defined as the ratio of the fourth order moment of the data to the square of the variance. The delay property is characterized by the mean delay τ_m and rms delay spread τ_{rms} . Subsequently, a joint likelihood ratio test is developed for NLOS identification.

In [85], a NLOS identification algorithm is proposed, depending on how much of the prior information on NLOS errors at each RD is available in a database. The algorithm also handles the situation where no knowledge of NLOS errors can be obtained through the improved residual algorithm. However, the creation of the database is costly, in terms of human effort and time. The residual algorithm relies on a sufficient number of available RDs, among which only a small part are in the NLOS condition.

Bartelmaos et al. [86] proposes a new MD location algorithm by taking into account possible large round trip time (RTT) measurement errors in NLOS. The algorithm uses redundancy that indicates more than three RDs are connected with the MD. A selection algorithm, based on a coherent criterion, is applied to identify and remove some strongly erroneous RTT measurements. The coherent criterion is a measurement of the difference between the MD-RD distances

calculated from the MD's estimated position and the time delay measurements. Finally, the MD's position is estimated by using only the three most reliable RTT measurements.

In a rich multipath environment, plenty of scatterers surround the RDs and MDs, which may lead to most of the RDs being in the NLOS area. Thus, the methods described above that only use LOS measurements cannot work well since they require the number of LOS RDs to be greater than the number of NLOS RDs and only a few of the measurements are affected by NLOS errors. This implies a need to exploit the whole set of information to estimate the location of the MD since NLOS observations can also provide some information to improve location-seeking performance to some degree.

The schemes in [87] and [88] localize the MD's location with all of the LOS and NLOS measurements by using scale factors to optimize a constraint equation that reduces the contribution of the NLOS measurements. A constraint quadratic programming scheme in [89] is adopted to find the maximum likelihood location of the MD in the limited area because of the bias in the NLOS measurements. In the three methods proposed above, the minimized NLOS error may sometimes not offer a reliable solution. The schemes in [90] and [91] provide novel algorithms to mitigate NLOS errors and perform cooperative localization in wireless networks with prior knowledge of NLOS information. The scheme in [92] proposes a low-complexity linear-programming (LP) approach to carry out the estimation. The LP algorithm changes the sum of the residual-error squares to a linear function form. The

NLOS information is used to confine the estimate region which helps improve the location-seeking performance. The scheme in [93] utilizes the constraint optimization algorithm to jointly determine the estimated location and NLOS error based on sequential quadratic programming. These two approaches do not need prior knowledge of NLOS errors. The method in [94] proposes a NLOS localization scheme by using virtual anchors together with prior knowledge of the environment.

Tang et al. [95] utilizes the temporal-spatial characteristics of the propagation channel to mitigate NLOS errors by constraining the MD's location to an enclosed region via TOA measurements and AOA bounds. To determine the MD's position, the objective function is taken to further limit the location, by minimizing the sum of squares of the distance between the MD's position and all of the endpoints in the area. A prior NLOS measurement correction scheme is presented in [96] to determine the extent of NLOS propagation from each RD in the previous stage to the location process. This information will enable us to efficiently correct the NLOS effect by subtracting the estimated error.

However, accuracy in these two methods [95], [96] mainly relies on the NLOS error model that may not be available in some cases.

[97] presents an omni directional cooperative location scheme via the measured TOA and AOA at the RDs. It assumes that only single bounce reflections are dominant between the RDs and the MD and that more than three single reflection paths are reflected from the same point. However, these assumptions

may not be feasible in a real indoor environment. The schemes in [98]-[100] use the bidirectional estimation of AOA and TOA measurement data at both the RD and MD so as to utilize the NLOS path to carry out localization. However the method in [99] only works well when NLOS errors are small, and an accurate initial guess of the MD's location is needed to prevent a nonconvergence of the estimation. To overcome the weakness, the methods in [98] and [100] propose a robust NLOS localization scheme to improve location accuracy in both LOS and extreme NLOS scenarios whereby an LOS path might not exist. The algorithm in [100] works by first deriving the line of possible MD locations (LPMD) from the LOS and NLOS single bounce scattering paths. Miao et al. [98] uses the least squares solution from one bounce scattering paths to find the MD's location. However, in the heavy multipath environment, the multiple bounce reflection paths become dominant. If these paths are mistakenly used for localization, location accuracy will be dramatically decreased. As a result, Seow and Tan [100] propose the proximity detection scheme to detect and discard the multiple bounce scattering paths. Furthermore, a mechanism is devised to select paths that do not converge with each other. Finally, the position of the MD can be determined at the intersection point of two LPMDs.

2.2.2 NLOS Localization with Prior Information

NLOS localization methods with prior information are extensively used in mobility tracking systems. The main idea is to exploit the redundant measurements in a time series to mitigate the NLOS error. The Kalman filter [101] and [102], based on a general Bayesian theory, allows the position and velocity of the MD to be tracked and produces an accurate location algorithm. The best estimates of the dynamic position and velocity state vector are found in terms of the observations up to time t . The method has two main steps: state prediction and measurement update. In the first step, the estimates of the next state and error covariance matrix are derived from the transition equation. Next, the updated estimate will be produced by the current measurement, the kalman gain and the predicted state vector. In [103] and [104], an estimator is designed to distinguish the transition mode by integrating the interacting multiple model (IMM) [105] into the kalman filter scheme. It has been shown that the estimator can greatly alleviate the NLOS errors on the range measurement. By leveraging this model, the extended kalman filter and data fusion of TOA/RSS measurement are used to improve localization performance [106]. However, it should be noted that this scheme requires prior knowledge of the NLOS probability distribution function (PDF), which may not be available in reality.

In the tracking system, the measurement data are always formulated to be in a nonlinear form. Thus, the extended kalman filter [107]-[112] has been proposed

to linearize the state transition and measurement equation, and eventually the standard kalman filter will be used to track the target.

Another tracking scheme is the particle filter [113]-[116], which is an implementation of a Bayesian filter using Monte Carlo sampling. Its key purpose is to evaluate the posterior density function through a set of random samples with relative weights and calculate the location of the MD using these samples and weights. It does not require any linearity or have any Gaussian limitation on transition or measurement models. There are three parts to the method: particle propagation, weights update and resampling. Particle propagation is used to generate a new set of samples. It is performed by passing the samples X_{K-1} to the transition equation to obtain the time-update samples X_K . For the resampling scheme, since the number of particles is finite and some have high weights that carry information while some may have small ones that are not useful for location estimation, resampling is a good remedy to eliminate the particles with small weights to further improve accuracy. However, a high number of particles and a large amount of memory are required to have a precise density estimate.

Chapter 3

LPMD-Based Localization Using Gaussian Weighting Function

Existing localization schemes make use of the Time of Arrival (TOA) and Angle of Arrival (AOA) of the LOS and single bounce scattering paths to derive the line of possible mobile device positions (LPMDs). The intersections of the LPMDs are then used to estimate the unknown position of the mobile device - referred to as the Line Segment Intersection. However, in a heavy multipath environment with many multiple reflection and diffraction paths, existing LPMD-based localization schemes require proper values of weighting factors and threshold values which are environment-specific to select the appropriate LPMDs for localization. A large localization error will come about if the LPMDs of multiple-bounce reflection or diffraction paths are mistakenly used for intersections. Existing schemes would also not work well in a multipath environment with high levels of TOA and AOA noise, especially when the angles between the LPMDs are small. The accuracy of the Line Segment Intersection also deteriorates as the distance traveled by the multipath

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signals becomes comparable to each other. This renders the weighting and threshold values ineffective.

A two-step weighting process [117] method is proposed for heavy multipath environments. In the first step, the weighting factor of each LPMD is developed as a function of the distance of the propagation path. The centroid of all weighted LPMDs is calculated to eliminate those LPMDs that are far from it. In the second step, the proximate point that is at the minimum distance between each pair of the remaining LPMDs will be found and the corresponding weighting factors will be calculated. Finally, the centroid of these proximate points will be located and the proximate points that are close to this centroid will be used to estimate the location of the MD.

In this chapter, we formulate a novel localization scheme to improve the robustness of the method used in [100] and [117]. More importantly, our proposed scheme does not require the use of specifically adjusted weighting factors or threshold values for the selection of the LPMDs for localization. The robustness and accuracy of the scheme is also greatly enhanced by our proposed Gaussian weighting process that does not require any threshold value to select the LPMD for localization. The rationale of this Gaussian weighting process is that since each measurement metric contains noise, the proximate point between a pair of LPMDs will also contain noise. The amount of noise variance at each proximate point can be analytically determined, and is subject to many factors such as distance travelled, and the relative alignments of LPMD pairs that form the proximate point. The proposed scheme will construct a

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Gaussian weighting function of each proximate point using the calculated variance, and assign weights to proximate points based on how close these points are to the proximate point of interest. More weight will be assigned to the proximate points that have a lower variance compared to their neighbors. This process removes the need for specifically-chosen weighting factors and threshold values as shown in Table 3-1. Formulations are expressed in two dimensions and can be easily extended to three dimensions.

3.1 Theory and Formulation

3.1.1 Concept of the Line of Possible Mobile Device

The concept of Line of Possible Mobile Device (LPMD) in a 2-D environment has been introduced in Seow and Tan [100]. It uses the AOA and TOA of one-bounce signal paths at both the RD and MD to construct possible positions for the MD, referred to as LPMD, shown in Fig. 3.1. An RD with a known location (x_R, y_R) measures AOA θ_i and TOA t_i while an MD with an unknown location (x, y) measures AOA ϕ_i and TOA τ_i where $i=1,2,...N$ denotes the number of the received path. The measured TOA $t_i(\tau_i)$ pertains to the propagation distance $d_i(r_i)$ where $d_i(r_i) = t_i(\tau_i) \times$ the speed of wave propagation. In Fig. 3.1, the true one bounce scattering path is RD- S_i -MD. Given the measurement metrics θ_i and $d_i(r_i)$, one possible location of MD is at MD₁ as shown in the figure.

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Consider the measurement metrics θ_i, ϕ_i and $d_i(r_i)$, it is noted that the location of S_i is not unique. One possible location of S_i is at S'_i as shown in Fig. 3.1. $r' = d_i - |RD - S'_i|$ is the distance between S'_i and the possible MD location. Therefore by leveraging on the AOA θ_i, ϕ_i and $d_i(r_i)$, another possible location of MD can be found at MD₂. As such, all possible MD locations can be identified and will lie on a straight line, which is referred to as the line of possible mobile device (LPMD).

Figure 3.1: Line of Possible Mobile Device Position (LPMD) [100].

As shown in Fig. 3.1, the equations for two dimensional LPMDs are obtained in the following equations:

$$X_{e_{i,1}} = x_R + d_i \cos(\theta_i)$$

$$Y_{e_{i,1}} = y_R + d_i \sin(\theta_i)$$

$$X_{e_{i,2}} = x_R - r_i \cos(\phi_i)$$

$$Y_{e_{i,2}} = y_R - r_i \sin(\phi_i)$$

(3.1)

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Where

$X_{e_{i,1}}, Y_{e_{i,1}}$ = coordinates of one end of the LPMD formed by the i^{th} signal path.

$X_{e_{i,2}}, Y_{e_{i,2}}$ = coordinates of the other end of the LPMD formed by the i^{th} signal path

Upon the construction of the LPMDs, Seow and Tan's methodology in [100] proposes the calculation of the centroid C for these LPMDs. As shown in Fig. 3.2, which is a typical multipath environment, the one bounce scattering paths' LPMDs will cluster together and multiple bounce scattering paths' LPMDs will be the outliers. Therefore, through the calculation of the centroid of all LPMDs, the selection of LPMDs is done based on the nearest distance to the centroid. As such, the multiple bounce scattering paths' LPMDs can be accurately isolated. The MD's location is estimated from the intersection of one bounce scattering paths' LPMDs.

Figure 3.2: LPMDs cluster map in Nanyang Technological University at school of EEE faulty block with MD location at coordinate (16, 8) [100].

3.1.2 Concept of Proximate Points

In a rich multipath environment such as an indoor scenario, existing LPMD-based localization schemes may not work well, as they require proper weighting factors and threshold values which are environment-specific. Large localization errors will occur if multiple bounce reflection or diffraction paths' LPMDs are mistakenly used for localization. In this section, the concept of the Gaussian proximate point is proposed to enhance localization accuracy. Proximate point exists on each LPMD satisfying the condition that the distance between these two points is the minimum. Figure 3.3 shows the proximate point P_a of a LPMD-pair in two dimensions.

Figure 3.3: The proximate point and the corresponding LPMDs pair.

As shown in Fig. 3.3, each pair of LPMDs has the same proximate point vector

$\vec{OP}_a$ which can be derived as:

$$\begin{aligned} \vec{l}_1 + \gamma_0 \vec{v}_1 & \text{ using LPMD}_j \\ \vec{l}_2 + \beta_0 \vec{v}_2 & \text{ using LPMD}_i \end{aligned} \quad (3.2)$$

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where $\vec{v}_1, \vec{v}_2$ are unit vectors along the LPMD_j and LPMD_i direction respectively, and $\vec{\ell}_1, \vec{\ell}_2$ are the vectors starting from the origin to two ends of two LPMDs, respectively.

γ_0 and β_0 are derived as follows:

$$\begin{aligned} 0 &= (\vec{\ell}_2 + \beta_0 \vec{v}_2) - (\vec{\ell}_1 + \gamma_0 \vec{v}_1) \\ &= \vec{\ell}_{12} - \gamma_0 \vec{v}_1 + \beta_0 \vec{v}_2 \end{aligned} \tag{3.3}$$

thus:

$$\begin{aligned} (\vec{\ell}_{12} - \gamma_0 \vec{v}_1 + \beta_0 \vec{v}_2) \cdot \vec{v}_1 &= 0 \\ \vec{\ell}_{12} \cdot \vec{v}_1 + \beta_0 \vec{v}_2 \cdot \vec{v}_1 - \gamma_0 &= 0 \end{aligned} \tag{3.4}$$

$$\begin{aligned} (\vec{\ell}_{12} - \gamma_0 \vec{v}_1 + \beta_0 \vec{v}_2) \cdot \vec{v}_2 &= 0 \\ \vec{\ell}_{12} \cdot \vec{v}_2 + \beta_0 - \gamma_0 \vec{v}_1 \cdot \vec{v}_2 &= 0 \end{aligned} \tag{3.5}$$

Solving equation (3.4) and (3.5):

$$\gamma_0 = \frac{(\vec{\ell}_{12} \cdot \vec{v}_1) - (\vec{\ell}_{12} \cdot \vec{v}_2)(\vec{v}_1 \cdot \vec{v}_2)}{1 - (\vec{v}_1 \cdot \vec{v}_2)^2} \quad \beta_0 = \frac{(\vec{\ell}_{12} \cdot \vec{v}_1)(\vec{v}_1 \cdot \vec{v}_2) - (\vec{\ell}_{12} \cdot \vec{v}_2)}{1 - (\vec{v}_1 \cdot \vec{v}_2)^2} \text{ where } \vec{\ell}_{12} = \vec{\ell}_2 - \vec{\ell}_1.$$

3.1.3 Localization Using Gaussian Weighting Function

Each LPMD can be assigned a normalized weight, which can be formulated as the square of the distance from the respective path. It is written as:

$$W_i = \frac{\frac{1}{0.25(d_i + r_i)^2}}{\sum_{j=1}^I \frac{1}{0.25(d_i + r_i)^2}} \quad (3.6)$$

The weighting factor of the proximate points can be obtained using the weight of each LPMD, and the angle between two LPMDs. If the angle between a pair of LPMDs is large, it is more likely that the location of the proximate point is well-conditioned. This is because the proximate point is the intersection of a pair of LPMDs. If the angle between two LPMDs is small, the solution will become singular [130]. Therefore, we will give more emphasis to the LPMD pairs that have larger angles as follows:

$$W_{P_a} = \left(\frac{W_n W_\ell}{W_n + W_\ell} \right) \sin \eta_{n,\ell} \quad (\ell \neq n) \quad (3.7)$$

Where $\ell, n = 1, 2, \dots, I$ where I is the number of paths from RD,

$a = 1, 2, \dots, A$ where A is the number of proximate points.

η : Angle between a pair of LPMDs.

As shown in the first part of equation (3.7), $\left(\frac{W_n W_\ell}{W_n + W_\ell} \right)$ is derived by taking into

account the weighting of each LPMD in the LPMD pair. If both of the two

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LPMDs have high weights, the proximate point will be given a high weight. If any of the two LPMDs has a low weight, the proximate point will be given a lower weight.

After assigning a weight for each proximate point using equation (3.7), the next step is to calculate the Gaussian weighting factor. It is calculated by considering the weight of the proximate points and the weight of their neighboring proximate points:

$$Wn_a = \sum_{k=1}^A \frac{Wp_k}{\sigma_{p_a} \sqrt{2\pi}} \times \exp\left(-\frac{\|\hat{p}_k - \hat{p}_a\|^2}{2\sigma_{p_a}^2}\right) \quad (3.8)$$

where σ_{p_a} is the location standard deviation of the proximate point a . $\hat{p}_k, Wp_k$ are the location coordinate and the weighting factor of neighboring proximate point k respectively.

Finally, the MD's location can be determined using:

$$\hat{MD} = \frac{1}{K} \sum_{a=1}^K (\hat{P}_a \times Wn_a)_{\delta_a < \delta_{th}} \quad (3.9)$$

where $\hat{P}_a = (x_a, y_a)$ is the position of the proximate point a .

δ_a is the distance between the a^{th} proximate point to the proximate point which has the greatest adjacent weighting.

$$\delta_{th} = 3\sigma_{p_a}$$

3.2 Results and Discussion

To test the applicability and accuracy of our proposed localization scheme, we compare our results with those presented in [100] under two different scenarios in a three dimensional environment: Scenario 1 has three RDs in the environment and Scenario 2 has only one RD in the environment. In Figures 3.4 and 3.8, RD denotes the reference node, while the node to be localized with respect to the RD is denoted as MD. The distance between the ceiling and the floor is 2.6m, and the height of all the scatterers is 2 m. The authors in [100] presented the results of their proposed scheme by selecting the two best LPMDs or one-bound scattering paths based on the following procedures: (1) each LPMD is assigned a weighting factor based on the length of the propagation path, (2) only LPMDs or paths that have weighting factors above a certain threshold value are included in the calculation. The optimum threshold value in [100] is found to be 0.1. In our proposed scheme, two LPMDs are required to obtain one proximate point. To give a fair comparison, we will use one proximate point with the highest Gaussian weighting factor as formulated in (3.8) to estimate the MD's position. Channel measurements in real environments [118], [119] were conducted to extract the TOA and AOA of the propagation paths and verified with ray tracing methodology [120]-[122]. Figure 3.4 shows the propagation paths between the RD and the MD using the TOA and AOA of the propagation paths from the measurement correlated with the ray tracing methodology. For a rigorous comparison with [100], the noise-free TOA and AOA of each signal path between the RD and the MD are subject to random TOA and AOA Gaussian noise with a mean of zero and a given

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variance. The averaged value of the distances from both RD and MD, d_a , is used to perform localization with its standard deviation σ_a . The root mean square (RMS) error is calculated as $\|MD - \hat{MD}\|$ with 10,000 independent simulation runs where $\hat{MD}$ denotes the estimated position of the MD.

Three RDs are positioned in the environment at (25, 9, 1), (18, 4, 1), (3, 14, 1) as shown in Figure 3.4 and the MD is positioned at various locations according to the following cases:

- Case A: MD is in LOS with three RDs
- Case B: MD is in LOS with two RDs
- Case C: MD is in LOS with one RDs

For case A, the MD is at position (16, 12, 1) in the layout as shown in Figure 3.4 (a). In this position, the MD is in LOS with three RDs. For case B, the MD is at position (16, 10, 1), whereby the MD is in LOS with two RDs. For case C, the MD is at position (16, 8, 1) whereby only one RD (18, 4, 1) is in LOS with the MD. Simulation results for case A to C are shown in Figure 3.5-3.7.

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(a)

(b)

Figure 3.4: Rays transverse between RD and MD for various propagation paths. (a) MD is in LOS with three RDs (b) MD is in LOS with two RDs (c) MD is in LOS with one RD.

Figure 3.5: Cumulative probability distribution (CDF) performance for MD in Figure 3.4 (a)

Figure 3.6: CDF performance for MD in Figure 3.4 (b).

Figure 3.7: CDF performance for MD in Figure 3.4 (c).

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Figures 3.5 to 3.7 illustrate that the proposed algorithm outperforms the existing localization scheme [100]. For example, in Figure 3.5, under condition 1: $\sigma_a = 3\text{m}, \sigma_\theta = \sigma_\phi = 5^\circ$, the proposed algorithm has about 2.4 m accuracy 90% of the time, compared to 3.9 m using the algorithm in [100]. Under condition 2: $\sigma_a = 4\text{m}, \sigma_\theta = \sigma_\phi = 10^\circ$, our proposed algorithm has about 3.6 m accuracy, compared to 6.6 m using the algorithm in [100]. This shows that our algorithm outperforms the algorithm in [100] and improves localization accuracy by up to 45%.

The reason for the substantial improvement is that our proposed scheme uses weighted intersection points (proximate points), while the intersection points are not weighted in [100]. It is noted that there is little improvement in Case C, as shown in Fig. 3.7, compared with that in Case A and B. This is because there are only three dominant paths in case C, as shown in Fig. 3.4(c). The simple intersection of the LPMDs and the weighted solution of the Gaussian weighting function give a fairly close performance.

To examine the accuracy and robustness of the proposed scheme in the multipath environment where there are many propagation paths with a similar amount of delay, the localization comparison in Scenario 2 is carried out in indoor environments. In Scenario 2, we compare our results with [100] and [117] in two different environments [118], [119] as shown in Figure 3.8 and Figure 3.10, respectively. In Figures 3.8 (a) and 3.8 (b), the RD is positioned at (5, 2, 1) and two different MDs are positioned at (13, 4, 1) and (16, 8, 1)

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respectively. In Figure 3.8 (a), the MD is in LOS with RD and the signal paths that will be used for localization include the LOS, ceiling and floor reflected paths (solid lines) and three one-bounce wall reflection paths (dashed-lines). Higher order scattering paths that must be mitigated include twelve two-bounce reflected paths (dotted-lines) and twenty-four three-bounce reflected paths (dotted-lines). In Figure 3.8 (b), there is no direct LOS path between the MD and the RD. The shortest dominant propagation path is the ceiling reflected path, shown as a solid line. The ceiling reflected path and the two one-bounce wall reflected paths could be exploited to perform localization. Higher order scattering paths that may cause localization errors include ten two-bounce and twenty-five three-bounce reflection paths.

Figure 3.9 shows the CDF performance of our proposed localization scheme compared with [100]. The AOA standard deviations for both the RD and the MD (σ_θ and σ_ϕ) are chosen to be 4 degrees (and 8 degrees) while the distance standard deviations σ_a is 2m (and 4 m), referred to as Conditions 1 and 2 respectively. In Figure 3.9, ω_{th} is the LPMD weighting threshold value used in [100] to choose the two best LPMDs for localization. In our simulation, we have simulated ω_{th} from 0 to 0.1 and have chosen the optimum threshold value for comparisons. However, it is worth noting that our proposed localization scheme does not differentiate between LOS and NLOS paths. The proximate point with the highest Gaussian weighting factor is the estimated location of the MD.

(a)

(b)

Figure 3.8: (a) MD is in LOS with the RD. (b) MD is in NLOS with the RD.

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Figure 3.9 shows that our proposed scheme outperforms Seow and Tan's scheme [100] by a significant margin. For example, in the LOS scenario (Figure 3.9 (a)) under condition 1: $\sigma_a = 2$ m, $\sigma_\theta = \sigma_\phi = 4^\circ$, our proposed Gaussian weighted schemes achieved an accuracy of 1.7m, compared to 2.4m for Seow and Tan's in [100] using 90 percent of CDF. This represents an improvement of about 29%. The margin of improvement increased to 42% as the TOA and AOA noise increased to Condition 2: $\sigma_a = 4$ m, $\sigma_\theta = \sigma_\phi = 8^\circ$. In Figure 3.9 (b), the MD is in NLOS with the RD with very severe multipath propagation i.e., the distances traveled by many multiple-bounce paths are comparable or shorter than the one-bounce scattering paths, making the weighting factors and threshold value in [100] ineffective. Table 3-1 shows the true propagation distance of single and multiple-bounce paths and their corresponding weighting factors for MD shown in Figure 3.8 (b). In this case, many multi-bounce paths have higher weighting compared with the single-bounce paths. Too high a threshold value may result in fewer than 2 paths being needed for localization. For example, only the ceiling reflected path would be chosen if ω_{th} is more than 0.04. On the other hand, if the threshold value is too low, we will not be able to exclude the multiple-bounce paths. Considerable errors will result if these multiple-bounce paths are used by mistake. For example, under condition 1, our proposed Gaussian weighted scheme achieved an accuracy of 1.6m for 90% of the time compared to 6.9m ($\omega_{th} = 0.03$) and 9.2m ($\omega_{th} = 0.02$) for Seow and Tan's in [100]. This represents a significant improvement of about 77% and 83% respectively as shown in Figure 3.9 (b).

(a)

(b)

Figure 3.9: (a) CDF performance for MD in Figure 3.8(a). (b) CDF performance for MD in Figure 3.8(b).

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Number of reflection	Propagation Distance	Weighting factor of LPMD
One bounce reflection path	12.9m	0.046
	14.8m	0.040
	21.7m	0.027
Two bounce reflection path	14.9m	0.040
	15.1m	0.039
	23.1m	0.025
	33.6m	0.018
Three bounce reflection path	15.7m	0.038
	20m	0.029
	22.7m	0.026
	25.7m	0.023
	55.1m	0.011

Table 3-1 Propagation Distance and weighting factor for one bounce and multiple bounce scattering paths.

We also make a comparison with [117] based on the same dimensions of the above-mentioned environment. One scatterer is generated according to the uniform distribution in the indoor environment [123]. The standard deviations of the angle at the RD and the MD are 10 degrees and 20 degrees, while the distance standard deviations are 2 m and 4m respectively. One RD is positioned in the environment at (1, 2, 1) and the MD is located in three different locations, (13, 6, 1), (18, 10, 1) and (20, 3, 1), as shown in Figure 3.10.

— LOS and One bounce reflection path
..... Multiple bounce reflection path

(a)

— LOS and One bounce reflection path
..... Multiple bounce reflection path

(b)

Figure 3.10: Rays transverse between RD and MD for various propagation paths (a) MD₁ is at (13, 6, 1) (b) MD₂ is at (18, 10, 1) (c) MD₃ is at (20, 3, 1).

Figure 3.11: CDF performance for MD location at (13, 6, 1).

Figure 3.12: CDF performance for MD location at (18, 10, 1).

Figure 3.13: CDF performance for MD location at (20, 3, 1).

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Figures 3.11-3.13 illustrate the CDF performance of the Gaussian Adjacent Weighting NLOS localization scheme in the multipath indoor environment, compared with [100] and [117]. Our proposed localization scheme is more accurate. Figure 3.11 shows that, when the MD is located at (13, 6, 1) and $\sigma_\theta = \sigma_\phi = 10^\circ, \sigma_a = 2\text{m}$, the NLOS localization scheme based on Gaussian weighting function has an accuracy of about 2.2m 90% of the time, compared to 3.2m in [117] and 8.4m in [100]. The margin of improvement is about 73%. When $\sigma_\theta = \sigma_\phi = 20^\circ, \sigma_a = 4\text{m}$, the use of the Gaussian weighting function provides an accuracy of about 5.1m 90% of the time, compared to 5.6m [117] and 8.9m [100]. The improvement is about 43%. Figure 3.12 shows that when the location of the MD is changed to (18, 10, 1) and $\sigma_\theta = \sigma_\phi = 10^\circ, \sigma_a = 2\text{m}$, the Gaussian weighting method achieves an accuracy of about 2.7m 90% of the time, compared to 5.2m in [117] and 10.4m in [100]. This is an improvement of up to 74%. When $\sigma_\theta, \sigma_\phi$ and σ_a change to 20° and 4m, the Gaussian weighting method has an accuracy of about 6.7m 90% of the time, compared to 8.1m in [117] and 10.6m in [100]. This represents an improvement of about 37%. When the location of the MD is (20, 3, 1) as shown in Figure 3.13 and $\sigma_\theta = \sigma_\phi = 10^\circ, \sigma_a = 2\text{m}$, the Gaussian weighting scheme has an accuracy of about 2.5m 90% of the time, compared to 4.4m in [117] and 8.4m in [100]. This is an improvement of up to 70%. When $\sigma_\theta, \sigma_\phi$ and σ_a increase to 20° and 4m, the Gaussian weighting scheme has an accuracy about 6.3m 90% of the time, compared to 7.8m in [117] and 14m in [100]. This represents an improvement of about 55%.

3.3 Remarks

A novel and robust NLOS localization scheme has been proposed by utilizing the proximate points and a Gaussian weighting factor. Simulation results show that the proposed Gaussian weighting function localization scheme outperforms the existing NLOS localization schemes in all cases in relation to various degree of TOA and AOA measurement noise in dense multipath environments. However, this proposed scheme requires at least two paths which are LOS or undergo one bounce reflection. Thus, it does not work if there is only one dominant path.

Chapter 4

APMD-Based Localization Using One Dominant Path

Chapter 3 presents a line intersection localization methodology. To improve localization accuracy, an area-based localization scheme is proposed in this chapter. This chapter focuses on formulating the area intersection-based localization scheme using LOS paths. The proposed scheme in Chapter 3 cannot exploit the different distance measurements at both the RD and the MD. In contrast, in this chapter, the different distance measurement can be used to enhance localization accuracy.

The most significant source of errors in wireless localization in a multipath environment is the presence of the indirect or scattered NLOS paths. Many schemes [85], [89], [90], [124], [125] have been developed to reduce the errors due to NLOS paths. However, these schemes do not perform satisfactorily if there are too few LOS RDs. For example, the conventional TOA localization schemes require at least three LOS RDs for 2D localization. If any RD is in a

NLOS condition, localization accuracy will be seriously degraded. This section presents a robust and novel method to overcome these limitations by using a single RD in the LOS to estimate the location of an MD. By measuring the LOS path's TOA and AOA at the RD and the MD, we are able to construct two areas that cover all of the possible locations where the MD may reside. These locations are called “areas of possible MD” (APMD). The intersection of these APMDs will give an estimate of an MD's location, improving localization accuracy and robustness.

4.1 Theory and Formulation

Figure 4.1 depicts the geometrical relationship between the RD and the MD in the 2D plane. The TOA (t , τ) and AOA (θ, ϕ) were measured at (RD, MD). The RD's coordinate (x_R, y_R) is known and the MD's position (x, y) is to be estimated from the measured TOAs and AOAs. The measured TOAs are related to the propagation path lengths which are $d = ct$, $r = c\tau$ where c is the speed of propagation of the waves.

The AOA and TOA data values are perturbed by measurement noise:

$$\begin{aligned} \theta &= \theta^0 + n_\theta, \phi = \phi^0 + n_\phi, d = d^0 + n_d, r = r^0 + n_r \\ n_m &= N(0, \sigma_m) \quad m = \theta, \phi, d, r \end{aligned} \tag{4.1}$$

where θ^0, ϕ^0 and d^0, r^0 are the true AOA and TOA values of the signal path,

and n_θ , n_ϕ and n_d , n_r refer to measurement noise and are assumed to be zero mean Gaussian random variables with known standard deviation σ_m . $\hat{RD}(\hat{MD})$ denotes the estimated position of the RD (MD) because of the measured metrics $\tau(t)$ and $\phi(\theta)$ at MD (RD). The LOS path can be identified from the NLOS path if the measured ϕ and θ satisfy $|\theta - \phi| \leq 180^\circ \pm \sigma_{a_{\max}}$ where $\sigma_{a_{\max}} = \max(3\sigma_\theta, 3\sigma_\phi)$.

Figure 4.1: Geometrical relationship between RD and MD

At the RD, the APMD can be confined to an enclosed region of possible MD locations, NOPQ, within $[\theta - 3\sigma_\theta, \theta + 3\sigma_\theta]$ and $[d - 3\sigma_d, d + 3\sigma_d]$ as shown in Figure 4.2 (a). Similarly, another APMD, STUV, can be found at the MD as shown in Figure 4.2 (b). Since the RD's position is known, we can flip the area STUV from the MD to the RD. A smaller APMD, ABCD, can be obtained by overlapping NOPQ and STUV at the RD as shown in Figure 4.2 (c). As illustrated, the enclosed area ABCD shows that the estimated location of the MD, $\hat{MD}$, is much nearer to the true location of the MD compared with Figure

Figure 4.2 Area of Possible Mobile Device (APMD)

The estimated location of the MD ($\hat{MD}$) can be determined from the intersection area of the APMD, ABCD as shown in Figure 4.2 (c). This is done by minimizing the sum of squares of the distance from $\hat{MD}$ to the vertices of the enclosed region i.e. A, B, C and D.

$$J = \sum_{k=1}^K \left((x_k - x)^2 + (y_k - y)^2 \right) \quad (4.2)$$

where (x, y) is the location of $\hat{MD}$, (x_k, y_k) is the location of each vertex of the enclosed region. $k=1, 2 \dots K$ corresponds to the A, B, C, D as shown in Figure 4.2 (c). (4.2) can be re-arranged in matrix form as

$$J = (\mathbf{CZ} - \boldsymbol{\lambda})^T (\mathbf{CZ} - \boldsymbol{\lambda}) \quad (4.3)$$

where $\mathbf{C} = [\mathbf{c}_1 \quad \mathbf{c}_2 \quad \dots \quad \mathbf{c}_K]^T$ and $\mathbf{c}_k = \mathbf{I}_{2 \times 2}$. $\boldsymbol{\lambda}$ is the coordinate vectors of these vertices and the location of $\hat{MD}$ is $\mathbf{Z} = [x, y]^T$.

$$\begin{aligned}
 \boldsymbol{\lambda} &= [\lambda_1, \lambda_2, \dots, \lambda_K]^T \\
 &= [x_A, y_A, x_B, y_B, x_C, y_C, x_D, y_D]^T \\
 &= [x_R + (l_{\max} - 3\sigma_{l_{\max}}) \cos(\alpha_{\max} - 3\sigma_{\alpha_{\max}}), y_R + (l_{\max} - 3\sigma_{l_{\max}}) \sin(\alpha_{\max} - 3\sigma_{\alpha_{\max}}), \\
 &\quad x_R + (l_{\max} - 3\sigma_{l_{\max}}) \cos(\alpha_{\min} + 3\sigma_{\alpha_{\min}}), y_R + (l_{\max} - 3\sigma_{l_{\max}}) \sin(\alpha_{\min} + 3\sigma_{\alpha_{\min}}), \\
 &\quad x_R + (l_{\min} + 3\sigma_{l_{\min}}) \cos(\alpha_{\min} + 3\sigma_{\alpha_{\min}}), y_R + (l_{\min} + 3\sigma_{l_{\min}}) \sin(\alpha_{\min} + 3\sigma_{\alpha_{\min}}), \\
 &\quad x_R + (l_{\min} + 3\sigma_{l_{\min}}) \cos(\alpha_{\max} - 3\sigma_{\alpha_{\max}}), y_R + (l_{\min} + 3\sigma_{l_{\min}}) \sin(\alpha_{\max} - 3\sigma_{\alpha_{\max}})]^T
 \end{aligned} \tag{4.4}$$

$$l_{\min} = \min(d, r), l_{\max} = \max(d, r).$$

$$\alpha_{\min} = \min(\theta, \phi \pm \pi), \alpha_{\max} = \max(\theta, \phi \pm \pi).$$

$$\sigma_{l_{\max}} = \begin{cases} \sigma_d & \text{if } l_{\max} = d \\ \sigma_r & \text{if } l_{\max} = r \end{cases}, \sigma_{\alpha_{\max}} = \begin{cases} \sigma_\theta & \text{if } \alpha_{\max} = \theta \\ \sigma_\phi & \text{if } \alpha_{\max} = \phi \end{cases}$$

$$\sigma_{l_{\min}} = \begin{cases} \sigma_d & \text{if } l_{\min} = d \\ \sigma_r & \text{if } l_{\min} = r \end{cases}, \sigma_{\alpha_{\min}} = \begin{cases} \sigma_\theta & \text{if } \alpha_{\min} = \theta \\ \sigma_\phi & \text{if } \alpha_{\min} = \phi \end{cases}$$

Therefore, the least squares solution for (4.3) will simply be:

$$\mathbf{Z} = (\mathbf{C}^T \mathbf{C})^{-1} \mathbf{C}^T \boldsymbol{\lambda} \tag{4.5}$$

4.2 Simulation and Discussion

To test the applicability and accuracy of our proposed localization scheme, we compare our simulation results with those presented in [100]. Three RDs were positioned in the environment at (25, 9), (18, 4), (3, 14). The mobile device was placed at these positions: for case A, the MD is at position (16, 12) in the layout as shown in Figure 4.3(a). In this position, the three RDs are in LOS with the MD. For case B, the MD is at position (16, 10) as shown in Figure 4.3(b), and two RDs are in LOS with the MD. For cases C and D, the MD is at position (14.5, 12) and (16, 8) as shown in Figure 4.3(c) and 4.3(d), respectively. In case C, the RD (3, 14) is in LOS with the MD, and in case D, the RD (18, 4) is in LOS with the MD. Simulation results for cases A to D are shown in Figure 4.4. In cases A and B, more than one LOS path exists in the environment. Our proposed localization scheme always chooses a LOS path which has the smallest intersection area as shown in Fig. 4.2(c) to find the MD's location.

(a)

(b)

(c)

(d)

Figure 4.3 (a): MD is in LOS with three RDs. (b): MD is in LOS with two RDs. (c): MD is in LOS with RD₁. (d): MD is in LOS with RD₃.

(a)

(b)

(c)

(d)

Figure 4.4 (a): Comparison of the CDF performance for MD in Figure 4.3(a). (b): Comparison of CDF performance for MD in Figure 4.3(b). (c): Comparison of CDF performance for MD in Figure 4.3(c). (d): Comparison of CDF performance for MD in Figure 4.3(d).

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The simulation results (Figures 4.4 (a)-(c)) indicate that our proposed scheme outperforms the existing localization scheme by a significant margin especially when TOA and AOA measurement noises become large. For example, using $\sigma_d = \sigma_r = 3\text{m}$, $\sigma_\theta = \sigma_\phi = 5^\circ$, Figure 4.4(a) shows that our proposed scheme achieves an accuracy of 2.6 m 90% of the time, compared to 2.8 m for Seow and Tan's method in [100], and an improvement of about 7% is shown in Figure 4.4(a). This margin increases to 46% using $\sigma_d = \sigma_r = 3\text{m}$, $\sigma_\theta = \sigma_\phi = 10^\circ$. However, in Fig. 4.4(d), the performance of our proposed localization degrades because the existing localization scheme [100] always uses two shortest paths from RD₃ to find the location of the MD compared to our proposed localization scheme that only uses one LOS path. If the proposed scheme uses two paths, its performance will be better than that in [100].

Furthermore, we also make a comparison with the conventional TOA and TOA/AOA schemes using four RDs in different multipath environments. The simulations are conducted in light and heavy multipath environments in a 20×20 m area. The four RDs are placed at (0, 0), (0, 20 m), (20 m, 0) and (20 m, 20 m). The scatterers are assumed to be uniformly distributed in the environments [123]. The probability of NLOS (LOS) paths at each RD is assumed to be 20% (80%) and 40% (60%) [90] for light and heavy multipath environments, respectively. The NLOS path is referred to the scattering path from the RD to the MD via a scatterer.

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At the RDs, the standard deviation of the TOA, σ_d , and AOA, σ_θ , are fixed at 3 m and 5° , respectively [125]. At the MD, the standard deviation of the TOA, σ_r , is 3 m, whereas the standard deviation of the AOA, σ_ϕ , varies from 5° to 20° . The performance comparison for the average location error (ALE) is illustrated with 10,000 uniformly distributed MD locations. The conventional TOA and TOA/AOA localization schemes [89], [124] exploit the mitigation scheme [89], [85] to reduce the NLOS error, whereas the TOA location scheme in [90] relies on the iterative parallel projection method. Our proposed scheme and the TOA/AOA scheme in [125] both employ bidirectional estimation. Our proposed single RD scheme and [125] use only one RD at (0, 0) to estimate the MD's location, whereas the other schemes utilize all four RDs.

Figure 4.5 demonstrates the ALE performance by comparing our proposed single RD localization scheme with [125] and conventional localization schemes. All simulation results are taken from the algorithm in [85], [89], [90] and [125] without any modification and assuming no prior knowledge of the environment. Our proposed scheme achieves an average error of 3.3 m (4.2 m) in the light (heavy) environment, compared to an average error of 7.8 m (11.8 m) in Seow and Tan [125], 6.7 m (10.6 m) in Jia and Buehrer [90], 7.7 m (11.7 m) in Wang et al. [89] and 4.5 m (7 m) in Cong and Zhuang [124], [85]. This represents an improvement of more than 27% and 40% in the light and heavy multipath environments, respectively. The simulation results show that the margin of accuracy increases as the probability of NLOS increases. As shown, our proposed localization scheme outperforms conventional schemes for the

escalations of σ_ϕ using one RD. A similar trend is observed if σ_r is changed from 1 to 5 m. It is noted that the ALE performance of our proposed localization scheme increases with a slow rate. This is because for the area intersection, as long as either one of the areas is accurate, location accuracy can be maintained.

Figure 4.5 ALE comparison for 10,000 uniformly distributed MD locations with $\sigma_d, \sigma_r = 3\text{ m}$, $\sigma_\theta = 5^\circ$ with varying σ_ϕ in multipath environment

4.3 Analytical Performance Bound

In order to understand the performance of our proposed scheme without running a simulation, its analytical performance is determined in terms of its mean and variance. An efficient estimator should have a noise variance near the Cramer Rao Lower Bound (CRLB) [126], which is the lower bound on the variance of the estimator.

From (4.5), we can derive the mean of the MD's location Z which is given as

$$E(\mathbf{Z}) = E\left\{(\mathbf{C}^T \mathbf{C})^{-1} \mathbf{C}^T \boldsymbol{\lambda}\right\} = (\mathbf{C}^T \mathbf{C})^{-1} \mathbf{C}^T E(\boldsymbol{\lambda}) \quad (4.6)$$

The covariance of the location error is given as

$$\begin{aligned} \mathbf{C}_Z &= E\left\{(\mathbf{Z} - E\{\mathbf{Z}\})(\mathbf{Z} - E\{\mathbf{Z}\})^T\right\} \\ &= E\left\{(\mathbf{C}^T \mathbf{C})^{-1} \mathbf{C}^T \boldsymbol{\lambda} \boldsymbol{\lambda}^T \mathbf{C} (\mathbf{C}^T \mathbf{C})^{-1}\right\} - E\left\{(\mathbf{C}^T \mathbf{C})^{-1} \mathbf{C}^T \boldsymbol{\lambda} E(\mathbf{Z})^T\right\} \\ &= (\mathbf{C}^T \mathbf{C})^{-1} \mathbf{C}^T E(\boldsymbol{\lambda} \boldsymbol{\lambda}^T) \mathbf{C} (\mathbf{C}^T \mathbf{C})^{-1} - E(\mathbf{Z}) E(\mathbf{Z})^T \end{aligned} \quad (4.7)$$

where $\mathbf{C} = [\mathbf{c}_1 \quad \mathbf{c}_2 \quad \dots \quad \mathbf{c}_K]^T$ and $\mathbf{c}_k = \mathbf{I}_{2 \times 2}$ where $\mathbf{I}$ is the identity matrix and the detailed derivation of $E(\mathbf{Z})$ and $E[\boldsymbol{\lambda} \boldsymbol{\lambda}^T]$ for $K=4$ is given in Appendix A.

Substituting (A.1)-(A.9) into (4.7), and traces of it will provide the covariance for the location error. From the equation (A.2)-(A.9), it is also observed that the location error is associated with the term of the cosine or sine function of angle standard deviation. Hence, regardless of the change in the angle standard

deviation, the change in the localization error is minor.

Figure 4.7 illustrates the CRLB and error variance comparison with varying $\sigma_\theta, \sigma_\phi$ using $\sigma_d = \sigma_r = 2\text{m}$ for MD in Figure 4.6. The standard deviation of the TOA at the RD and the MD are set to 2m, whereas $\sigma_\theta, \sigma_\phi$ are varied from 1 degree to 7 degrees to test the robustness and stability of our proposed localization scheme to variations in AOA noise. As shown in Figure 4.7, the RMS error of our proposed APMD localization scheme, using (4.5), the error variance derived using (4.7) and its CRLB [126] are shown. The derived error variance is not equivalent to the CRLB bound, but does not deviate much from the CRLB limit.

Figure 4.6 Ray tracing between the RD and MD for various propagation paths.

Figure 4.7 CRLB and error variance comparison with varying $\sigma_\theta, \sigma_\phi$ using $\sigma_d = \sigma_r = 2\text{m}$ for MD in Figure 4.6.

4.4 Remarks

The proposed single RD localization scheme, which exploits the concept of APMD at both the RD and the MD, outperforms existing conventional localization schemes by a significant margin in the multipath environment, especially under a heavy multipath environment.

Chapter 5

Virtual Reference Device- Based NLOS Localization

In Chapter 4, the dominant path is the LOS path. However, in the absence of the LOS path, the scheme presented in Chapter 4 is not applicable for localization. In this chapter, we will present a scheme that can use the NLOS path by extending the concept of APMD to the NLOS path. Many schemes [85], [90] have studied NLOS identification and mitigation. Recently, localization schemes that locate MD by using NLOS paths directly have been reported [99], [100]. In [99], a Taylor series methodology is applied to find the MD's location by means of an initial guess of the MD's location and single bounce paths. In [100], the MD's location is determined if at least two dominant NLOS paths exist without the need for an initial estimate of the MD's location.

This chapter presents a novel method to significantly improve localization accuracy by using the concept of a virtual RD to determine the location of the MD, referred to as virtual reference device-based (VRDB) localization scheme.

The position of the virtual RD on a given NLOS path can be determined by an initial guess of the MD's location [99]. Alternatively, the location of the virtual RD can also be found if the MD transits from an LOS region to a NLOS region. After the positions of all virtual RDs have been identified, the subsequent locations of the MD can be determined by using just one dominant NLOS path and its corresponding virtual RD. The performance of our proposed localization scheme is evaluated using a simulation and an experiment in an indoor environment. The results show that our proposed scheme outperforms existing localization schemes by a significant margin for all simulated and measured locations.

5.1 Estimation of Virtual RD Position

We assume there is a one bounce reflection path between the RD and the MD. Figure 5.1(a) illustrates the geometrical relationship between the RD, the MD and a virtual RD which is associated with a one bounce reflection path. The RD has a known location (x_R, y_R) with measured data, AOA θ . The MD has an unknown location (x, y) with measured data, AOA ϕ . $\hat{MD}$ is the estimated MD position through the initial guess using a Taylor Series [99] or using the available LOS measurement metrics [90], [99], [100], [124], [128]. The measurement data TOA t is related to the propagation distance using $d = ct$ where c is the speed of wave propagation. The TOA (distance d) and AOA measurement values are assumed to be perturbed by Gaussian noise:

$$\theta = \theta^0 + n_\theta, \phi = \phi^0 + n_\phi, d = d^0 + n_d, \quad n_\beta = N(0, \sigma_\beta) \quad \beta = \theta, \phi, d \quad (5.1)$$

where θ^0, ϕ^0 and d^0 are the true AOA and TOA values of the signal path, and n_θ, n_ϕ and n_d denote the zero mean Gaussian random noise with standard deviation σ_β .

As shown in Figure 5.1(a), I_1 is the true virtual RD of signal path RD-F-MD because of reflection at surface RS. $\hat{I}_1$ is the estimated value of I_1 . The position of the virtual RD can be constructed from the RD with the vector $d_I = |d_I| \angle \eta$ where $\eta = (\theta + \phi) / 2$. $|d_I|$ is the distance between RD and $\hat{I}_1$ which can be written as:

$$|d_I| = \mathbf{a}^T \mathbf{a} + \mathbf{b}^T \mathbf{b} - 2\mathbf{a}^T \mathbf{b} \quad (5.2)$$

where $\mathbf{a} = |\mathbf{a}| \angle \phi$ and $\mathbf{b} = RD - \hat{MD}$. $|\mathbf{a}|$ is the distance between $\hat{MD}$ and $\hat{I}_1$, approximately equal to the measured TOA (distance) due to the signal path RD-F-MD.

The position of the virtual RD derived from the RD can be constrained to an enclosed region, $uvqp$, with the angle and distance measured from RD within $[\eta - 3\sigma_\eta, \eta + 3\sigma_\eta]$ and $[|d_I| - 3\sigma_{|d_I|}, |d_I| + 3\sigma_{|d_I|}]$ where $\sigma_\eta = (\sigma_\theta + \sigma_\phi) / 2$ and $\sigma_{d_I} = \sigma_d |d_I| / |\mathbf{a}|$ as depicted in Figure 5.1(a).

(a)

(b)

Figure 5.1 (a) Position of the virtual RD originated from the RD. (b) Position of the virtual RD originated from $\hat{MD}$ (c) Intersection of virtual RD regions.

Similarly, the position of the virtual RD derived from $\hat{MD}$ can be constructed within $[\phi - 3\sigma_\phi, \phi + 3\sigma_\phi]$, $[|a| - 3\sigma_d, |a| + 3\sigma_d]$ which is shown as *eghi* in Figure 5.1(b).

The estimated virtual RD is determined from the N vertices of the intersections of the two earlier obtained virtual RD regions, *abfmnr*, as shown in Figure 5.1(c). Without any loss of generality, a is chosen as (x_1, y_1) and r as (x_N, y_N) . The coordinates of the N ($N=6$ in this case) vertices are ordered clockwise from a , (x_1, y_1) to r , (x_N, y_N) . To determine $\hat{I}_1$ using the weighted least squares distance methodology [127], the intersection area is divided into a set of $N-2$ triangles with a as a reference. In this case, there will be four triangles namely *abf*, *afm*, *amn* and *anr*. J is the weighted least squares distance to all the

triangular centroid points, which is defined as

$$J = \sum_{j=1}^{N-2} w_j \left((x_{cj} - x_l)^2 + (y_{cj} - y_l)^2 \right) \quad (5.3)$$

where (x_l, y_l) is the location of $\hat{l}_1$, (x_{cj}, y_{cj}) is the centroid of the j^{th} triangular.

w_j is the weighting factor which is chosen to be proportional to the area of the j^{th} triangle. (5.3) can be re-arranged in matrix form as

$$J = (\mathbf{H}\hat{\mathbf{l}}_1 - \mathbf{C})^T \mathbf{W} (\mathbf{H}\hat{\mathbf{l}}_1 - \mathbf{C}) \quad (5.4)$$

where $\mathbf{C}$ is the coordinate of all triangular centroids and is given as

$$\mathbf{C} = [\mathbf{C}_1, \dots, \mathbf{C}_j, \dots, \mathbf{C}_{N-2}]^T = [x_{c1}, y_{c1}, \dots, x_{cj}, y_{cj}, \dots, x_{cN-2}, y_{cN-2}]^T .$$

$\mathbf{H} = [\mathbf{h}_1, \mathbf{h}_2, \dots, \mathbf{h}_j, \dots, \mathbf{h}_{N-2}]$ and $\mathbf{h}_j = I_{2 \times 2}$, a 2×2 identity matrix.

$$\mathbf{W} = \frac{1}{\sum_{k=1}^{N-1} \det(\mathbf{P}_k) + \begin{vmatrix} x_N & y_N \\ x_1 & y_1 \end{vmatrix}} \text{diag}(\mathbf{B}_1 \dots \mathbf{B}_j \dots \mathbf{B}_{N-2})$$

where $\mathbf{P}_k = \begin{bmatrix} x_k & y_k \\ x_{k+1} & y_{k+1} \end{bmatrix}$, $\mathbf{B}_j = \text{diag}(\det(\mathbf{S}_{j+1} \times \mathbf{S}_{j+2}), \det(\mathbf{S}_{j+1} \times \mathbf{S}_{j+2}))$,

$\mathbf{S}_{j+1} = [x_{j+1} - x_1 \quad y_{j+1} - y_1]$, and $\mathbf{S}_{j+2} = [x_{j+2} - x_1 \quad y_{j+2} - y_1]$. Finally, the

estimated virtual RD $\hat{l}_1$ corresponding to the NLOS path RD-F-MD can be calculated using

$$\hat{\mathbf{l}}_1 = [x_l \ y_l]^T = \arg \{ \min J \} = (\mathbf{H}^T \mathbf{W} \mathbf{H})^{-1} \mathbf{H}^T \mathbf{W} \mathbf{C} \quad (5.5)$$

The virtual RDs for other NLOS paths can be determined similarly. When the MD moves to a new location, the virtual RD that corresponds to the dominant NLOS path at the new location can be identified by using the measured TOA and AOA of that path. Based on the measured TOA, AOA and the corresponding virtual RD, the new position of the MD can be determined as:

$$\hat{\mathbf{MD}} = [x \ y]^T = \hat{\mathbf{I}}_1 + \mathbf{D} = (\mathbf{H}^T \mathbf{W} \mathbf{H})^{-1} \mathbf{H}^T \mathbf{W} \mathbf{C} + \mathbf{D} \quad (5.6)$$

where $\mathbf{D} = [d \cos([\phi - \theta]/2 + \alpha) \ d \sin([\phi - \theta]/2 + \alpha)]^T$ is the measured path vector due to a dominant NLOS path with $\alpha = \tan^{-1}[(y_R - y_I)/(x_R - x_I)]$ (see Figure 5.1 (b)). At each location of the MD, all virtual RDs will be recalculated. It is noteworthy that (5.6) only requires measured TOA and AOA to estimate the MD's location. It does not require prior knowledge of the location, orientation and the nature of the obstacles in the environment.

5.2 Simulation and Experimental Results

To check the accuracy and robustness of our proposed localization scheme, the simulation and experiment will be carried out in an indoor environment, which has dimensions of 16.4m $\times$ 9.5m along the X and Y axes such that $0 \leq x \leq 16.4\text{m}$ and $0 \leq y \leq 9.5\text{m}$. This dimension also corresponds to the Internet of Things (IoT) laboratory at the School of EEE, Nanyang Technological University (NTU) as shown in Figure 5.2. In this simulation, the RD is fixed at (12.9m, 0.7m) with 5,000 uniformly distributed MD locations. The obstacles are assumed to be randomly distributed with the probability of a NLOS path

assumed to be $1 - e^{-r/\lambda}$ [123] where r is the direct distance between the RD and the MD, while λ is the mean distance from the RD to obstacles. λ is chosen to be 5m and 10m [123] which translates to NLOS path's probability of 70% and 45% respectively. The standard deviation of the distance is assumed to be 2m. Angle standard deviations vary from 1° to 10° [100].

Figure 5.2 Geometry of the IoT laboratory at School of EEE, NTU.

Figure 5.3 depicts the comparison of the average location error (ALE) from our proposed localization scheme and the existing NLOS localization schemes in [99] and [100]. A comparison is also made with conventional TOA/AOA and TOA localization schemes, with their NLOS mitigation schemes in [85] and [90], respectively. Since [85] and [100] require at least two and three RDs respectively, another three RDs are placed symmetrically at (3.5m, 0.7m), (3.5m, 8.8m) and (12.9m, 8.8m) near the other three corners. In other words, [85] and [100] use four RDs to perform localization. In our proposed VRDB localization scheme and [99], the initial location of the MD is assumed to be

randomly distributed within a circle centered at the location of the MD with a radius equal to 5% of the distance between the RD and the MD [99]-[100]. As shown in Figure 5.3, our proposed VRDB localization scheme based on one RD achieves an ALE of less than 2m under both cases: $\lambda=5\text{m}$ and 10m , outperforming all existing localization schemes. The reason is that in our proposed localization scheme, the virtual RD for a NLOS path can be identified and estimated by using the weighted least squares solution for the intersection of two areas. The MD location is estimated by one NLOS path and its corresponding virtual RD. Cong and Zhuang [85] achieves ALEs of 8.7m and 6.5m, while Jia and Buehrer [90] has ALEs of 8.5m and 6.1m for $\lambda=5\text{m}$ and 10m , respectively. The accuracy for these two conventional localization schemes is poor because they mistakenly use the NLOS path to find the MD's location. The ALE results for Seow and Tan [100] and Li et al. [99] are not shown as the ALEs are greater than 15m. The ALEs are high in [100] because accuracy suffers significantly when the angle between obstacles is very small. In [99], the Taylor series methodology only works well when there is a good initial guess and small standard deviations for the measured parameters.

Figure 5.3 ALE performance comparisons

To test the accuracy and robustness of our proposed VRDB localization scheme in a real environment, an experiment is conducted at the IoT laboratory by the measurement team. The laboratory contains various obstacles: glass windows, concrete walls and five dominant metallic obstacles (denoted as S1, S2, S3, S4 and S5) as shown in Figure 5.2. In the experiment, the RD is fixed at (12.9m, 0.7m) while the MD moves from MD₁ to MD₇. MD₁ and MD₇ are in an LOS condition and the rest are in an NLOS condition. The experiment is carried out using a vector network analyzer (VNA) with frequency sweeps from 2 to 3 GHz over 1601 frequency points. A 4×4 virtual antenna array with an element spacing of 5cm, corresponding to half a wavelength at 3 GHz, is used at both the RD and the MD. At each location of the MD, 16 S21 measurements for each frequency point are used to obtain the average. Using these averages, the TOA and AOA of the two dominant paths at each location of the MD will be

calculated by the parameter estimation EM algorithm [57]. The EM algorithm can extract the TOA and AOA of the signal path as long, as the signal is above the threshold. The paths shown in Fig. 5.2 are the two strongest paths extracted from EM algorithm. These extracted TOA and AOA values are used to determine the location of the MD using equation (5.6). The root mean square (RMS) error pertains to the actual location of the MD and is given as $\sqrt{(x-x^0)^2+(y-y^0)^2}$, where (x^0, y^0) and (x, y) are the true and estimated MD locations respectively.

Using the measured TOA and AOA data obtained from the average of 16 measurements at each of the 7 location points, the standard deviation of the angle of the dominant paths at both the RD and the MD are 5.1° and 7.0° respectively. The standard deviation of the distance is found to be 0.51m. Table 5-1 compares the localization RMS errors between the proposed VRDB localization scheme and existing NLOS localization schemes [99]-[100]. The average RMS error of our proposed localization scheme for the 7 location points is 1.6m, while the average RMS error is 21.3m and 8.6m in [99] and [100] respectively. At each location of the MD, the identification of the LOS path was discussed in Chapter 4, as shown in Figure 4.1. The identification of one bounce reflection path is as shown in Figure 5.4. Based on the estimated location of the MD, the known location of the RD and the measured d, θ, ϕ , we can use the triangular method to determine whether the path is a one bounce reflection if it fulfills the triangular one bounce relationship.

Figure 5.4 Geometrical depiction of the triangulation method.

	MD ₁	MD ₂	MD ₃	MD ₄	MD ₅	MD ₆	MD ₇
Proposed scheme	0.34	0.26	0.48	2.87	3.05	3.66	0.84
Seow and Tan [100]	0.62	0.4	0.57	4.04	14.9	38.7	1.22
Li et al. [99]	0.34	0.35	46.6	47	37	17	0.76

Table 5-1 Comparison of RMS errors (m) from MD₁ to MD₇

Table 5-2 shows the correlation of the parametric estimation based on the EM algorithm and the ray tracing methodology [118] at MD₁ and MD₂. At MD₁ the dominant paths are the LOS path (P_{LOS}) and the one bounce reflected path from the window (P_{win}). In comparison, at MD₂, there are two one-reflected paths from the window and S4 (P_{win} and P_{S4}). As shown, the propagation paths simulated using ray tracing are well-correlated with the measured paths in the experiment. Thus, we can use the extracted TOA and AOA from the ray tracing methodology and add Gaussian noise statistically to evaluate the performance of our proposed VRDB localization scheme. The true TOA and AOA of each

signal path between the RD and the MD are subjected to Gaussian noise with zero mean and known standard deviation. The RMS error is then calculated for 5,000 simulation runs. To compare the method presented here with [85] and [90], another three RDs are placed at the same positions as the one in the ALE performance comparison.

	Extracted path from measured data (d, ϕ, θ)			Ray traced path (d, ϕ, θ)
MD ₁	6m	302°	122.9°	P _{LOS} (5.7m, 302°, 122°)
	11.1m	334°	25°	P _{win} (11m, 334°, 26°)
MD ₂	12m	335°	21°	P _{win} (12m, 336°, 24°)
	11.7m	359°	61°	P _{S4} (11.7m, 358°, 62°)

Table 5-2 Correlation between EM Algorithm [57] and Ray Tracing [118]

Figure 5.5 and 5.6 compares the accuracy of the proposed VRDB localization scheme with existing localization schemes in terms of their CDF when the MD transits from an LOS condition at MD₁ (9.9m, 5.5m) to an NLOS condition at MD₂ (8.8m, 5.5m). At MD₁, the first dominant LOS path is exploited to estimate the MD [128]. After the MD's location has been estimated, the virtual RD corresponding to the NLOS path P_{win} can be determined. When the MD moves to the next position, MD₂, based on equation (5.6), we can use the calculated virtual RD associated with P_{win} and the new measured data (TOA and AOA) at MD₂ to estimate the location of MD₂. As shown in Figure 5.6, our proposed localization scheme using one reflection path outperforms the existing localization schemes. For example, under $\sigma_d = 1\text{m}$, $\sigma_\theta = \sigma_\phi = 5^\circ$, our proposed

localization scheme achieves an accuracy of 2.3m for 90% of the time, compared with 3.6m and 4.5m in [100] and [85] respectively. The margins of improvement are 36% and 49% respectively. In addition, we also illustrate the location accuracy of the last point, MD₆ under NLOS condition in Figure 5.7. As shown, our proposed VRDB localization scheme superiorly outperforms the conventional and existing localization schemes and significantly improves location accuracy.

Figure 5.5 Comparison of cumulative distribution function (CDF) performance for MD₁ at (9.9m, 5.5m) under $\sigma_d = \sigma_r = 1\text{m}$, $\sigma_\theta = \sigma_\phi = 5^\circ$.

Figure 5.6 Comparison of cumulative distribution function (CDF) performance for MD₂ at (8.8m, 5.5m) under $\sigma_d = \sigma_r = 1\text{m}$, $\sigma_\theta = \sigma_\phi = 5^\circ$.

Figure 5.7 Comparison of cumulative distribution function (CDF) performance for MD₆ at (7.4m, 2.5m) under $\sigma_d = \sigma_r = 1\text{m}$, $\sigma_\theta = \sigma_\phi = 5^\circ$.

5.3 Remarks

A novel NLOS localization scheme has been proposed based on the concept of a virtual RD. Simulation and experimental results show that the proposed VRDB NLOS localization scheme using one RD outperforms existing localization schemes by a significant margin at the measured and simulated locations. However, the virtual RD methodology is only applicable to reflection paths or paths reflected from a plane surface. It is not applicable to signal paths that undergo diffraction.

Chapter 6

Elliptical Lagrange-Based NLOS

Localization

The novel NLOS localization scheme proposed in Chapter 5 leverages the position of a virtual RD to determine the MD's location. Once the positions of all possible virtual RDs are identified, the location of the MD can be estimated by relying on the dominant NLOS path. However, when the MD is moving in the indoor environment, the position of the virtual RD may be changed and this change may not be detectable because of diffraction or reflection from different obstacles, each with small and different changes in the measurement value. If the wrong virtual RD is used to perform localization, location accuracy will be dramatically degraded.

Figure 6.1 and 6.2 show two scenarios for the moving trajectory of the MD. Figure 6.1 shows that when the MD moves from MD₁ to MD₂, one diffraction propagation path between the RD and the MD comes from the same edge. However, the position of the virtual RD has changed from I₁ to I₂ and the

change of the virtual RD will not be able to be identified from the measured TOA and AOA of the corresponding propagation path.

Figure 6.1: Propagation path and corresponding virtual RD for MD_1 and MD_2 due to diffraction at an edge.

Figure 6.2: Propagation path and corresponding virtual RD for MD_1 and MD_2 due to different reflection of different obstacles.

On the other hand, in Figure 6.2, when the MD's position shifts from MD_1 to MD_2 , the position of the virtual RD has changed due to reflections from the different plane. Nevertheless, because of the small differences in measurement parameter values, the change in the virtual RD may also not be detectable. In this chapter, we will propose a novel elliptical Lagrange-based (ELB) NLOS scheme to tackle these problems.

Instead of using the virtual RD concept from Chapter 5 [129], we use the concept of scattering points to resolve the ambiguity in the detection of the virtual RD and the issue of diffraction. Meissner et al. [94] proposes a range-based statistical algorithm to find the target location. Also, Miao et al. [98] propose a NLOS location scheme by using scattering points. They use a maximum likelihood algorithm to jointly estimate the scattering points and the MD's location. In our proposed localization scheme, the locations of the scattering point and MD are estimated based on the measured TOA and AOA and the geometric relationship. The scattering point for the corresponding NLOS path is estimated by using the TOA and AOA measurement data and the initial estimated position of MD. After the position of the scattering point is found, the successive position of the MD can be determined by relying on one NLOS path which undergoes either reflection or diffraction. Simulation and an experiment demonstrate that the proposed localization scheme outperforms the existing localization scheme for all simulated and measured MD trajectories.

6.1 Theory and Formulation

6.1.1 Estimation of Scattering Point

Figure 6.3: Position of scattering point derived from RD.

Figure 6.3 demonstrates the geometrical relationship with a one bounce scattering path between the RD, the MD and a scattering point R. The RD with a known location (x_R, y_R) measures AOA θ while MD with an unknown location (x, y) measures AOA ϕ . $\hat{MD}$ is the initial estimated MD location based on the approach in [99]. The measurement TOA t is related to the propagation distance using $d = ct$ where c is the speed of wave propagation. The measured TOA (distance d) and AOA data are assumed to be perturbed by Gaussian noise:

$$\begin{aligned} \theta &= \theta^0 + n_\theta, \phi = \phi^0 + n_\phi, d = d^0 + n_d \\ n_w &= N(0, \sigma_w) \quad w = \theta, \phi, d \end{aligned}$$

(6.1)

where θ^0, ϕ^0 and d^0 are the true AOA and TOA measurement values and n_θ, n_ϕ and n_d indicate the measurement noise, which is considered to have a zero mean Gaussian distribution.

As shown in Figure 6.3, R is the true position of the scattering point which is associated with a one bounce scattering path RD-R-MD. Given the measurement TOA d , it should be noted that $|\hat{R} - RD| + |\hat{R} - MD| = d$. In other words, the sum of the distance from the scattering point to RD and MD is always equal to the measured TOA value. As such, all possible scattering points, R' , are joined together to form an ellipse and the position of the scattering point is located at any point along this ellipse. However, considering the measured AOA θ from RD, the location of the scattering point, $\hat{R}_b$ can be determined by using the Lagrange constraint of the possible scattering points to the straight line ℓ that cuts across the ellipse, as shown in Figure 6.3.

Similarly, another possible position of the scattering point, $\hat{R}_c$ can be estimated by using the Lagrange constraint of the ellipse with another line from MD with the measured AOA ϕ . The third estimated scattering point can be obtained through the least-squares intersection of these two lines that arises from the AOA θ and ϕ .

The exact position of the scattering point, $\hat{R}$ is determined from the least-squares intersection of the three estimated scattering points obtained earlier.

This is done by minimizing the sum of squares distance from $\hat{R}$ to all intersection points.

$$J = (\mathbf{H}\hat{\mathbf{R}} - \boldsymbol{\varepsilon})^T (\mathbf{H}\hat{\mathbf{R}} - \boldsymbol{\varepsilon}) \quad (6.2)$$

where the estimated location of the scattering point is $\hat{\mathbf{R}} = [x_r, y_r]^T$.

$\mathbf{H} = [\mathbf{h}_1, \mathbf{h}_2 \dots \mathbf{h}_K]^T$ and $\mathbf{h}_i = \mathbf{I}_{2 \times 2}$. $\boldsymbol{\varepsilon}$ is the coordinate of all intersection points

given as $\boldsymbol{\varepsilon} = [\boldsymbol{\varepsilon}_1, \boldsymbol{\varepsilon}_2 \dots \boldsymbol{\varepsilon}_K]^T = [x_A, y_A, x_B, y_B, x_C, y_C]^T$. $[x_A, y_A]^T$ is the

intersection point of the two lines with the measured AOA, θ and ϕ . It is given

as $\begin{bmatrix} x_A \\ y_A \end{bmatrix} = (\mathbf{S}^T \mathbf{S})^{-1} \mathbf{S}^T \mathbf{p}$ where $\mathbf{S} = \begin{bmatrix} -\tan \theta & 1 \\ -\tan \phi & 1 \end{bmatrix}$ and $\mathbf{p} = \begin{bmatrix} y_R - \tan \theta x_R \\ y - \tan \phi x \end{bmatrix}$ where

(x, y) is the initial estimated MD location. $[x_B, y_B]^T$ is estimated from the

ellipse with measured TOA, d and one straight line with measured AOA, θ . It

is formulated as a constrained optimization problem in the following manner:

$$\hat{\mathbf{R}}_B = \arg \min \mathbf{R}_B^T \mathbf{D} \mathbf{R}_B + \mathbf{E} \mathbf{R}_B + \mathbf{g} \quad (6.3)$$

subject to

$$\begin{aligned} & \mathbf{R}_B^T \mathbf{G} \mathbf{R}_B + \mathbf{M} \mathbf{R}_B + \mathbf{q} \\ & \mathbf{U} \mathbf{R}_B - y_R \geq 0 \quad 0 < \theta \leq \pi \\ & \mathbf{U} \mathbf{R}_B - y_R \leq 0 \quad \pi < \theta \leq 2\pi \end{aligned} \quad (6.4)$$

Where

$$\mathbf{R}_B = [x_B, y_B]^T, \quad \mathbf{D} = \begin{bmatrix} \tan^2 \theta & -\tan \theta \\ -\tan \theta & 1 \end{bmatrix},$$

$$\mathbf{E} = [2 \tan \theta (y_R - \tan \theta x_R) \quad -2(y_R - \tan \theta x_R)]$$

and $g = (y_R - \tan \theta x_R)^2$. $\mathbf{U} = [0 \quad 1]$ and $v = y_R$.

$$\mathbf{G} = \begin{bmatrix} a^2 - c^2 \cos^2 \beta & -c^2 \sin \beta \cos \beta \\ -c^2 \sin \beta \cos \beta & a^2 - c^2 \sin^2 \beta \end{bmatrix},$$

$$\mathbf{M} = [2c^2 x_a \cos \beta - a^2(x_R + x) \quad 2c^2 x_a \sin \beta - a^2(y_R + y)] \text{ and}$$

$$q = a^2(x_a^2 + y_a^2 + c^2) - a^4 - c^2 x_a^2 \text{ where } \beta = \arctan\left(\frac{y_R - y}{x_R - x}\right), \quad a = \frac{d}{2} \text{ and}$$

$$c = \frac{\sqrt{(x_R - x)^2 + (y_R - y)^2}}{2}. \quad x_a = \frac{(x_R + x)}{2} \cos \beta + \frac{(y_R + y)}{2} \sin \beta.$$

$$y_a = -\frac{(x_R + x)}{2} \sin \beta + \frac{(y_R + y)}{2} \cos \beta.$$

We consider solving the optimization equation by applying a Lagrange multiplier into (6.3) and (6.4) to produce the final estimation $\mathbf{R}_B$

$$\Lambda(\mathbf{R}_B, \boldsymbol{\lambda}) = \mathbf{R}_B^T \mathbf{D} \mathbf{R}_B + \mathbf{E} \mathbf{R}_B + g + \boldsymbol{\lambda} \mathbf{W} \tag{6.5}$$

where $\boldsymbol{\lambda} = [\lambda_1 \quad \lambda_2]$ is the Lagrange multiplier.

$$\mathbf{W} = \begin{bmatrix} \mathbf{R}_B^T \mathbf{G} \mathbf{R}_B + \mathbf{M} \mathbf{R}_B + q \\ \mathbf{U} \mathbf{R}_B - v \end{bmatrix} \text{ when } 0 < \theta \leq \pi$$

$$\mathbf{W} = \begin{bmatrix} \mathbf{R}_B^T \mathbf{G} \mathbf{R}_B + \mathbf{M} \mathbf{R}_B + \mathbf{q} \\ \mathbf{v} - \mathbf{U} \mathbf{R}_B \end{bmatrix} \text{ when } \pi < \theta \leq 2\pi.$$

Similarly, $[x_C, y_C]^T$ is estimated from the ellipse with a measured TOA, d and another straight line with a measured AOA, ϕ . The Lagrange equation is given as

$$\Lambda(\mathbf{R}_C, \lambda) = \mathbf{R}_C^T \mathbf{D}' \mathbf{R}_C + \mathbf{E}' \mathbf{R}_C + \mathbf{g}' + \lambda \mathbf{W} \quad (6.6)$$

where

$$\mathbf{R}_C = [x_C, y_C]^T, \mathbf{D}' = \begin{bmatrix} \tan^2 \phi & -\tan \phi \\ -\tan \phi & 1 \end{bmatrix},$$

$$\mathbf{E}' = [2 \tan \phi (y_R - \tan \phi x_R) \quad -2(y_R - \tan \phi x_R)]$$

$$\text{and } \mathbf{g}' = (y_R - \tan \phi x_R)^2. \mathbf{W}_2 = \begin{cases} \mathbf{U} \mathbf{R}_B - y & 0 < \phi \leq \pi \\ y - \mathbf{U} \mathbf{R}_B & \pi < \phi \leq 2\pi \end{cases}$$

Therefore, the scattering point for the NLOS signal path RD-R-MD is calculated as:

$$\hat{\mathbf{R}} = (\mathbf{H}^T \mathbf{H})^{-1} \mathbf{H}^T \boldsymbol{\varepsilon} \quad (6.7)$$

6.1.2 Estimation of MD Using Estimated Scattering Point

After finding the scattering point of the NLOS signal path, the final MD position can be determined by a new ellipse with the two focus points, RD and $\hat{R}$ as shown in Figure 6.4.

Figure 6.4: Position of MD from scattering point.

As shown in Figure 6.4, r is the distance between the RD and $\hat{R}$ which is written as $r = d - |RD - \hat{R}|$. The rotation angle of the ellipse is equal to the measurement AOA, θ . The length of the semi-major axis is:

$$a' = \frac{r + \sqrt{r^2 + |RD - \hat{R}|^2 - 2|RD - \hat{R}|r\cos(\phi - \theta)}}{2} \quad (6.8)$$

Based on the $|RD - \hat{R}|$, θ and a' , a new ellipse can be constructed and the final MD location is determined from the Lagrange equation below:

$$\Lambda(\mathbf{Z}, \lambda) = \mathbf{Z}^T \mathbf{D}' \mathbf{Z} + \mathbf{E}_Z \mathbf{Z} + \mathbf{g}' + \lambda \mathbf{W}_Z \quad (6.9)$$

where

$$\mathbf{Z} = [x, y]^T, \quad \mathbf{E}_Z = [2 \tan \phi (y_r - \tan \phi x_r) \quad -2(y_r - \tan \phi x_r)] \quad \text{and} \\ \mathbf{g}' = (y_r - \tan \phi x_r)^2.$$

$$\mathbf{W}_{Z1} = \mathbf{Z}^T \mathbf{G}_Z \mathbf{Z} + \mathbf{M}_Z \mathbf{Z} + \mathbf{q}_Z \quad \text{Where} \quad \mathbf{G}_Z = \begin{bmatrix} a'^2 - c'^2 \cos^2 \theta & -c'^2 \sin \theta \cos \theta \\ -c'^2 \sin \theta \cos \theta & a'^2 - c'^2 \sin^2 \theta \end{bmatrix},$$

$$\mathbf{M}_Z = \begin{bmatrix} 2c'^2 x_b \cos \theta - a'^2 (x_R + x_r) \\ 2c'^2 x_b \sin \theta - a'^2 (y_R + y_r) \end{bmatrix}^T, \quad \mathbf{q}_Z = a'^2 (x_b^2 + y_b^2 + c'^2) - a'^4 - c'^2 x_b^2 \quad \text{and}$$

$$v_Z = y_r, \quad c' = \frac{|RD - \hat{R}|}{2}, \quad x_b = \frac{(x_R + x_r)}{2} \cos \theta + \frac{(y_R + y_r)}{2} \sin \theta.$$

$$y_b = -\frac{(x_R + x_r)}{2} \sin \theta + \frac{(y_R + y_r)}{2} \cos \theta. \quad \mathbf{W}_{Z2} = \mathbf{U} \mathbf{Z} - v_Z \quad \text{where } v_Z = y_r \quad \text{when } \pi <$$

$$\phi \leq 2\pi. \quad \mathbf{W}_{Z2} = v_Z - \mathbf{U} \mathbf{Z} \quad \text{when } 0 < \phi \leq \pi.$$

6.2 Analytical Performance Bound

To understand the performance of our proposed scheme without running a simulation, the analytical performance is determined in terms of the mean and variance. An efficient estimator should have a noise variance near the Cramer Rao Lower Bound (CRLB) [126] which is the lower bound on the variance of the estimator.

From equation (6.9), we observe that the accuracy of the scattering point position partially affects the performance of the localization scheme. Thus, we firstly derive the mean and variance of the scattering point's location, which are given as

$$\mathbf{E}(\hat{\mathbf{R}}) = \mathbf{E}\left\{(\mathbf{H}^T \mathbf{H})^{-1} \mathbf{H}^T \boldsymbol{\varepsilon}\right\} = (\mathbf{H}^T \mathbf{H})^{-1} \mathbf{H}^T \mathbf{E}(\boldsymbol{\varepsilon}) \quad (6.10)$$

$$\begin{aligned} \text{cov}(\hat{\mathbf{R}}) &= \mathbf{E}\left\{(\hat{\mathbf{R}} - \mathbf{E}\{\hat{\mathbf{R}}\})(\hat{\mathbf{R}} - \mathbf{E}\{\hat{\mathbf{R}}\})^T\right\} \\ &= (\mathbf{H}^T \mathbf{H})^{-1} \mathbf{H}^T \mathbf{E}(\boldsymbol{\varepsilon} \boldsymbol{\varepsilon}^T) \mathbf{H} (\mathbf{H}^T \mathbf{H})^{-1} - \mathbf{E}(\boldsymbol{\varepsilon}) \mathbf{E}(\boldsymbol{\varepsilon})^T \end{aligned} \quad (6.11)$$

The detail derivation for $\mathbf{E}(\boldsymbol{\varepsilon})$ and $\mathbf{E}(\boldsymbol{\varepsilon} \boldsymbol{\varepsilon}^T)$ are as follow. We notice that the solution for $\boldsymbol{\varepsilon}_k$ where $k=1,2,3$ is equivalent to

$$\hat{\boldsymbol{\varepsilon}}_k = \arg \min F_k \quad (6.12)$$

where

$$F_k = (y_m - \tan \theta x_m - y_R + \tan \theta x_R)^2 + (y_m - \tan \phi x_m - y + \tan \phi x)^2 \quad (6.13)$$

$$\begin{aligned} F_k &= \left[(a^2 - c^2 \cos^2 \beta) x_m^2 + (a^2 - c^2 \sin^2 \beta) y_m^2 - 2c^2 \sin \beta \cos \beta x_m y_m \right. \\ &\quad \left. + (2c^2 x_a \cos \beta - a^2 (x_R + x)) x_m - (a^2 (y_R + y) - 2c^2 x_a \sin \beta) y_m - x_a^2 c^2 \right. \\ &\quad \left. - a^4 + a^2 (x_a^2 + y_a^2 + c^2) \right]^2 + (y_m - \tan \delta x_m - y_R + \tan \delta x_R)^2 \end{aligned} \quad (6.14)$$

$$\text{where } \begin{cases} m = A, & k = 1 \\ m = B, \delta = \theta & k = 2 \\ m = C, \delta = \phi & k = 3 \end{cases}$$

It is clear that (x_m, y_m) satisfies

$$\nabla_{x_m} F_k = \nabla_{y_m} F_k = 0 \quad (6.15)$$

Now we assume that the measurement noise n_w is sufficiently small. As a result,

(x_m, y_m) is in the reasonable vicinity of the true location (x_m^0, y_m^0) and we can use a Taylor series to expand (6.15) around the true location up to the first order term:

$$\left. \frac{\partial F_k}{\partial x_m} \right|_{\substack{x_m=x_m^0 \\ y_m=y_m^0}} \approx -(x_m - x_m^0) \left. \frac{\partial^2 F_k}{\partial x_m^2} \right|_{\substack{x_m=x_m^0 \\ y_m=y_m^0}} - (y_m - y_m^0) \left. \frac{\partial^2 F_k}{\partial x_m \partial y_m} \right|_{\substack{x_m=x_m^0 \\ y_m=y_m^0}} \quad (6.16)$$

$$\left. \frac{\partial F_k}{\partial y_m} \right|_{\substack{x_m=x_m^0 \\ y_m=y_m^0}} \approx -(x_m - x_m^0) \left. \frac{\partial^2 F_k}{\partial x_m \partial y_m} \right|_{\substack{x_m=x_m^0 \\ y_m=y_m^0}} - (y_m - y_m^0) \left. \frac{\partial^2 F_k}{\partial y_m^2} \right|_{\substack{x_m=x_m^0 \\ y_m=y_m^0}} \quad (6.17)$$

Taking the expectations at both sides in (6.16) , it yields

$$E\left(\left. \frac{\partial F_k}{\partial x_m} \right|_{\substack{x_m=x_m^0 \\ y_m=y_m^0}}\right) \approx -E(x_m - x_m^0) E\left(\left. \frac{\partial^2 F_k}{\partial x_m^2} \right|_{\substack{x_m=x_m^0 \\ y_m=y_m^0}}\right) - E(y_m - y_m^0) E\left(\left. \frac{\partial^2 F_k}{\partial x_m \partial y_m} \right|_{\substack{x_m=x_m^0 \\ y_m=y_m^0}}\right) \quad (6.18)$$

Since n_w is very small,

$$\begin{aligned} E\left(\left. \frac{\partial F_k}{\partial x_m} \right|_{\substack{x_m=x_m^0 \\ y_m=y_m^0}}\right) &= -2 \tan \theta^0 (y_m^0 - \tan \theta^0 x_m^0 - y_R + \tan \theta^0 x_R) \\ &\quad - 2 \tan \phi^0 (y_m^0 - \tan \phi^0 x_m^0 - y^0 + \tan \phi^0 x^0) = 0 \end{aligned}$$

Hence, $E(x_m) = x_m^0$ and $E(y_m) = y_m^0$. Similarly, we can obtain that $E(\mathbf{\epsilon}) = \mathbf{\epsilon}^0$ where $\mathbf{\epsilon}^0$ is the true location, which indicates an unbiased estimator for the NLOS path.

$E(\mathbf{\epsilon}\mathbf{\epsilon}^T)$ is derived by taking the square of (6.16) and (6.17) and multiplying (6.16) and (6.17)

$$\begin{aligned}
 E\left[\left(\frac{\partial F_k}{\partial x_m}\right)^2\right]_{\substack{x_m=x_m^0 \\ y_m=y_m^0}} &\approx E(x_m^2)\left[E\left(\frac{\partial^2 F_k}{\partial x_m^2}\right)\right]^2 + E(y_m^2)\left[E\left(\frac{\partial^2 F_k}{\partial x_m \partial y_m}\right)\right]^2 \\
 &\quad + 2E(x_m y_m)E\left(\frac{\partial^2 F_k}{\partial x_m^2}\right)E\left(\frac{\partial^2 F_k}{\partial x_m \partial y_m}\right) + MM_1 \Big|_{\substack{x_m=x_m^0 \\ y_m=y_m^0}}
 \end{aligned} \tag{6.19}$$

$$\begin{aligned}
 E\left[\left(\frac{\partial F_k}{\partial y_m}\right)^2\right]_{\substack{x_m=x_m^0 \\ y_m=y_m^0}} &\approx E(x_m^2)\left[E\left(\frac{\partial^2 F_k}{\partial x_m \partial y_m}\right)\right]^2 + E(y_m^2)\left[E\left(\frac{\partial^2 F_k}{\partial y_m^2}\right)\right]^2 \\
 &\quad + 2E(x_m y_m)E\left(\frac{\partial^2 F_k}{\partial y_m^2}\right)E\left(\frac{\partial^2 F_k}{\partial x_m \partial y_m}\right) + MM_2 \Big|_{\substack{x_m=x_m^0 \\ y_m=y_m^0}}
 \end{aligned} \tag{6.20}$$

$$\begin{aligned}
 E\left[\left(\frac{\partial F_k}{\partial x_m}\right)\left(\frac{\partial F_k}{\partial y_m}\right)\right]_{\substack{x_m=x_m^0 \\ y_m=y_m^0}} &\approx E(x_m^2)E\left(\frac{\partial^2 F_k}{\partial x_m^2}\right)E\left(\frac{\partial^2 F_k}{\partial x_m \partial y_m}\right) \\
 &\quad + E(y_m^2)E\left(\frac{\partial^2 F_k}{\partial y_m^2}\right)E\left(\frac{\partial^2 F_k}{\partial x_m \partial y_m}\right) \\
 &\quad + E(x_m y_m)\left[E\left(\frac{\partial^2 F_k}{\partial x_m^2}\right)E\left(\frac{\partial^2 F_k}{\partial y_m^2}\right) + E\left(\frac{\partial^2 F_k}{\partial x_m \partial y_m}\right)^2\right] + MM_3 \Big|_{\substack{x_m=x_m^0 \\ y_m=y_m^0}}
 \end{aligned} \tag{6.21}$$

Where

$$\begin{aligned}
 MM_1 &= -x_m^2 \left[E \left(\frac{\partial^2 F_k}{\partial x_m^2} \right) \right]^2 - 2x_m y_m E \left(\frac{\partial^2 F_k}{\partial x_m^2} \right) E \left(\frac{\partial^2 F_k}{\partial x_m \partial y_m} \right) - y_m^2 \left[E \left(\frac{\partial^2 F_k}{\partial x_m \partial y_m} \right) \right]^2 \\
 MM_2 &= -x_m^2 \left[E \left(\frac{\partial^2 F_k}{\partial x_m \partial y_m} \right) \right]^2 - 2x_m y_m E \left(\frac{\partial^2 F_k}{\partial y_m^2} \right) E \left(\frac{\partial^2 F_k}{\partial x_m \partial y_m} \right) - y_m^2 \left[E \left(\frac{\partial^2 F_k}{\partial y_m^2} \right) \right]^2 \\
 MM_3 &= -x_m^2 E \left(\frac{\partial^2 F_k}{\partial x_m^2} \right) E \left(\frac{\partial^2 F_k}{\partial x_m \partial y_m} \right) - x_m y_m \left[E \left(\frac{\partial^2 F_k}{\partial x_m^2} \right) E \left(\frac{\partial^2 F_k}{\partial y_m^2} \right) + E \left(\frac{\partial^2 F_k}{\partial x_m \partial y_m} \right)^2 \right] \\
 &\quad - y_m^2 E \left(\frac{\partial^2 F_k}{\partial y_m^2} \right) E \left(\frac{\partial^2 F_k}{\partial x_m \partial y_m} \right)
 \end{aligned}$$

By means of solving (6.19)-(6.21) with respect to $E(x_m^2)$, $E(y_m^2)$ and $E(x_m y_m)$,

the solution is as follows:

$$E(x_m^2) = \frac{DD_1}{DD}, E(y_m^2) = \frac{DD_2}{DD}, E(x_m y_m) = \frac{DD_3}{DD} \tag{6.22}$$

where

$$DD = \begin{vmatrix} DD^{11} & DD^{12} & DD^{13} \end{vmatrix}$$

where

$$\begin{aligned}
 DD^{11} &= \begin{bmatrix} \left[E \left(\frac{\partial^2 F_k}{\partial x_m^2} \right) \right]^2 & \left[E \left(\frac{\partial^2 F_k}{\partial x_m \partial y_m} \right) \right]^2 & E \left(\frac{\partial^2 F_k}{\partial x_m^2} \right) E \left(\frac{\partial^2 F_k}{\partial x_m \partial y_m} \right) \end{bmatrix}^T \\
 DD^{12} &= \begin{bmatrix} 2E \left(\frac{\partial^2 F_k}{\partial x_m^2} \right) E \left(\frac{\partial^2 F_k}{\partial x_m \partial y_m} \right) & 2E \left(\frac{\partial^2 F_k}{\partial y_m^2} \right) E \left(\frac{\partial^2 F_k}{\partial x_m \partial y_m} \right) \\ \left[E \left(\frac{\partial^2 F_k}{\partial x_m^2} \right) E \left(\frac{\partial^2 F_k}{\partial y_m^2} \right) + E \left(\frac{\partial^2 F_k}{\partial x_m \partial y_m} \right)^2 \right] \end{bmatrix}^T
 \end{aligned}$$

$$DD^{13} = \left[\left[E \left(\frac{\partial^2 F_k}{\partial x_m \partial y_m} \right) \right]^2 \quad \left[E \left(\frac{\partial^2 F_k}{\partial y_m^2} \right) \right]^2 \quad E \left(\frac{\partial^2 F_k}{\partial y_m^2} \right) E \left(\frac{\partial^2 F_k}{\partial x_m \partial y_m} \right) \right]^T$$

$$DD_1 = \begin{vmatrix} DD_1^{11} & DD_1^{12} & DD_1^{13} \end{vmatrix}$$

where

$$DD_1^{11} = \left[E \left[\left(\frac{\partial F_k}{\partial x_m} \right)^2 \right] - MM_1 \quad E \left[\left(\frac{\partial F_k}{\partial y_m} \right)^2 \right] - MM_2 \quad E \left[\left(\frac{\partial F_k}{\partial x_m} \right) \left(\frac{\partial F_k}{\partial y_m} \right) \right] - MM_3 \right]^T$$

$$DD_1^{12} = DD^{12}$$

$$DD_1^{13} = DD^{13}$$

$$DD_2 = \begin{vmatrix} DD_2^{11} & DD_2^{12} & DD_2^{13} \end{vmatrix}$$

where

$$DD_2^{11} = DD^{11}$$

$$DD_2^{12} = DD^{12}$$

$$DD_2^{13} = DD_1^{11}$$

$$DD_3 = \begin{vmatrix} DD_3^{11} & DD_3^{12} & DD_3^{13} \end{vmatrix}$$

where

$$DD_3^{11} = DD^{11}$$

$$DD_3^{12} = DD_1^{11}$$

$$DD_3^{13} = DD^{13}$$

We can similarly calculate $E(x_m x_k)$, $E(y_m y_k)$ and $E(x_m y_k)$ where $m=1, 2, 3$ and

$k=1, 2, 3 \ m \neq k$.

$$E(x_m x_k) = \frac{AA_{m,k}^1}{AA_{m,k}}, \quad E(y_m y_k) = \frac{AA_{m,k}^2}{AA_{m,k}}, \quad E(x_m y_k) = \frac{AA_{m,k}^3}{AA_{m,k}} \quad (6.23)$$

where

$$AA_{m,k_{11}} = \begin{vmatrix} E\left(\frac{\partial^2 F_m}{\partial x_m^2}\right) E\left(\frac{\partial^2 F_k}{\partial x_k^2}\right) \\ E\left(\frac{\partial^2 F_m}{\partial x_m \partial y_m}\right) E\left(\frac{\partial^2 F_k}{\partial x_k \partial y_k}\right) \\ E\left(\frac{\partial^2 F_m}{\partial x_m^2}\right) E\left(\frac{\partial^2 F_k}{\partial x_k \partial y_k}\right) \\ E\left(\frac{\partial^2 F_m}{\partial x_m \partial y_m}\right) E\left(\frac{\partial^2 F_k}{\partial x_k^2}\right) \end{vmatrix} \quad AA_{m,k_{12}} = \begin{vmatrix} E\left(\frac{\partial^2 F_m}{\partial x_m^2}\right) E\left(\frac{\partial^2 F_k}{\partial x_k \partial y_k}\right) \\ E\left(\frac{\partial^2 F_m}{\partial x_m \partial y_m}\right) E\left(\frac{\partial^2 F_k}{\partial y_k^2}\right) \\ E\left(\frac{\partial^2 F_m}{\partial x_m^2}\right) E\left(\frac{\partial^2 F_k}{\partial y_k^2}\right) \\ E\left(\frac{\partial^2 F_m}{\partial x_m \partial y_m}\right) E\left(\frac{\partial^2 F_k}{\partial x_k \partial y_k}\right) \end{vmatrix}$$

$$AA_{m,k_{13}} = \begin{vmatrix} E\left(\frac{\partial^2 F_k}{\partial x_k^2}\right) E\left(\frac{\partial^2 F_m}{\partial x_m \partial y_m}\right) \\ E\left(\frac{\partial^2 F_k}{\partial x_k \partial y_k}\right) E\left(\frac{\partial^2 F_m}{\partial y_m^2}\right) \\ E\left(\frac{\partial^2 F_m}{\partial x_m \partial y_m}\right) E\left(\frac{\partial^2 F_k}{\partial x_k \partial y_k}\right) \\ E\left(\frac{\partial^2 F_m}{\partial y_m^2}\right) E\left(\frac{\partial^2 F_k}{\partial x_k^2}\right) \end{vmatrix} \quad AA_{m,k_{14}} = \begin{vmatrix} E\left(\frac{\partial^2 F_m}{\partial x_m \partial y_m}\right) E\left(\frac{\partial^2 F_k}{\partial x_k \partial y_k}\right) \\ E\left(\frac{\partial^2 F_m}{\partial y_m^2}\right) E\left(\frac{\partial^2 F_k}{\partial y_k^2}\right) \\ E\left(\frac{\partial^2 F_m}{\partial x_m \partial y_m}\right) E\left(\frac{\partial^2 F_k}{\partial y_k^2}\right) \\ E\left(\frac{\partial^2 F_m}{\partial y_m^2}\right) E\left(\frac{\partial^2 F_k}{\partial x_k \partial y_k}\right) \end{vmatrix}$$

$$AA_{m,k}^1 = \begin{vmatrix} AA_{m,k_{11}}^1 & AA_{m,k_{12}}^1 & AA_{m,k_{13}}^1 & AA_{m,k_{14}}^1 \end{vmatrix}$$

$$AA_{m,k_{12}}^1 = AA_{m,k_{12}}, \quad AA_{m,k_{13}}^1 = AA_{m,k_{13}}, \quad AA_{m,k_{14}}^1 = AA_{m,k_{14}}$$

$$\begin{aligned}
 AA_{m,k_{11}}^1 &= \begin{vmatrix} E\left(\frac{\partial F_m}{\partial x_m} \frac{\partial F_k}{\partial x_k}\right) - NN_1 \\ E\left(\frac{\partial F_m}{\partial y_m} \frac{\partial F_k}{\partial y_k}\right) - NN_2 \\ E\left(\frac{\partial F_m}{\partial x_m} \frac{\partial F_k}{\partial y_k}\right) - NN_3 \\ E\left(\frac{\partial F_m}{\partial y_m} \frac{\partial F_k}{\partial x_k}\right) - NN_4 \end{vmatrix} \\
 AA_{m,k}^2 &= \begin{vmatrix} AA_{m,k_{11}}^2 & AA_{m,k_{12}}^2 & AA_{m,k_{13}}^2 & AA_{m,k_{14}}^2 \end{vmatrix} \\
 AA_{m,k_{11}}^2 &= AA_{m,k_{11}}, \quad AA_{m,k_{12}}^2 = AA_{m,k_{12}}, \quad AA_{m,k_{13}}^2 = AA_{m,k_{13}}, \quad AA_{m,k_{14}}^2 = AA_{m,k_{11}}^1 \\
 AA_{m,k}^3 &= \begin{vmatrix} AA_{m,k_{11}}^3 & AA_{m,k_{12}}^3 & AA_{m,k_{13}}^3 & AA_{m,k_{14}}^3 \end{vmatrix} \quad k = (m+1) \text{ or } (m+2) \\
 AA_{m,k_{11}}^3 &= AA_{m,k_{11}}, \quad AA_{m,k_{12}}^3 = AA_{m,k_{11}}^1, \quad AA_{m,k_{13}}^3 = AA_{m,k_{13}}, \quad AA_{m,k_{14}}^3 = AA_{m,k_{14}} \\
 AA_{m,k}^3 &= \begin{vmatrix} AA_{m,k_{11}}^3 & AA_{m,k_{12}}^3 & AA_{m,k_{13}}^3 & AA_{m,k_{14}}^3 \end{vmatrix} \quad k = (m-1) \text{ or } (m-2) \\
 AA_{m,k_{11}}^3 &= AA_{m,k_{11}}, \quad AA_{m,k_{12}}^3 = AA_{m,k_{12}}, \quad AA_{m,k_{13}}^3 = AA_{m,k_{11}}^1, \quad AA_{m,k_{14}}^3 = AA_{m,k_{14}}
 \end{aligned}$$

where

$$\begin{aligned}
 NN_1 &= -x_m x_k E\left(\frac{\partial^2 F_m}{\partial x_m^2}\right) E\left(\frac{\partial^2 F_k}{\partial x_k^2}\right) - x_m y_k E\left(\frac{\partial^2 F_m}{\partial x_m^2}\right) E\left(\frac{\partial^2 F_k}{\partial x_k \partial y_k}\right) \\
 &\quad - y_m x_k E\left(\frac{\partial^2 F_k}{\partial x_k^2}\right) E\left(\frac{\partial^2 F_m}{\partial x_m \partial y_m}\right) - y_m y_k E\left(\frac{\partial^2 F_m}{\partial x_m \partial y_m}\right) E\left(\frac{\partial^2 F_k}{\partial x_k \partial y_k}\right) \\
 NN_2 &= -x_m x_k E\left(\frac{\partial^2 F_m}{\partial x_m \partial y_m}\right) E\left(\frac{\partial^2 F_k}{\partial x_k \partial y_k}\right) - x_m y_k E\left(\frac{\partial^2 F_m}{\partial x_m \partial y_m}\right) E\left(\frac{\partial^2 F_k}{\partial y_k^2}\right) \\
 &\quad - y_m x_k E\left(\frac{\partial^2 F_k}{\partial x_k \partial y_k}\right) E\left(\frac{\partial^2 F_m}{\partial y_m^2}\right) - y_m y_k E\left(\frac{\partial^2 F_m}{\partial y_m^2}\right) E\left(\frac{\partial^2 F_k}{\partial y_k^2}\right) \\
 NN_3 &= -x_m x_k E\left(\frac{\partial^2 F_m}{\partial x_m^2}\right) E\left(\frac{\partial^2 F_k}{\partial x_k \partial y_k}\right) - x_m y_k E\left(\frac{\partial^2 F_m}{\partial x_m^2}\right) E\left(\frac{\partial^2 F_k}{\partial y_k^2}\right) \\
 &\quad - y_m x_k E\left(\frac{\partial^2 F_m}{\partial x_m \partial y_m}\right) E\left(\frac{\partial^2 F_k}{\partial x_k \partial y_k}\right) - y_m y_k E\left(\frac{\partial^2 F_m}{\partial x_m \partial y_m}\right) E\left(\frac{\partial^2 F_k}{\partial y_k^2}\right)
 \end{aligned}$$

$$\begin{aligned}
 NN_4 = & -x_m x_k E\left(\frac{\partial^2 F_m}{\partial x_m \partial y_m}\right) E\left(\frac{\partial^2 F_k}{\partial x_k^2}\right) - x_m y_k E\left(\frac{\partial^2 F_m}{\partial x_m \partial y_m}\right) E\left(\frac{\partial^2 F_k}{\partial x_k \partial y_k}\right) \\
 & - y_m x_k E\left(\frac{\partial^2 F_m}{\partial y_m^2}\right) E\left(\frac{\partial^2 F_k}{\partial x_k^2}\right) - y_m y_k E\left(\frac{\partial^2 F_m}{\partial y_m^2}\right) E\left(\frac{\partial^2 F_k}{\partial x_k \partial y_k}\right)
 \end{aligned}$$

Substitute (6.19)-(6.23) into (6.11) and a trace of it will yield the covariance of the error for the scattering point.

Next, the mean of the MD's location is derived by using a method similar to that in (6.15)

$$\nabla_x L = \nabla_y L = 0 \quad (6.24)$$

where

$$\begin{aligned}
 L = & \left[(a'^2 - c'^2 \cos^2 \theta) x^2 + (a'^2 - c'^2 \sin^2 \theta) y^2 - 2c'^2 \sin \theta \cos \theta xy \right. \\
 & + (2c'^2 x_b \cos \theta - a'^2 (x_R + x_r)) x - (a'^2 (y_R + y_r) - 2c'^2 x_b \sin \theta) y - x_b^2 c'^2 \\
 & \left. - a'^4 + a'^2 (x_b^2 + y_b^2 + c'^2) \right]^2 + (y - \tan \phi x - y_r + \tan \phi x_r)^2
 \end{aligned}$$

Using a Taylor series to expand (6.15) around the true location up to the first order term and then taking the expected value produces:

$$E\left(\frac{\partial L}{\partial x} \Big|_{x=x^0, y=y^0}\right) \approx -E(x - x^0) E\left(\frac{\partial^2 L}{\partial x^2} \Big|_{x=x^0, y=y^0}\right) - E(y - y^0) E\left(\frac{\partial^2 L}{\partial x \partial y} \Big|_{x=x^0, y=y^0}\right) \quad (6.25)$$

Since the noise is very small, the higher order term can be ignored. As a result,

$E(\mathbf{Z}) = \mathbf{Z}^0$ which is an unbiased estimator.

The variance of the MD's location can be similarly computed as

$$E(x^2) = \frac{FF_1}{FF}, E(y^2) = \frac{FF_2}{FF} \quad (6.26)$$

where

$$FF = \begin{vmatrix} FF^{11} & FF^{12} & FF^{13} \end{vmatrix}$$

where

$$FF^{11} = \begin{bmatrix} \left[E \left(\frac{\partial^2 L}{\partial x^2} \right) \right]^2 & \left[E \left(\frac{\partial^2 L}{\partial x \partial y} \right) \right]^2 & E \left(\frac{\partial^2 L}{\partial x^2} \right) E \left(\frac{\partial^2 L}{\partial x \partial y} \right) \end{bmatrix}^T$$

$$FF^{12} = \begin{bmatrix} 2E \left(\frac{\partial^2 L}{\partial x^2} \right) E \left(\frac{\partial^2 L}{\partial x \partial y} \right) & 2E \left(\frac{\partial^2 L}{\partial y^2} \right) E \left(\frac{\partial^2 L}{\partial x \partial y} \right) \\ \left[E \left(\frac{\partial^2 L}{\partial x^2} \right) E \left(\frac{\partial^2 L}{\partial y^2} \right) + E \left(\frac{\partial^2 L}{\partial x \partial y} \right)^2 \right] \end{bmatrix}^T$$

$$FF^{13} = \begin{bmatrix} \left[E \left(\frac{\partial^2 L}{\partial x \partial y} \right) \right]^2 & \left[E \left(\frac{\partial^2 L}{\partial y^2} \right) \right]^2 & E \left(\frac{\partial^2 L}{\partial y^2} \right) E \left(\frac{\partial^2 L}{\partial x \partial y} \right) \end{bmatrix}^T$$

$$FF_1 = \begin{vmatrix} FF_1^{11} & FF_1^{12} & FF_1^{13} \end{vmatrix}$$

where

$$FF_1^{11} = \begin{bmatrix} E \left[\left(\frac{\partial L}{\partial x} \right)^2 \right] - PP_1 & E \left[\left(\frac{\partial L}{\partial y} \right)^2 \right] - PP_2 & E \left[\left(\frac{\partial L}{\partial x} \right) \left(\frac{\partial L}{\partial y} \right) \right] - PP_3 \end{bmatrix}^T$$

$$FF_1^{12} = FF^{12}$$

$$FF_1^{13} = FF^{13}$$

$$FF_2 = \begin{vmatrix} FF_2^{11} & FF_2^{12} & FF_2^{13} \end{vmatrix}$$

where

$$FF_2^{11} = FF^{11}$$

$$FF_2^{12} = FF^{12}$$

$$FF_2^{13} = FF_1^{11}$$

$$PP_1 = -x^2 \left[E \left(\frac{\partial^2 L}{\partial x^2} \right) \right]^2 - 2xy E \left(\frac{\partial^2 L}{\partial x^2} \right) E \left(\frac{\partial^2 L}{\partial x \partial y} \right) - y^2 \left[E \left(\frac{\partial^2 L}{\partial x \partial y} \right) \right]^2$$

$$PP_2 = -x^2 \left[E \left(\frac{\partial^2 L}{\partial x \partial y} \right) \right]^2 - 2xy E \left(\frac{\partial^2 L}{\partial y^2} \right) E \left(\frac{\partial^2 L}{\partial x \partial y} \right) - y^2 \left[E \left(\frac{\partial^2 L}{\partial y^2} \right) \right]^2$$

$$PP_3 = -x^2 E \left(\frac{\partial^2 L}{\partial x^2} \right) E \left(\frac{\partial^2 L}{\partial x \partial y} \right) - xy \left[E \left(\frac{\partial^2 L}{\partial x^2} \right) E \left(\frac{\partial^2 L}{\partial y^2} \right) + E \left(\frac{\partial^2 L}{\partial x \partial y} \right)^2 \right] \\ - y^2 E \left(\frac{\partial^2 L}{\partial y^2} \right) E \left(\frac{\partial^2 L}{\partial x \partial y} \right)$$

6.3 Simulation and Experimental Results

To test the accuracy and applicability of our proposed ELB localization scheme in a multipath environment, a simulation is conducted in an indoor environment with dimensions of 16.4m×9.5m ($0 \leq x \leq 16.4\text{m}$ and $0 \leq y \leq 9.5\text{m}$). This location was the Internet of Things (IoT) laboratory at the School of EEE, Nanyang Technological University (NTU) as shown in Figure 6.5.

Figure 6.5: Geometry of IoT laboratory at School of EEE, NTU.

In the simulation, one RD and one scatterer are generated to be uniformly distributed in the environment. The MD's moving trajectory is generated from five location points which are 2m apart from each other. Figure 6.6 and Figure 6.7 depict the two examples of the MD's tracking trajectory, A and B respectively, when the RD is placed at (3.5, 8.8).

Fig. 6.8 and Fig. 6.9 show the estimated scattering points based on one simulation run for trajectory A and B, respectively. R^0 and $\hat{R}$ are the true and estimated locations of the scattering point. At MD_1 , the scattering point is calculated from equation (6.7) by using the initial guess of the MD location and measured TOA and AOA of one bounce scattering path. After finding the location of the scatterer point, the final location of MD $\hat{MD}_1$ is calculated from

equation (6.9). When MD moves to the next location, the initial MD location at new location is firstly estimated by using the new measured TOA and AOA and the corresponding scattering point which is obtained at previous location. The location of the scattering point and $\hat{MD}_2$ can be estimated using (6.7) and (6.9) respectively.

Figure 6.6: Example of MD moving trajectory A in an indoor environment.

Figure 6.7: Example of MD moving trajectory B in an indoor environment.

Figure 6.8: The estimated location of scattering point at trajectory A.

Figure 6.9: The estimated location of scattering point at trajectory B.

Figure 6.10 and 6.11 illustrate the accuracy of our proposed localization scheme based on these two moving trajectories and compare them to the existing localization scheme via CDF under the condition $\sigma_d = 2\text{m}$, $\sigma_\theta = \sigma_\phi = 5^\circ$. The true measurement data values are simulated using the ray tracing methodology and Gaussian noise is added to carry out the localization. The root mean square (RMS) error relates to the actual location of the MD and is calculated as $\sqrt{(x-x^0)^2 + (y-y^0)^2}$. In our proposed localization scheme [129], the initial location of the MD, MD_1 , is randomly generated within a circle centered at MD's location with a radius equal to 5% of the distance between RD and MD

[99]-[100]. Because [85] and [90] are the conventional TOA/AOA and TOA localization schemes and need at least two or three RDs respectively, another three RDs are placed at (3.5m, 0.7m), (12.9m, 0.7m) and (12.9m, 8.8m) near the other three corners. In the simulation results, we assume the signals at the four RDs undergo one bounce reflection in the heavy multipath environment. [99] and [100] are the existing NLOS localization scheme and require at least two paths. Thus, another scatterer is randomly generated in the environment.

Figure 6.10: CDF performance for trajectory A under $\sigma_d = 2\text{m}$, $\sigma_\theta = \sigma_\phi = 5^\circ$.

Figure 6.11: CDF performance for trajectory B under $\sigma_d = 2\text{m}$, $\sigma_\theta = \sigma_\phi = 5^\circ$.

As shown in Figure 6.10 and 6.11, our proposed localization scheme based on one scattering path outperforms the existing localization schemes. It is worth noting that when the MD moves from MD₁ to MD₅, the location of the virtual RD in [129] also changes while the scattering point remains at the same location. Hence, our proposed localization achieves an accuracy of 2.9m and 2m 90% of the time, compared with 3.6m and 3.8m in [129] respectively. The improvement is about 20% and 47% respectively.

The average location error (ALE) performance comparison is depicted in Figure 6.12 with 5,000 simulation runs. The TOA standard deviation is assumed to be 2m. AOA standard deviations are varied from 1° to 10° . As

shown, our proposed tracking localization scheme using one RD achieves an average error of 2.7m compared with the error of 4.4m in [129], 11.1m in [85] and 13.7m in [90]. The margin of improvement is at least 40%. The performance of [99] and [100] are not shown, as in [100] the accuracy is dramatically degraded when the angle between the two scatterers is very small, while in [99] the Taylor series methodology only works well when there is a good initial guess and small variance of measurement parameters.

Figure 6.12: ALE performance comparison.

To check the accuracy of our proposed indoor location tracking scheme in a real environment, an experiment is carried out at IoT laboratory by the measurement team. The laboratory contains glass windows, concrete walls and five dominant metallic obstacles, namely S1, S2, S3, S4 and S5. In the experiment, RD is fixed at (3.5m, 8.8m) while MD moves from MD₁ to MD₇ as shown in Figure 6.13. MD₁ and MD₇, are in LOS and the rest are in an NLOS

condition. The experiment is conducted using a vector network analyzer (VNA) with frequency sweep from 2 to 3 GHz over 1601 frequency points. A 4×4 virtual antenna array with an element spacing of 5cm that corresponds to half a wavelength at 3 GHz is used at both the RD and the MD. At each MD location, 16 S21 measurement data for each frequency point is used to obtain the average. Using the averaged data, the TOA and AOA of the two dominant paths at each MD location will be calculated by the EM parameter estimation algorithm [57]. The EM algorithm can extract the TOA and AOA of the signal path as long as its signal is above the threshold, as shown in Table 6-1. These values are used to determine the MD's location using equations (6.7) and (6.9). The root mean square (RMS) error pertaining to the actual location of the MD is given as $\sqrt{(x - x^0)^2 + (y - y^0)^2}$ where (x^0, y^0) and (x, y) are the true and estimated MD locations respectively.

	Extracted path from measured data (d, ϕ, θ)			Power level
MD ₁	11m	154°	205°	-58.0dB
	6m	122°	302°	-60.0dB
MD ₂	12m	155°	201°	-57.0dB
	11.7m	179°	241°	-62.0dB
MD ₃	9.9m	239°	305°	-62.0dB
	12.9m	178°	244°	-64.0dB
MD ₄	13.8m	188°	196°	-66.0dB
	11m	237°	299°	-66.5dB
MD ₅	7.8m	215°	317°	-64.5dB
	11.4m	240°	240°	-63.5dB
MD ₆	6.9m	154°	29°	-57.0dB
	8.7m	234°	311°	-57.5dB
MD ₇	6m	179°	352°	-56.0dB
	6.3m	167°	20°	-59.0dB

Table 6-1 The extracted paths and their power levels from the EM Algorithm.

Figure 6.13: MD tracking trajectory at IoT laboratory.

The d, θ, ϕ are extracted using the EM methodology [57] and correlated with the ray tracing algorithm. The reflected paths from glass windows, concrete walls and five dominant metallic obstacles are obtained using ray tracing subject to Gaussian noise. The RMS error is calculated for 5,000 simulation runs. To compare with [85] and [90], another three RDs are placed at the same positions as the one in the ALE performance result.

Figure 6.14 and 6.15 show the CDF performance at MD_4 and MD_6 , compared to the existing localization schemes. As shown in Figure 6.14, under $\sigma_d = 1m, \sigma_\theta = \sigma_\phi = 5^\circ$, our proposed localization scheme has an accuracy of 1.65m 90% of the time. The margin is greater than that in [129] and [100] by around 35% and 20% respectively. When the MD moved to MD_7 , our proposed

scheme achieves an accuracy of 1.84m 90% of the time, compared with 2.54m in [129], which is an improvement of around 30%.

Figure 6.14: CDF performance for MD₄ under $\sigma_d = 1\text{m}$, $\sigma_\theta = \sigma_\phi = 5^\circ$.

Figure 6.15: CDF performance for MD₆ under $\sigma_d = 1\text{m}$, $\sigma_\theta = \sigma_\phi = 5^\circ$.

Figure 6.16 illustrates the CRLB and error variance comparison with varying $\sigma_\theta, \sigma_\phi$ using $\sigma_d = 1\text{m}$ at MD₂ when the RD is in a NLOS state with the MD. The TOA standard deviation at the RD and the MD are set to 1m, whereas $\sigma_\theta, \sigma_\phi$ are varied from 1degree to 10degrees to test the robustness and stability of our proposed ELB localization scheme in the variation of AOA noise. Figure 6.14 depicts the comparison between the RMS error of our proposed ELB localization scheme, using (6.9), and the error variance derived using (6.26) and its CRLB [100]. The derived error variance is not equivalent to the CRLB bound, but does not deviate much from the CRLB limit.

Figure 6.16: CRLB and error variance comparison with varying $\sigma_\theta, \sigma_\phi$ using $\sigma_d = 1\text{m}$ for MD₂.

6.4 Remarks

A novel NLOS localization and tracking scheme has been proposed based on the concept of scattering points. Experimental simulation results have shown that our proposed ELB NLOS localization scheme using one RD outperforms the existing localization schemes by a significant margin at the simulated locations.

Chapter 7

Conclusion and Recommendations

7.1 Conclusion

In this research study, we have presented novel and robust localization schemes which work in dense multipath environments by using NLOS measurement information without any identification and mitigation schemes.

Chapter 3 presented a LPMD based localization scheme for indoor environments based on the Gaussian weighting function and a proximate point. A Gaussian weighting function is constructed based on the calculated variance and the weighting factor is assigned to the intersection points based on how close these points are to the intersection point of interest. The proposed Gaussian weighting process improves the robustness of the localization process by using the measurement data (TOA and AOA) at both sides without identification and mitigation schemes. The performance of the localization scheme is assessed via simulations in an indoor environment. The results show that our proposed NLOS localization scheme outperforms the existing NLOS

Chapter 7 Conclusion and Recommendations

localization schemes in all cases in relation to various degree of TOA and AOA measurement noise.

Chapter 4 presented a novel APMD based localization algorithm by employing a single dominant path to estimate the location of the MD without any weighting factor. The proposed scheme uses the measured TOA and AOA at both the RD and the MD, and the characteristics of the probability distribution of the measurement data to form an intersection area to estimate the location of the MD.

Chapter 5 proposed a virtual RD based localization scheme in heavy multipath environments without any prior knowledge of the whole environment. The location of the virtual RD can be determined when the initial location of the MD is estimated or when MD transits from the LOS to the NLOS region. With the help of information on the location of the virtual RD, the proposed NLOS localization scheme requires only one signal path, which can even undergo multiple bounce reflection. Simulation and experimental results show that our proposed NLOS localization scheme using one RD outperforms existing localization schemes by a significant margin.

Chapter 6 proposed an indoor localization scheme to exploit the scattering point of one bounce scattering path or a diffraction path to track the MD's trajectory and condition. The constrained function is constructed to estimate the locations of the scattering points. The performance of the proposed ELB localization is assessed based on the simulation and experimental results, and illustrates the

proposed tracking localization scheme significantly to improve location accuracy compared to existing localization schemes.

7.2 Recommendations for Future Work

Two areas of future work can be explored.

The first area explores the integration of an inertial navigation (IN) scheme with a wireless localization algorithm to improve location accuracy. In the IN system, the new position of a mobile device is determined from the previous estimated location and its measured acceleration and angular velocity. However, measurement errors accumulate over time, resulting in position drift. Therefore, a wireless localization scheme can be combined into the IN system to improve localization performance.

The second area of research that can be delved into is real-time parameter estimation for multipath environments. Currently, the parametric estimation of TOA and AOA in the experiment conducted here used the EM algorithm, which is highly computational in time. There is a need for real-time subspace parametric estimation of TOA and AOA in multipath environments, such as matrix pencil and tensor schemes which can work in multipath environments.

Appendix A

$$E(\mathbf{Z}) = (\mathbf{C}^T \mathbf{C})^{-1} \mathbf{C}^T E \begin{pmatrix} x_R + (l_{\max} - 3\sigma_{l_{\max}}) \cos(\alpha_{\max} - 3\sigma_{\alpha_{\max}}) \\ y_R + (l_{\max} - 3\sigma_{l_{\max}}) \sin(\alpha_{\max} - 3\sigma_{\alpha_{\max}}) \\ x_R + (l_{\min} + 3\sigma_{l_{\min}}) \cos(\alpha_{\min} + 3\sigma_{\alpha_{\min}}) \\ y_R + (l_{\min} + 3\sigma_{l_{\min}}) \sin(\alpha_{\min} + 3\sigma_{\alpha_{\min}}) \\ x_R + (l_{\max} - 3\sigma_{l_{\max}}) \cos(\alpha_{\min} + 3\sigma_{\alpha_{\min}}) \\ y_R + (l_{\max} - 3\sigma_{l_{\max}}) \sin(\alpha_{\min} + 3\sigma_{\alpha_{\min}}) \\ x_R + (l_{\min} + 3\sigma_{l_{\min}}) \cos(\alpha_{\max} - 3\sigma_{\alpha_{\max}}) \\ y_R + (l_{\min} + 3\sigma_{l_{\min}}) \sin(\alpha_{\max} - 3\sigma_{\alpha_{\max}}) \end{pmatrix}$$

$$E(\mathbf{Z}) = \frac{1}{4} E \begin{pmatrix} 4x_R + \begin{pmatrix} l_{\max} + l_{\min} \\ -3\sigma_{l_{\max}} + 3\sigma_{l_{\min}} \end{pmatrix} \begin{bmatrix} \cos(\alpha_{\max} - 3\sigma_{\alpha_{\max}}) \\ + \cos(\alpha_{\max} - 3\sigma_{\alpha_{\max}}) \end{bmatrix} \\ 4y_R + \begin{pmatrix} l_{\max} + l_{\min} \\ -3\sigma_{l_{\max}} + 3\sigma_{l_{\min}} \end{pmatrix} \begin{bmatrix} \sin(\alpha_{\max} - 3\sigma_{\alpha_{\max}}) \\ + \sin(\alpha_{\max} - 3\sigma_{\alpha_{\max}}) \end{bmatrix} \end{pmatrix}$$

(A.1)

$$E\left(\begin{bmatrix} \lambda \lambda^T \end{bmatrix}_{1,1}\right) = x_R^2 + 2x_R(l_o - 3\sigma_{l_{\max}}) \cos(\alpha_o - 3\sigma_{\alpha_{\max}}) \\ + (l_o^2 + 10\sigma_{l_{\max}}^2 - 6l_o\sigma_{l_{\max}}) \times \frac{1 + \cos(2(\alpha_o - 3\sigma_{\alpha_{\max}}))}{2}$$

$$E\left(\left[\lambda\lambda^T\right]_{1,2}\right) = x_R y_R + (l_o - 3\sigma_{l_{\max}}) \begin{pmatrix} x_R \sin(\alpha_o - 3\sigma_{\alpha_{\max}}) \\ + y_R \sin(\alpha_o - 3\sigma_{\alpha_{\max}}) \end{pmatrix} \\ + \frac{1}{2}(l_o^2 + 10\sigma_{l_{\max}}^2 - 6l_o\sigma_{l_{\max}}) \sin(2(\alpha_o - 3\sigma_{\alpha_{\max}}))$$

$$E\left(\left[\lambda\lambda^T\right]_{1,3}\right) = x_R^2 + x_R \begin{bmatrix} (l_o + 3\sigma_{l_{\min}}) \cos(\alpha_o + 3\sigma_{\alpha_{\min}}) \\ + (l_o - 3\sigma_{l_{\max}}) \cos(\alpha_o - 3\sigma_{\alpha_{\max}}) \end{bmatrix} \\ + \frac{1}{2} \begin{bmatrix} \cos(2\alpha_o) \\ + \cos(3\sigma_{\alpha_{\min}} + 3\sigma_{\alpha_{\max}}) \end{bmatrix} \begin{pmatrix} l_o^2 + 3\sigma_{l_{\min}} l_o \\ -3\sigma_{l_{\max}} l_o - 9\sigma_{l_{\max}} \sigma_{l_{\min}} \end{pmatrix}$$

$$E\left(\left[\lambda\lambda^T\right]_{1,4}\right) = x_R y_R + x_R (l_o + 3\sigma_{l_{\min}}) \sin(\alpha_o + 3\sigma_{\alpha_{\min}}) \\ + y_R (l_o - 3\sigma_{l_{\max}}) \cos(\alpha_o - 3\sigma_{\alpha_{\max}}) \\ + \frac{1}{2} \begin{bmatrix} \sin(2\alpha_o) \\ + \sin(3\sigma_{\alpha_{\min}} + 3\sigma_{\alpha_{\max}}) \end{bmatrix} \begin{pmatrix} l_o^2 + 3\sigma_{l_{\min}} l_o \\ -3\sigma_{l_{\max}} l_o - 9\sigma_{l_{\max}} \sigma_{l_{\min}} \end{pmatrix}$$

$$E\left(\left[\lambda\lambda^T\right]_{1,5}\right) = x_R^2 + 2x_R (l_o - 3\sigma_{l_{\max}}) \cos(\alpha_o - 3\sigma_{\alpha_{\max}}) \\ + \left(l_o^2 + 10\sigma_{l_{\max}}^2 - 6l_o\sigma_{l_{\max}} \right) \times \frac{1}{2} \begin{bmatrix} \cos(2\alpha_o) + \\ \cos(3\sigma_{\alpha_{\min}} + 3\sigma_{\alpha_{\max}}) \end{bmatrix}$$

$$E\left(\left[\lambda\lambda^T\right]_{1,6}\right) = x_R y_R + (l_o - 3\sigma_{l_{\max}}) \begin{pmatrix} x_R \sin(\alpha_o + 3\sigma_{\alpha_{\min}}) \\ + y_R \cos(\alpha_o - 3\sigma_{\alpha_{\max}}) \end{pmatrix} \\ + \frac{1}{2}(l_o^2 + 10\sigma_{l_{\max}}^2 - 6l_o\sigma_{l_{\max}}) \begin{bmatrix} \sin(2\alpha_o) \\ + \sin(3\sigma_{\alpha_{\min}} + 3\sigma_{\alpha_{\max}}) \end{bmatrix}$$

$$E\left(\left[\lambda\lambda^T\right]_{1,7}\right) = x_R^2 + x_R \begin{pmatrix} 2l_o - 3\sigma_{l_{\max}} \\ + 3\sigma_{l_{\min}} \end{pmatrix} \cos(\alpha_o - 3\sigma_{\alpha_{\max}}) \\ + \left(l_o^2 + 3\sigma_{l_{\min}} l_o - 3\sigma_{l_{\max}} l_o - 9\sigma_{l_{\max}} \sigma_{l_{\min}} \right) \times \frac{1}{2} [1 + \cos(2(\alpha_o - 3\sigma_{\alpha_{\max}}))]$$

$$\begin{aligned}
 E\left(\left[\lambda\lambda^T\right]_{1,8}\right) &= x_R y_R + x_R (l_o + 3\sigma_{l_{\min}}) \sin(\alpha_o - 3\sigma_{\alpha_{\max}}) \\
 &+ y_R (l_o - 3\sigma_{l_{\max}}) \cos(\alpha_o - 3\sigma_{\alpha_{\max}}) \\
 &+ \left(\frac{l_o^2 + 3\sigma_{l_{\min}} l_o - 3\sigma_{l_{\max}} l_o - 9\sigma_{l_{\max}} \sigma_{l_{\min}}}{2}\right) \times \frac{\sin(2(\alpha_o - 3\sigma_{\alpha_{\max}}))}{2}
 \end{aligned}
 \tag{A.2}$$

$$\begin{aligned}
 E\left(\left[\lambda\lambda^T\right]_{2,2}\right) &= y_R^2 + 2y_R (l_o - 3\sigma_{l_{\max}}) \sin(\alpha_o - 3\sigma_{\alpha_{\max}}) \\
 &+ (l_o^2 + 10\sigma_{l_{\max}}^2 - 6l_o \sigma_{l_{\max}}) \times \frac{1 - \cos(2(\alpha_o - 3\sigma_{\alpha_{\max}}))}{2}
 \end{aligned}$$

$$\begin{aligned}
 E\left(\left[\lambda\lambda^T\right]_{2,3}\right) &= x_R y_R + y_R (l_o + 3\sigma_{l_{\min}}) \cos(\alpha_o + 3\sigma_{\alpha_{\min}}) \\
 &+ x_R (l_o - 3\sigma_{l_{\max}}) \sin(\alpha_o - 3\sigma_{\alpha_{\max}}) \\
 &+ \frac{1}{2} \left[\frac{\sin(2\alpha_o) - \sin(3\sigma_{\alpha_{\min}} + 3\sigma_{\alpha_{\max}})}{\sin(3\sigma_{\alpha_{\min}} + 3\sigma_{\alpha_{\max}})} \right] \begin{pmatrix} l_o^2 + 3\sigma_{l_{\min}} l_o \\ -3\sigma_{l_{\max}} l_o - 9\sigma_{l_{\max}} \sigma_{l_{\min}} \end{pmatrix}
 \end{aligned}$$

$$\begin{aligned}
 E\left(\left[\lambda\lambda^T\right]_{2,4}\right) &= y_R^2 + y_R \begin{bmatrix} (l_o + 3\sigma_{l_{\min}}) \sin(\alpha_o + 3\sigma_{\alpha_{\min}}) \\ + (l_o - 3\sigma_{l_{\max}}) \sin(\alpha_o - 3\sigma_{\alpha_{\max}}) \end{bmatrix} \\
 &+ \frac{1}{2} \begin{bmatrix} \cos(3\sigma_{\alpha_{\min}} + 3\sigma_{\alpha_{\max}}) \\ -\cos(2\alpha_o) \end{bmatrix} \begin{pmatrix} l_o^2 + 3\sigma_{l_{\min}} l_o \\ -3\sigma_{l_{\max}} l_o - 9\sigma_{l_{\max}} \sigma_{l_{\min}} \end{pmatrix}
 \end{aligned}$$

$$\begin{aligned}
 E\left(\left[\lambda\lambda^T\right]_{2,5}\right) &= x_R y_R + \begin{pmatrix} l_o \\ -3\sigma_{l_{\max}} \end{pmatrix} \begin{pmatrix} x_R \sin(\alpha_o - 3\sigma_{\alpha_{\max}}) + \\ y_R \cos(\alpha_o + 3\sigma_{\alpha_{\min}}) \end{pmatrix} \\
 &+ \frac{1}{2} \begin{pmatrix} l_o^2 + 10\sigma_{l_{\max}}^2 \\ -6l_o \sigma_{l_{\max}} \end{pmatrix} \begin{bmatrix} \sin(2\alpha_o) - \sin(3\sigma_{\alpha_{\min}} + 3\sigma_{\alpha_{\max}}) \end{bmatrix}
 \end{aligned}$$

$$\begin{aligned}
 E\left(\left[\lambda\lambda^T\right]_{2,6}\right) &= y_R^2 + 2y_R (l_o - 3\sigma_{l_{\max}}) \sin(\alpha_o) \\
 &+ \frac{1}{2} \begin{bmatrix} \cos(3\sigma_{\alpha_{\min}} + 3\sigma_{\alpha_{\max}}) \\ -\cos(2\alpha_o) \end{bmatrix} (l_o^2 + 10\sigma_{l_{\max}}^2 - 6l_o \sigma_{l_{\max}})
 \end{aligned}$$

$$\begin{aligned}
 E\left(\left[\lambda\lambda^T\right]_{2,7}\right) &= x_R y_R + y_R (l_o + 3\sigma_{l_{\min}}) \cos(\alpha_o - 3\sigma_{\alpha_{\max}}) \\
 &+ x_R (l_o - 3\sigma_{l_{\max}}) \sin(\alpha_o - 3\sigma_{\alpha_{\max}}) \\
 &+ \frac{1}{2} \sin\left[2(\alpha_o - 3\sigma_{\alpha_{\max}})\right] \begin{pmatrix} l_o^2 + 3\sigma_{l_{\min}} l_o \\ -3\sigma_{l_{\max}} l_o - 9\sigma_{l_{\max}} \sigma_{l_{\min}} \end{pmatrix}
 \end{aligned}$$

$$\begin{aligned}
 E\left(\left[\lambda\lambda^T\right]_{2,8}\right) &= y_R^2 + y_R \begin{bmatrix} (l_o + 3\sigma_{l_{\min}}) \sin(\alpha_o - 3\sigma_{\alpha_{\max}}) \\ +(l_o - 3\sigma_{l_{\max}}) \sin(\alpha_o - 3\sigma_{\alpha_{\max}}) \end{bmatrix} \\
 &+ \frac{1}{2} [1 - \cos(2(\alpha_o - 3\sigma_{\alpha_{\max}}))] \begin{pmatrix} l_o^2 + 3\sigma_{l_{\min}} l_o \\ -3\sigma_{l_{\max}} l_o - 9\sigma_{l_{\max}} \sigma_{l_{\min}} \end{pmatrix}
 \end{aligned}$$

(A.3)

$$\begin{aligned}
 E\left(\left[\lambda\lambda^T\right]_{3,3}\right) &= x_R^2 + 2x_R (l_o + 3\sigma_{l_{\min}}) \cos(\alpha_o + 3\sigma_{\alpha_{\min}}) \\
 &+ (l_o^2 + 10\sigma_{l_{\min}}^2 + 6l_o \sigma_{l_{\min}}) \times \frac{1 + \cos(2(\alpha_o + 3\sigma_{\alpha_{\min}}))}{2}
 \end{aligned}$$

$$\begin{aligned}
 E\left(\left[\lambda\lambda^T\right]_{3,4}\right) &= x_R y_R + x_R (l_o + 3\sigma_{l_{\min}}) \sin(\alpha_o + 3\sigma_{\alpha_{\min}}) \\
 &+ y_R (l_o + 3\sigma_{l_{\min}}) \cos(\alpha_o + 3\sigma_{\alpha_{\min}}) \\
 &+ \frac{1}{2} (l_o^2 + 10\sigma_{l_{\min}}^2 + 6l_o \sigma_{l_{\min}}) \sin[2(\alpha_o + 3\sigma_{\alpha_{\min}})]
 \end{aligned}$$

$$\begin{aligned}
 E\left(\left[\lambda\lambda^T\right]_{3,5}\right) &= x_R^2 + x_R \begin{pmatrix} 2l_o + \\ 3\sigma_{l_{\min}} - 3\sigma_{l_{\max}} \end{pmatrix} \cos(\alpha_o + 3\sigma_{\alpha_{\min}}) \\
 &+ \begin{pmatrix} l_o^2 + 3\sigma_{l_{\min}} l_o \\ -3\sigma_{l_{\max}} l_o - 9\sigma_{l_{\max}} \sigma_{l_{\min}} \end{pmatrix} \times \frac{1 + \cos(2(\alpha_o + 3\sigma_{\alpha_{\min}}))}{2}
 \end{aligned}$$

$$\begin{aligned}
 E\left(\left[\lambda\lambda^T\right]_{3,6}\right) &= x_R y_R + x_R (l_o - 3\sigma_{l_{\max}}) \sin(\alpha_o + 3\sigma_{\alpha_{\min}}) \\
 &+ y_R (l_o + 3\sigma_{l_{\min}}) \cos(\alpha_o + 3\sigma_{\alpha_{\min}}) \\
 &+ \frac{1}{2} \begin{pmatrix} l_o^2 + 3\sigma_{l_{\min}} l_o \\ -3\sigma_{l_{\max}} l_o - 9\sigma_{l_{\max}} \sigma_{l_{\min}} \end{pmatrix} \sin[2(\alpha_o + 3\sigma_{\alpha_{\min}})]
 \end{aligned}$$

$$\begin{aligned}
 E\left(\left[\lambda\lambda^T\right]_{3,7}\right) &= x_R^2 + 2x_R (l_o + 3\sigma_{l_{\min}}) \cos(\alpha_o) \\
 &+ \frac{1}{2} \begin{bmatrix} \cos(2\alpha_o) \\ +\cos(3\sigma_{\alpha_{\min}} + 3\sigma_{\alpha_{\max}}) \end{bmatrix} (l_o^2 + 10\sigma_{l_{\min}}^2 + 6l_o \sigma_{l_{\min}})
 \end{aligned}$$

$$\begin{aligned}
 E\left(\left[\lambda\lambda^T\right]_{3,8}\right) &= x_R y_R + x_R (l_o + 3\sigma_{l_{\min}}) \sin(\alpha_o - 3\sigma_{\alpha_{\max}}) \\
 &+ y_R (l_o + 3\sigma_{l_{\min}}) \cos(\alpha_o + 3\sigma_{\alpha_{\min}}) \\
 &+ \frac{1}{2} (l_o^2 + 10\sigma_{l_{\min}}^2 + 6l_o \sigma_{l_{\min}}) \begin{bmatrix} \sin(2\alpha_o) \\ -\sin(3\sigma_{\alpha_{\min}} + 3\sigma_{\alpha_{\max}}) \end{bmatrix}
 \end{aligned}$$

(A.4)

$$\begin{aligned}
 E\left(\left[\lambda\lambda^T\right]_{4,5}\right) &= x_R y_R + y_R \cos(\alpha_o + 3\sigma_{\alpha_{\min}}) (l_o - 3\sigma_{l_{\max}}) \\
 &+ x_R (l_o + 3\sigma_{l_{\min}}) \sin(\alpha_o + 3\sigma_{\alpha_{\min}}) \\
 &+ \frac{1}{2} \sin[2(\alpha_o + 3\sigma_{\alpha_{\min}})] \begin{pmatrix} l_o^2 + 3\sigma_{l_{\min}} l_o \\ -3\sigma_{l_{\max}} l_o - 9\sigma_{l_{\max}} \sigma_{l_{\min}} \end{pmatrix}
 \end{aligned}$$

$$\begin{aligned}
 E\left(\left[\lambda\lambda^T\right]_{4,6}\right) &= y_R^2 + y_R \begin{pmatrix} 2l_o + \\ 3\sigma_{l_{\min}} - 3\sigma_{l_{\max}} \end{pmatrix} \sin(\alpha_o + 3\sigma_{\alpha_{\min}}) \\
 &+ \frac{1}{2} [1 - \cos(2(\alpha_o + 3\sigma_{\alpha_{\min}}))] \begin{pmatrix} l_o^2 + 3\sigma_{l_{\min}} l_o \\ -3\sigma_{l_{\max}} l_o - 9\sigma_{l_{\max}} \sigma_{l_{\min}} \end{pmatrix}
 \end{aligned}$$

$$E\left(\left[\lambda\lambda^T\right]_{4,7}\right) = x_R y_R + (l_o + 3\sigma_{l_{\min}}) \begin{pmatrix} x_R \sin(\alpha_o + 3\sigma_{\alpha_{\min}}) \\ + y_R \cos(\alpha_o - 3\sigma_{\alpha_{\max}}) \end{pmatrix} \\ + \frac{1}{2}(l_o^2 + 10\sigma_{l_{\min}}^2 + 6l_o\sigma_{l_{\min}}) \begin{bmatrix} \sin(2\alpha_o) \\ + \sin(3\sigma_{\alpha_{\min}} + 3\sigma_{\alpha_{\max}}) \end{bmatrix}$$

$$E\left(\left[\lambda\lambda^T\right]_{4,8}\right) = y_R^2 + 2y_R(l_o + 3\sigma_{l_{\min}})\sin(\alpha_o) \\ + \frac{1}{2} \begin{bmatrix} \cos(3\sigma_{\alpha_{\min}} + 3\sigma_{\alpha_{\max}}) \\ - \cos(2\alpha_o) \end{bmatrix} (l_o^2 + 10\sigma_{l_{\min}}^2 + 6l_o\sigma_{l_{\min}})$$

(A.5)

$$E\left(\left[\lambda\lambda^T\right]_{5,5}\right) = x_R^2 + 2x_R(l_o - 3\sigma_{l_{\max}})\cos(\alpha_o + 3\sigma_{\alpha_{\min}}) \\ + (l_o^2 + 10\sigma_{l_{\max}}^2 - 6l_o\sigma_{l_{\max}}) \times \frac{1 + \cos(2(\alpha_o + 3\sigma_{\alpha_{\min}}))}{2}$$

$$E\left(\left[\lambda\lambda^T\right]_{5,6}\right) = x_R y_R + x_R(l_o - 3\sigma_{l_{\max}})\sin(\alpha_o + 3\sigma_{\alpha_{\min}}) \\ + y_R(l_o - 3\sigma_{l_{\max}})\cos(\alpha_o + 3\sigma_{\alpha_{\min}}) \\ + \frac{1}{2}(l_o^2 + 10\sigma_{l_{\max}}^2 - 6l_o\sigma_{l_{\max}})\sin[2(\alpha_o + 3\sigma_{\alpha_{\min}})]$$

$$E\left(\left[\lambda\lambda^T\right]_{5,7}\right) = x_R^2 + x_R \begin{bmatrix} (l_o + 3\sigma_{l_{\min}})\cos(\alpha_o - 3\sigma_{\alpha_{\max}}) \\ + (l_o - 3\sigma_{l_{\max}})\cos(\alpha_o + 3\sigma_{\alpha_{\min}}) \end{bmatrix} \\ + \frac{1}{2} \begin{bmatrix} \cos(2\alpha_o) \\ + \cos(3\sigma_{\alpha_{\min}} + 3\sigma_{\alpha_{\max}}) \end{bmatrix} \begin{pmatrix} l_o^2 + 3\sigma_{l_{\min}} l_o \\ - 3\sigma_{l_{\max}} l_o - 9\sigma_{l_{\max}} \sigma_{l_{\min}} \end{pmatrix}$$

$$\begin{aligned}
 E\left(\left[\lambda\lambda^T\right]_{5,8}\right) &= x_R y_R + x_R (l_o + 3\sigma_{l_{\min}}) \sin(\alpha_o - 3\sigma_{\alpha_{\max}}) \\
 &+ y_R (l_o - 3\sigma_{l_{\max}}) \cos(\alpha_o + 3\sigma_{\alpha_{\min}}) \\
 &+ \frac{1}{2} \begin{pmatrix} l_o^2 + 3\sigma_{l_{\min}} l_o - \\ 3\sigma_{l_{\max}} l_o - 9\sigma_{l_{\max}} \sigma_{l_{\min}} \end{pmatrix} \begin{bmatrix} \sin(2\alpha_o) \\ -\sin(3\sigma_{\alpha_{\min}} + 3\sigma_{\alpha_{\max}}) \end{bmatrix}
 \end{aligned}
 \tag{A.6}$$

$$\begin{aligned}
 E\left(\left[\lambda\lambda^T\right]_{6,6}\right) &= y_R^2 + 2y_R (l_o - 3\sigma_{l_{\max}}) \sin(\alpha_o + 3\sigma_{\alpha_{\min}}) \\
 &+ \frac{1}{2} \left[1 - \cos(2(\alpha_o + 3\sigma_{\alpha_{\min}})) \right] (l_o^2 + 10\sigma_{l_{\max}}^2 - 6l_o \sigma_{l_{\max}})
 \end{aligned}$$

$$\begin{aligned}
 E\left(\left[\lambda\lambda^T\right]_{6,7}\right) &= x_R y_R + x_R \sin(\alpha_o + 3\sigma_{\alpha_{\min}}) (l_o - 3\sigma_{l_{\max}}) \\
 &+ y_R \cos(\alpha_o - 3\sigma_{\alpha_{\max}}) (l_o + 3\sigma_{l_{\min}}) \\
 &+ \frac{1}{2} \begin{pmatrix} l_o^2 + 3\sigma_{l_{\min}} l_o \\ -3\sigma_{l_{\max}} l_o - 9\sigma_{l_{\max}} \sigma_{l_{\min}} \end{pmatrix} \begin{bmatrix} \sin(2\alpha_o) \\ +\sin(3\sigma_{\alpha_{\min}} + 3\sigma_{\alpha_{\max}}) \end{bmatrix}
 \end{aligned}$$

$$\begin{aligned}
 E\left(\left[\lambda\lambda^T\right]_{6,8}\right) &= y_R^2 + y_R \begin{bmatrix} (l_o + 3\sigma_{l_{\min}}) \sin(\alpha_o - 3\sigma_{\alpha_{\max}}) \\ + (l_o - 3\sigma_{l_{\max}}) \sin(\alpha_o + 3\sigma_{\alpha_{\min}}) \end{bmatrix} \\
 &+ \frac{1}{2} \begin{bmatrix} \cos(3\sigma_{\alpha_{\min}} + 3\sigma_{\alpha_{\max}}) \\ -\cos(2\alpha_o) \end{bmatrix} \begin{pmatrix} l_o^2 + 3\sigma_{l_{\min}} l_o \\ -3\sigma_{l_{\max}} l_o - 9\sigma_{l_{\max}} \sigma_{l_{\min}} \end{pmatrix}
 \end{aligned}
 \tag{A.7}$$

$$\begin{aligned}
 E\left(\left[\lambda\lambda^T\right]_{7,7}\right) &= x_R^2 + 2x_R (l_o + 3\sigma_{l_{\min}}) \cos(\alpha_o - 3\sigma_{\alpha_{\max}}) \\
 &+ (l_o^2 + 10\sigma_{l_{\min}}^2 + 6l_o \sigma_{l_{\min}}) \times \frac{1 + \cos(2(\alpha_o - 3\sigma_{\alpha_{\max}}))}{2}
 \end{aligned}$$

Appendix A

$$\begin{aligned}
 E\left(\left[\lambda\lambda^T\right]_{7,8}\right) &= x_R y_R + x_R (l_o + 3\sigma_{l_{\min}}) \sin(\alpha_o - 3\sigma_{\alpha_{\max}}) \\
 &\quad + y_R (l_o + 3\sigma_{l_{\min}}) \cos(\alpha_o - 3\sigma_{\alpha_{\max}}) \\
 &\quad + \frac{1}{2} (l_o^2 + 10\sigma_{l_{\min}}^2 + 6l_o\sigma_{l_{\min}}) \sin(2(\alpha_o - 3\sigma_{\alpha_{\max}}))
 \end{aligned}
 \tag{A.8}$$

$$\begin{aligned}
 E\left(\left[\lambda\lambda^T\right]_{8,8}\right) &= y_R^2 + 2y_R (l_o + 3\sigma_{l_{\min}}) \sin(\alpha_o - 3\sigma_{\alpha_{\max}}) \\
 &\quad + \frac{1}{2} [1 - \cos(2(\alpha_o - 3\sigma_{\alpha_{\max}}))] (l_o^2 + 10\sigma_{l_{\min}}^2 + 6l_o\sigma_{l_{\min}})
 \end{aligned}
 \tag{A.9}$$

$$E\left(\left[\lambda\lambda^T\right]_{n,m}\right) = E\left(\left[\lambda\lambda^T\right]_{m,n}\right) \quad m = 1 \dots 8, n = 1 \dots 8, m \neq n$$

Author's Publications

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