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**INDOOR LOCALIZATION
WITH
ULTRA WIDEBAND RADIO**

ZHOU YUAN

School of Electrical and Electronic Engineering

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SUMMARY

Location-awareness has been drawing significant attention in recent years. In particular, the emerging Ultra Wideband (UWB) technology has the potential to revolutionize the systems and applications in many sectors. Due to its fine temporal resolution, UWB radio is especially promising for localization in indoor environment. This thesis focuses on two-step localization and investigates the UWB technology for indoor localization.

Indoor environment often creates multipath in radio propagation, and the receiver receives multiple copies of UWB pulses with different delays and amplitudes. When the multipath signals are well-separated from each other, they can be resolved by conventional sliding correlator and do not interfere with the direct path (DP) signal. However, in a dense multipath channel, the subsequent multipath signal could overlap with the DP signal, which distorts the correlator output and introduces error in Time-of-Arrival (TOA) estimation. To measure the TOA accurately, more sophisticated algorithms are required to resolve the overlapping signal components. Most works in the literature adopt iterative approach to find the TOA of each signal components, and the convergence rate depends on the number of signal components. In Chapter 3 of the thesis, a non-iterative Modified Phase-Only Correlator (MPOC) is proposed for high-resolution multiple TOA estimation. The MPOC deconvolves the multipath channel frequency response from the received signal by dividing the latter with the local template spectrum. Due to the inherent spectral nulls of the

local template, the MPOC suffers from noise amplification problem. In Chapter 3, a kurtosis-based outlier detection method is also proposed to identify and suppress the amplified noise. Both simulation and experiment verifies the ability of MPOC to resolve overlapping UWB pulses and renders it for high-resolution TOA estimation.

Besides multipath, the other major source of error in indoor localization is the Non-Line-of-Sight (NLOS) propagation problem, where the DP signal is either obstructed or diffracted. The NLOS problem introduces a positive bias in the TOA estimation. The NLOS measurement should be either discarded or imposed as region constraint. A prerequisite for both treatments is to identify the received signal that undergoes NLOS propagation. Identification of NLOS propagation is therefore critical for accurate target localization. In Chapter 4 of the thesis, a NLOS identification technique based on hybrid Received Signal Strength (RSS) and TOA is proposed. The basic idea of the proposed technique is to detect the divergence in the signal propagation distances estimated from RSS measurement and from TOA measurement. In more practical hyperbolic and elliptical localization systems where the target is not synchronized with the anchor, simple anchor cooperation is needed and the divergence in the range difference is used instead as the detection metric. Performance analysis and result show that the proposed technique works best if the DP signal is attenuated significantly and the bias in time measurement is small.

Once the TOA of the signal is estimated, it is converted to meaningful target locus. Conversion of TOA to target locus depends on the ranging protocol,

which is mainly determined by the level of synchronization. The concept of elliptical localization is proposed in Chapter 5. In elliptical localization, the target position is found from the intersection of ellipses defined by the sum of ranges from the anchor transmitter to the target and from the target to the anchor receivers. Leveraging on the knowledge of anchor positions, the proposed elliptical localization system requires no explicit synchronization, and timing information is obtained by measurement of the differential TOA between the signal from the anchor transmitter and the signal from the target. Elimination of explicit synchronization is a significant advantage and makes the system suitable for ad-hoc applications where quick set-up is desired.

Almost every localization system requires the position of the anchors. While knowledge of anchor position is essential, how to obtain the anchor positions is rarely studied. Chapter 6 of the thesis fills the gap by studying the anchor position calibration problem. The anchors are assumed to be capable of conducting range measurement among them. Depending on the implementation of ranging protocol, the ranges between anchor pairs can be absolute or relative. Absolute range is measured either by highly synchronized anchors or by two-way ranging technique. The major drawbacks are extra hardware complexity and clock drift error correspondingly. When the anchors are synchronized as in hyperbolic localization system, the relative range among the anchors can be estimated by rotational time difference measurement and ranking of the inter-anchor ranges can then be obtained. With the absolute value or the ranking of the inter-anchor ranges, classical and ordinal multi-dimensional scaling (MDS) can be applied to find the local map of the anchors.

Similar to most real-world problems, there is no solution that is best for all. Different applications have different constraint and requirement for the localization system. The optimum or proper implementation and architecture are determined by factors such as cost, set-up time, application scenario, and targeted accuracy. Often, design of a localization system involves performance-cost trade-off, which is addressed in this thesis by comparing various solutions and outlining their advantages and drawbacks for various scenarios.

LIST OF ABBREVIATIONS

ADC:	Analog-to-Digital Converter
APOC:	Asymmetric Phase-Only Correlator
AWGN:	Additive White Gaussian Noise
BPSK:	Binary Phase Shift Keying
CLS:	Constrained Least Squares
CM:	Channel Model
CPHSR:	Correlation Peak to Highest Sidelobe Ratio
CRLB:	Cramer-Rao Lower Bound
dB:	Decibel
DC:	Direct Coupling
DDP:	Detectable Direct Path
DP:	Direct Path
DTOA:	Differential Time-of-Arrival
ECC:	European Communications Commission
ED:	Energy Detector
FCC:	Federal Communications Commission

FFT:	Fast Fourier Transform
FIM:	Fisher Information Matrix
GDOP:	Geometric Dilution of Precision
GLRT:	Generalized Likelihood Ratio Test
GPS:	Global Positioning System
GS:	Global Synchronous
IFFT:	Inverse Fast Fourier Transform
IR-UWB:	Impulse-Radio Ultra Wideband
LOS:	Line-of-Sight
LS:	Least Squares
MAC:	Medium Access Control
MC-UWB:	Multi-Carrier Ultra Wideband
MDS:	Multidimensional Scaling
ML:	Maximum Likelihood
MPOC:	Modified Phase-Only Correlator
NLOS:	Non-Line-of-Sight
NP:	Neyman-Pearson
NTU:	Nanyang Technological University

OLS:	Ordinary Least Squares
OOK:	On-Off keying
PAM:	Pulse Amplitude Modulation
PHY:	Physical layer
POC:	Phase-Only Correlator
PPM:	Pulse Position Modulation
PRF:	Pulse Repetition Frequency
PWTC:	Positioning and Wireless Technology Centre
RF:	Radio Frequency
RLS:	Recursive Least Squares
RS:	Receiver Synchronous
RSS:	Received Signal Strength
RX:	Receiver
SDS-TWR:	Symmetric Double-Sided Two-Way Ranging
SI:	Spherical Interpolation
SNR:	Signal-to-Noise Ratio
TDOA:	Time-Difference-of-Arrival
TOA:	Time-of-Arrival

TOF:	Time-of-Flight
TR:	Transmitted Reference
TWR:	Two-Way Ranging
TX:	Transmitter
UDP:	Undetectable Direct Path
UWB:	Ultra Wideband
ZZB:	Ziv-Zakai Bound

LIST OF SYMBOLS

A_{ij}	True value of x_{ij} in noiseless case
c	Signal propagation speed
$C(k)$	FFT of channel impulse response
$\mathbf{C}_{Asyn}$	Error covariance for asynchronous case
$\mathbf{C}_{DC}$	Error covariance for DC signal TOA estimation
$\mathbf{C}_{GS}$	Error covariance for global synchronous case
$\mathbf{C}_{RS}$	Error covariance for receiver synchronous case
d_{rs}	Distance between point r and point s
D	Dimension of localization problem
$\mathbf{D}$	Matrix of squared dissimilarities
E_p	Pulse energy
F	Effective bandwidth
F_s	Sampling frequency
$\mathbf{I}_m$	$m \times m$ identity matrix

$\mathbf{J}(\boldsymbol{\theta})$:	Fisher information matrix for parameter $\boldsymbol{\theta}$
l_i :	Distance bias due to NLOS RSS
ℓ_i :	Range bias due to NLOS TOA
L_i :	Distance between anchor transmitter and anchor receiver i
$L(\boldsymbol{\theta}, \lambda)$:	Lagrange cost function
$n(t)$:	Noise in received signal
N_o :	Single-sided noise power spectral density
$N(k)$:	FFT of noise $n(t)$
P_D :	Probability of detection
P_{FA} :	Probability of false alarm
$\mathbf{p}$:	Target position vector
$\mathbf{p}_t$:	Position vector for anchor transmitter
$\mathbf{p}_i$:	Position vector for anchor receiver i
$Q(\cdot)$:	Q-function
$Q^{-1}(\cdot)$:	Inverse of Q-function
r_i :	Pseudorange between anchor i and target

$r_{ij} :$	Range difference between anchor i and anchor j
$r(t) :$	Received signal
$r'_i :$	Estimated sum of ranges from anchor transmitter to target and from target to anchor receiver i
$r_{ij}^k :$	Range difference of the signal transmitted from anchor k and received by anchor i and anchor j
$R_i :$	True range between Anchor i and target
$R(k) :$	FFT of received signal $r(t)$
$\mathbf{r}_{Asyn} :$	Range vector in asynchronous case
$\mathbf{r}_{GS} :$	Range difference vector in global synchronous case
$\mathbf{r}_{RS} :$	Range difference vector in receiver synchronous case
$\mathbf{R} :$	True range vector
$\mathbf{R}_b :$	Vector of biased range
$\mathbf{R}_u :$	Vector of unbiased range
$\mathbf{R}_{GS} :$	True absolute range vector in global synchronous case
$\mathbf{R}_{RS} :$	True absolute range vector in receiver synchronous case
$s(t) :$	Transmitted signal / template signal

$S(k) :$	FFT of template signal $s(t)$
$t_P :$	Propagation time or Time-of-Flight
$T_f :$	Frame duration
$T_s :$	Sampling interval
$T(.) :$	Test statistic for NLOS identification in synchronous case
$T'(.):$	Test statistic for NLOS identification in asynchronous case
$u_i :$	True distance
$\tilde{u}_i :$	Estimated distance from RSS (LOS)
$\tilde{u}'_i :$	Estimated distance from RSS (NLOS)
$\tilde{u}_i :$	Distance estimation from RSS measurement in general
$\mathbf{V}_D :$	Matrix of eigenvectors corresponding to D largest eigenvalues
$x_{ij} :$	Simplified test statistic for NLOS identification in asynchronous case
$\alpha_l :$	Attenuation of path l
$\beta_{ij} :$	Deflection coefficient
$\delta_{rs} :$	Proximity between point r and point s

Δ_i :	DTOA at anchor i
γ :	Path loss exponent
$\hat{\boldsymbol{\theta}}$:	Estimation of parameter $\boldsymbol{\theta}$
$\boldsymbol{\Lambda}_D$:	Diagonal matrix of the D largest eigenvalues
$\Lambda(f(\boldsymbol{\theta});\boldsymbol{\theta})$:	Log-likelihood function for parameter $\boldsymbol{\theta}$
μ_i :	True pseudorange
$\tilde{\mu}_i$:	Estimated pseudorange from TOA (LOS)
$\tilde{\mu}'_i$:	Estimated pseudorange from TOA (NLOS)
$\tilde{\mu}_i$:	Pseudorange estimation from TOA measurement in general
σ_{sh} :	Standard deviation of log-normal shadowing
σ_i^2 :	Variance of pseudorange estimation from TOA (LOS)
$\sigma_i'^2$:	Variance of pseudorange estimation from TOA (NLOS)
ς_i^2 :	Variance of distance estimation from RSS (LOS)
$\varsigma_i'^2$:	Variance of distance estimation from RSS (NLOS)
τ_i :	TOA at anchor i
τ_{ij} :	TDOA of signal between anchor i and anchor j

$\tau_{AT} :$	Time when device A transmit a ranging packet
$\tau_{AR} :$	Time when device A receivers a ranging packet
$\psi :$	Offset between pseudorange and absolute range
$\mathbf{\Omega} :$	Centering matrix
$\Omega(u_i) :$	RSS at distance u_i
$\Delta\Omega_i :$	Attenuation of RSS due to NLOS propagation
$\Omega_0 :$	RSS at reference distance
$\mathbf{1}_m :$	$m \times 1$ vector of all ones

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CHAPTER 1 INTRODUCTION

1.1 Motivation

Recent years have seen a growing interest in location-aware services and applications. In the United States, the Federal Communications Commission (FCC)'s enhanced-911 (E-911) telecommunication initiative requires the mobile service providers to locate any subscriber making a 911 emergency call with expected positioning accuracy of up to 150 meters 95 percent of the time. Since then, many companies were motivated to develop localization systems that support the initiative. The capability to determinate a subscriber's position also enables new consumer services. Using its position information, a mobile user can find the nearest petrol station, bus stop, or post office, for example. This kind of 'mobile consumerism' or 'm-commerce' is touted to be the 'next big thing' by many business speculators [1].

Besides consumer services, location-awareness also has the potential to revolutionize the applications in many other sectors, and numerous application opportunities exist. For example, the capability of communication devices to locate people helps fire fighters to communicate with each other and find the injured personnel quickly. Similarly, military can reduce accidental deaths and injuries by identification of friendly soldiers. Some more fascinating applications include smart home, patient monitoring, and student tracking. Location-awareness can also be used for asset management, inventory control,

and shipment tracking in industrial, commercial, and transportation sectors. Last but not least, location information may benefit applications in sensor networks by aiding their network configuration and providing service for higher layers [2].

Outdoor localization systems have existed for a long time, the most well-known probably being the GPS [3], which has become part of our daily lives and an essential element in commercial and public infrastructure. Other than GPS, some earlier navigation systems include Omega, Decca, and LORAN. These systems have been designed for long-range outdoor use, and they usually fail in indoor environment due to interference from multipath and signal attenuation by walls.

On 14 Feb, 2002, the FCC' first report amended the rules and permitted the deployment of the Ultra Wideband (UWB) devices [4]. Since then, tremendous attention has been paid to this emerging technology. Impulse-Radio UWB (IR-UWB) is a promising and enabling technology for high-accuracy localization systems and has the potential to realize location-aware applications, especially in indoor environment where conventional localization systems are denied. Although UWB is well-suited for indoor localization, few UWB-based localization systems that can provide accurate target positioning with practical low-cost implementation have been demonstrated. Despite its popularity, most research works focus on individual module. What is lacking is an integrated and practical measurement system as well as perspective on the entire deployment process of the localization system. It is the value of the technology and the

discrepancy in research that forms the motivation for this thesis.

1.2 Objectives

The main aim of this research is to fill the above discrepancy and develop practical UWB localization methods and techniques, as well as to demonstrate their accurate localization capability via hardware prototypes and measurement. The research bears several objectives:

- 1) The system should achieve centimeter level accuracy. Accuracy is critical for some localization systems and location-aware services. For indoor environment with confined area and coverage, centimeter level accuracy will enable many potential applications and services. One application example is interactive gaming, where the precise location of sensors is needed to track the gamer's movement and posture accurately. Another example is elderly care, where it is important not only to know the location of the person, but also to monitor his/her status such as walking and falling. This again requires the accurate location of several sensors. Some other examples include structural monitoring, and remote operation and control of precision instruments.
- 2) The performance-cost trade-off should be addressed. There is often a trade-off between system cost and performance. Admittedly sophisticated systems may offer better performance such as improved accuracy, but they are more likely to demand more expensive hardware

and implementation. It is therefore critical to strike a balance between the two often contradictory factors and offer different options for different application requirements.

- 3) The system should be practical. That is to say, it should be deployed easily, and can be used even for ad-hoc applications with minimum knowledge of the surroundings and little calibration. Deployment also includes the prior setup before the target localization process, and it is preferable that the system can be set up quickly.

1.3 Major Contributions

With the research objectives outlined in 1.2, the major contributions of the research include:

- 1) Various Time-of-Arrival (TOA) estimation methods have been reviewed in Chapter 3. A high-resolution TOA estimation algorithm is also proposed to meet the requirement of centimeter level accuracy in indoor environment with multipath interference.
- 2) A Non-Line-of-Sight (NLOS) identification protocol is proposed in Chapter 4 to mitigate the NLOS error, which is one of the most significant error sources. In contrast to most works in the literature, the proposed method addresses the ‘small NLOS error’, which is hard to

mitigate but is detrimental to accurate localization.

- 3) An elliptical localization system with asynchronous range measurement is proposed in Chapter 5. The proposed system eliminates the need for explicit synchronization mechanism that could be costly and inefficient, and facilitates ad-hoc localization applications.
- 4) The anchor position calibration problem has been studied, and several options for anchor position calibration have been discussed and compared in Chapter 6. The ability of anchors to range and locate themselves is especially important for ad-hoc applications that require easy and quick setup and deployment, such as in an emergency personnel positioning system.

1.4 Organization of the Thesis

The rest of the thesis is organized as follows. The localization process is first introduced in Chapter 2. The advantage of UWB for indoor localization is also highlighted. The first step towards target localization is to estimate the time metric of the received signal. A high-resolution algorithm is proposed in Chapter 3 to measure the TOA of the received signal in a multipath channel. Another major source of error in time measurement based on radio signal is the NLOS propagation issue. In Chapter 4, a method to identify the NLOS propagation condition is proposed. From a system perspective, Chapter 5 deals

with conversion of time measurement to range information and calculation of target position. A new ranging protocol is proposed in Chapter 5 for asynchronous elliptical localization. An often overlooked issue in a localization system is anchor position calibration. This research gap is fulfilled in Chapter 6, where the techniques to construct local anchor map are discussed based on multi-dimensional scaling (MDS). The thesis is concluded in Chapter 7 with recommendations for future work.

To verify the performance of the proposed methods, experimental measurements have been conducted. As discussed in Chapter 2, this thesis adopts a two-step localization process. Hence, there are two types of measurement setup: one is for single-link range measurement, and the other is for position measurement with multiple links. All the measurements were conducted in the laboratory room of the Positioning and Wireless Technology Centre, Nanyang Technological University, Singapore. The layout and the photograph of the laboratory are shown in Fig. 1.1 and Fig. 1.2, respectively. Due to hardware and space limitation, we mainly focus on 2-D measurements. The proposed methods, however, can be extended to 3-D cases as well.

Fig. 1.1 Floor plan of the laboratory room.

Fig. 1.2 Photograph of the laboratory room

CHAPTER 2 BACKGROUND

2.1 Localization Basics

The terms ‘localization’ and ‘positioning’ are often used interchangeably. To remove this ambiguity, in this thesis, ‘localization’ refers to the entire process of locating the target, and ‘positioning’ refers to the computation to find the unknown target position based on given inputs, and in most cases is part of the localization process.

A typical localization system comprises some nodes whose positions are known. These nodes are called anchors. The anchors provide position reference for target localization. The anchor and target positions can be absolute in longitude and latitude, as obtained from GPS. They can also be relative. That is to say, the anchor and target positions can be rotated and translated in the global absolute coordinate frame, but their relative positions remain fixed [5]. For most indoor/small coverage applications, relative anchor position suffices. In fact, it is often more meaningful in these cases to know the relative position of the target with respect to the anchors instead of its global coordinates in longitude and latitude. In the relative positioning case, the coordinates of the localization system can be constructed based on the anchor positions alone.

Localization can be achieved in a single step or two steps. In one-step localization, also referred to as direct localization, the position of the target is

found directly from the received signal [6-9]. While one-step localization provides the optimum position estimation, it is much more computationally intensive. Hence in this thesis we will focus on two-step localization, which is illustrated in Fig. 2.1. In two-step localization, measurement is first conducted to obtain some intermediate signal metrics that are related to the target position. These metrics are then converted to the target locus and used by the following positioning step which finds the best intersection of the target loci. Although it is sub-optimum, two-step localization is advantageous in terms of implementation, as the measurement hardware is usually available to extract the signal parameters [10]. Corresponding to the two steps towards target localization, two types of measurements in the thesis were mainly conducted: one is for the measurement in the first step, and the other is for position calculation by combining the measurement result in the first step. All measurements were conducted in the same laboratory room shown in Fig. 1.1 and Fig. 1.2.

Fig. 2.1 Illustration of the two-step localization process

Depending mainly on the power constraint, the measurement and information processing capability of anchors and target can differ significantly. In the majority of the cases, the anchors are treated as part of the localization system infrastructure and have constant power supply. In contrast, the target to be located may often operate on battery and is usually power-constrained. Hence it has very limited processing capability. In this case, the target merely broadcasts its presence by emitting signature waveforms to the anchors, which act as the central processing unit to measure the target signal metric and calculate the target position.

In the first step towards target localization, metrics of the received signal are estimated from measurement. Signals metrics that are of typical interest include angle and range. The signal metrics will be used in the next step for position calculation. Besides angle and range, there are also other metrics such as connectivity that are especially popular in sensor networks [11]. These metrics are useful for multi-hop large coverage areas and are less accurate. Hence they will not be addressed in this thesis.

To measure the Angle-of-Arrival (AOA) of the signal, multiple antennas are required. The angle information is embedded in the difference in times of arrival (or phase difference) of the signal at each antenna, and from the known geometry of the antenna array, AOA can be estimated. Estimation of AOA has received much interest for narrowband signals with the development of well-known algorithms such as MUSIC and ESPRIT [12]. For wideband signals, however, the assumptions in these narrowband algorithms are not valid because

time delay can no longer be approximated by phase-shift. Instead, it is more meaningful to consider the time delayed version of the received signal directly [10]. It has been shown in [13] that such AOA measurement does not improve localization accuracy beyond that achieved by time measurement. As the use of antenna array may not be feasible for applications demanding low-cost, we will only consider range measurement in this thesis.

Range finding can be based on Received Signal Strength (RSS) or TOA measurement. In RSS-based range measurement, the propagation distance of the signal is calculated from the RSS based on a path loss model. Absolute propagation distance of the signal can be inferred from RSS measurement. RSS ranging is less accurate, but RSS information may be helpful for NLOS identification, as discussed in Chapter 4. An alternative to RSS ranging is TOA, or time-based ranging. There are many ways to find the TOA of the signal. For example, it can be estimated by correlating the received signal with a local template [14, 15], or detecting the time when the received signal energy exceeds a threshold [16, 17]. Time measurement is more precise when the signal has a fast rising edge. Depending on the ranging protocol, the measured TOA can be converted to absolute range or relative range. TOA estimation techniques are discussed in Chapter 3, and ranging protocols are discussed in Chapter 5.

The estimated TOA alone is not useful unless it can be converted to meaningful range information. Conversion of TOA to range information depends on the ranging protocol, which is largely determined by the level of

synchronization. The synchronization mechanism or the ranging protocol determines whether the estimated TOA can be converted to absolute range or relative range. For example, when the target and anchor are synchronized as illustrated in Fig. 2.2, TOA is equal to Time-of-Flight (TOF), and we can find the absolute range between them as:

$$r_i = c \times \tau_i \quad (2.1)$$

where r_i is the measured range between anchor i and target, and c is the signal propagation speed, and τ_i is the TOA at anchor i , which equals to the signal propagation time, or TOF. The range measurement defines a circular target locus with the anchor being the centre and the range being the radius.

Fig. 2.2 Illustration of synchronized ranging

In cases where target-locator synchronization is not possible, one may alternatively resort to relative range measurement that only requires receiver synchronization. To eliminate the unknown clock offset between the target and

the anchor, the signal TOA at a reference receiver j is subtracted from the TOA at another receiver i to obtain the Time-Difference-of-Arrival (TDOA) as:

$$\tau_{ij} = \tau_i - \tau_j \quad (2.2)$$

and from the TDOA we are able to obtain the difference between ranges from the target to the two anchors:

$$r_{ij} = r_i - r_j = c \times \tau_{ij} \quad (2.3)$$

The relative range measurement is illustrated in Fig. 2.3. The range difference defines a hyperbolic locus that the target resides on. Depending on the target locus, conventional localization systems are often classified to be circular or hyperbolic, as illustrated in Fig. 2.4 and Fig. 2.5 respectively. If, instead of the absolute range or range difference, the sum of ranges between the target and two anchors are available, the target locus will be elliptical, as illustrated in Fig. 2.6. In Chapter 5 of the thesis, elliptical localization will also be discussed.

Fig. 2.3 Illustration of relative ranging

Fig. 2.4 Illustration of circular localization

Fig. 2.5 Illustration of hyperbolic localization

Fig. 2.6 Illustration of elliptical localization

Based on the target loci obtained in the measurement step, the position of the

target is next calculated in the positioning step. The simplest and most straightforward way is to find the intersection of the target loci. If the estimated ranges are perfect, the loci yield a unique intersection. However, in most cases, the estimated ranges are corrupted by errors, and more than one intersection exists. Basically, the positioning step then becomes an optimization process that minimizes an error function based on the target loci. Various position estimation algorithms will be discussed in Chapter 5.

2.2 *Major Sources of Error*

In a practical indoor environment, localization of a single user suffers from several errors. The major error sources include multipath and NLOS propagation, which is depicted in Fig. 2.7. There are five reference receivers (anchors) labeled A to E. The target is an active transmitter. For anchor A, it receives the LOS target signal without any background reflections or scatterings. Therefore the only error in anchor A's received signal is the Additive White Gaussian Noise (AWGN). Similar to anchor A, anchor B also received the Line-of-Sight (LOS) target signal. Apart from that, it also receives the reflected signal from the wall. As shown in the subsequent section, when the reflected multipath signal is well separated from the direct LOS signal, the TOA of the direct signal can still be estimated accurately. However, if the reflected signal overlaps with the direct signal, TOA estimation is deteriorated.

So far the propagations are all LOS, where the direct signal path is

unobstructed. When the direct signal is obstructed during propagation, NLOS error arises, as in the anchor C to E's reception. Depending on the type of blockage, the direct signal may permeate through the obstruction (anchor C), be totally obstructed (anchor D), or diffract around it (anchor E). For anchor C and anchor E, although they are still able to receive the signal from target, the signal is delayed due to additional travel distance in diffraction or the low propagation speed in obstruction media. The 'direct path' signal is usually severely attenuated too. When the NLOS anchor also receives multipath signal as in anchor C, the multipath signal may be stronger and mask the direct signal. The occurrence of total obstruction (anchor D) is easy to detect, because the received signal is dominated by noise. It becomes difficult to detect and mitigate the NLOS propagation when there is some signal component received, as the anchor needs to find out whether the received signal is LOS or NLOS. In NLOS case, the received signal could be the diffracted direct path signal, the partially blocked signal, or a multipath signal. In any of these cases, the NLOS propagation creates a positive bias in the TOA estimation, ranging from less than 1 ns in diffraction case to a few nanoseconds in multipath case.

Fig. 2.7 Common sources of error in indoor localization

2.3 *Performance Error Bound*

In both TOA estimation and position estimation, it is often useful and desirable to have a criterion to benchmark the performance of estimators. One such criterion is the Cramer-Rao Lower Bound (CRLB), which is the lower bound on the variance of any unbiased estimator and can be achieved asymptotically by the maximum-likelihood (ML) estimator [18]. Admittedly there are also other performance bounds other than CRLB such as the Ziv-Zakai Bound (ZZB) [19-21]. ZZB accounts for the ‘thresholding effect’ and is a tighter bound in low Signal-to-Noise Ratio (SNR) conditions where false alarm and missed detection dominate. However, such accuracy is seldom tolerable for

practical applications and it is a common practice to smooth the received signal by accumulating multiple frames of received signal. In this way the SNR is boosted to the level where the ZZB and CRLB tend to agree and are tight [19]. It will also be shown that in addition to being a performance benchmark for the potential accuracy of an estimator, CRLB also gives us insights on system design. Hence we will focus on CRLB as the sole performance bound in this thesis. In this section, the CRLB for position estimation and TOA estimation is discussed.

The variance of any unbiased estimator $\hat{\boldsymbol{\theta}}$ should satisfy:

$$\text{var}(\hat{\boldsymbol{\theta}}) \geq \text{CRLB} = \mathbf{J}(\boldsymbol{\theta})^{-1} \quad (2.4)$$

where $\text{var}(\hat{\boldsymbol{\theta}})$ is the covariance matrix of $\hat{\boldsymbol{\theta}}$ and

$$\mathbf{J}(\boldsymbol{\theta}) = E \left[\left(\frac{\partial \Lambda(f(\boldsymbol{\theta}); \boldsymbol{\theta})}{\partial \boldsymbol{\theta}} \right) \left(\frac{\partial \Lambda(f(\boldsymbol{\theta}); \boldsymbol{\theta})}{\partial \boldsymbol{\theta}} \right)^T \right] \quad (2.5)$$

is the Fisher information matrix (FIM) and $\Lambda(f(\boldsymbol{\theta}); \boldsymbol{\theta})$ is the log-likelihood function of range or position measurement. It can be shown that when the measurement is Gaussian distributed as $N(f(\boldsymbol{\theta}), \mathbf{C})$, $\mathbf{J}(\boldsymbol{\theta})$ can be written as [18] :

$$\mathbf{J}(\boldsymbol{\theta}) = \left(\frac{\partial f(\boldsymbol{\theta})}{\partial \boldsymbol{\theta}} \right)^T \mathbf{C}^{-1} \left(\frac{\partial f(\boldsymbol{\theta})}{\partial \boldsymbol{\theta}} \right). \quad (2.6)$$

2.3.1 Positioning Error Bound

We first derive the positioning CRLB assuming that the range measurement result is readily available with zero-mean Gaussian distributed error. From (2.6), for Gaussian distributed range measurement error, the positioning FIM is given by:

$$\mathbf{J}(\mathbf{p}) = \left(\frac{\partial \mathbf{R}}{\partial \mathbf{p}} \right)^T \mathbf{C}^{-1} \left(\frac{\partial \mathbf{R}}{\partial \mathbf{p}} \right) \quad (2.7)$$

where $\mathbf{R}$ is the vector of all the range measurements, $\mathbf{p}$ is the target position vector, and $\mathbf{C}$ is the range measurement error covariance. Not shown explicitly is that the range vector is a function of the target position. The dependence of $\mathbf{R}$ on $\mathbf{p}$ is omitted in (2.7). The positioning CRLB is equal to the inverse of FIM. From (2.7), it is straightforward to observe that the FIM or CRLB is determined by the range measurement error covariance. Hence the potential positioning accuracy improves with the quality of range measurement. For given ranging quality, the other factor that affects the CRLB is the derivative of range with respect to target position. Although not obvious on a first sight, it can be shown that the derivative is related to the target-anchor geometry. When the range measurement error covariance is an identity matrix, the CRLB becomes the well-known Geometric Dilution of Precision (GDOP) metric, which is an indicator of the amount of amplification of range measurement error onto the position solutions by the target-anchor geometry [22]. Hence the anchor placement will also affect the potential positioning accuracy. It will also

be shown in Chapter 5 that the level of synchronization and ranging protocol also come into play and affect the CRLB. As the CRLB provides insight in factors affecting the system performance, in Chapter 5 we will also present how the positioning CRLB aids us in the localization system design.

The discussion above assumes that all the range measurements are unbiased. When there is a bias in the range measurement, say, due to NLOS propagation, the FIM decreases, as the bias introduces additional measurement uncertainty and reduces the ranging information. Assuming that the estimator wishes to estimate the bias, the CRLB is known as joint CRLB. Accounting for the range bias, the FIM is modified to be [23]:

$$\mathbf{J}(\boldsymbol{\theta}) = \begin{bmatrix} \mathbf{J}_{11} & \mathbf{J}_{12} \\ \mathbf{J}_{21} & \mathbf{J}_{22} \end{bmatrix} \quad (2.8)$$

where

$$\mathbf{J}_{11} = \left(\frac{\partial \mathbf{R}_u}{\partial \mathbf{p}} \right)^T \mathbf{C}_u^{-1} \left(\frac{\partial \mathbf{R}_u}{\partial \mathbf{p}} \right) + \left(\frac{\partial \mathbf{R}_b}{\partial \mathbf{p}} \right)^T \mathbf{C}_b^{-1} \left(\frac{\partial \mathbf{R}_b}{\partial \mathbf{p}} \right)$$

$$\mathbf{J}_{12} = \mathbf{J}_{21}^T = \left(\frac{\partial \mathbf{R}_b}{\partial \mathbf{p}} \right)^T \mathbf{C}_b^{-1}$$

$$\mathbf{J}_{22} = \mathbf{C}_b^{-1}.$$

In the derivation of the above FIM, the range vector is formed by concatenation of the biased range vector $\mathbf{R}_b$ with the unbiased range vector $\mathbf{R}_u$ as

$$\mathbf{R} = \begin{bmatrix} \mathbf{R}_b^T & \mathbf{R}_u^T \end{bmatrix}^T, \quad (2.9)$$

and the parameter to be estimated comprises the position vector and the vector of all biases:

$$\boldsymbol{\theta} = \begin{bmatrix} \mathbf{p}^T & \mathbf{b}^T \end{bmatrix}^T = \begin{bmatrix} \mathbf{p}^T & b_1 & b_2 & \cdots & b_B \end{bmatrix}^T. \quad (2.10)$$

The CRLB for position estimation in this case is the top left D by D block matrix of the inverse of FIM, where D is the dimension of the problem. Using the Schur complement, the positioning CRLB is:

$$\begin{aligned} CRLB &= [\mathbf{J}(\boldsymbol{\theta})]_{D \times D}^{-1} = \left[\mathbf{J}_{11} - \mathbf{J}_{12} \mathbf{J}_{22}^{-1} \mathbf{J}_{21} \right]^{-1} \\ &= \left(\frac{\partial \mathbf{R}_u}{\partial \mathbf{p}} \right)^T \mathbf{C}_u^{-1} \left(\frac{\partial \mathbf{R}_u}{\partial \mathbf{p}} \right) \end{aligned} \quad (2.11)$$

which depends exclusively on the unbiased range measurement only. Hence when some range measurements are biased, these biased range measurements do not help to improve the position estimation accuracy if no prior knowledge of the bias is available. This result also justifies why the ranging results in multipath case and in NLOS case should be treated differently: in multipath case, it is assumed that the LOS signal exists and is the direct path signal. The ranging information can be used in the subsequent positioning step. The NLOS case, on the other hand, assumes no direct path signal exists. Without prior knowledge, the ranging measurement conveys no useful information on target position, and it should be discarded in the positioning step [24].

The above derivation of the positioning CRLB adopts the decoupled two-step localization point of view. That is to say, once the range measurement has been conducted, the received signal is no longer used at the subsequent positioning step. The only information available in the second step is the range measurement result. A more fundamental approach to derive the positioning CRLB from the received signal in multipath channel can be found in the work by Shen and Win [13, 25].

2.3.2 TOA Estimation Error Bound

Despite the difference in ranging protocols, almost every time-based range measurement requires the estimation of TOA of the received signal. Hence accurate TOA estimation is critical for precise localization. Similar to the positioning error bound, we will discuss the CRLB for TOA estimation in this section.

The received signal $r(t)$ is modeled as:

$$r(t) = \sqrt{E_p} s(t - \tau) + n(t) \quad (2.12)$$

where $s(t)$ is the single received signal waveform with unit energy and E_p is the pulse energy. It is assumed that the only source of error is the Additive White Gaussian Noise (AWGN) $n(t)$ with single-sided noise density N_o . The variance of the estimation $\hat{\tau}$ of τ is bounded by:

$$\text{Var}(\hat{\tau}) = \text{E}\left\{(\hat{\tau} - \tau)^2\right\} \geq \text{CRLB}. \quad (2.13)$$

Derivation of the CRLB for TOA estimation is shown in Appendix A and the CRLB is given by [2, 18]:

$$\text{CRLB} = \frac{1}{8\pi^2 F^2 \text{SNR}} \quad (2.14)$$

where SNR is the Signal-to-Noise ratio defined as:

$$\text{SNR} = \frac{E_p}{N_o} \quad (2.15)$$

and F is the effective bandwidth defined as:

$$F = \sqrt{\frac{\int_{-\infty}^{\infty} f^2 |S(f)|^2 df}{\int_{-\infty}^{\infty} |S(f)|^2 df}} \quad (2.16)$$

where $S(f)$ is the Fourier transform of $s(t)$. With the assumption that $s(t)$ has unit energy, (2.16) can be simplified as:

$$F = \sqrt{\int_{-\infty}^{\infty} f^2 |S(f)|^2 df} .$$

From (2.14), the variance of TOA estimation is inversely proportional to the SNR and the squared effective bandwidth. In other words, the impact of SNR on CRLB is linear, while the impact of bandwidth on CRLB is quadratic. Therefore, increasing the signal bandwidth effectively improves the TOA estimation accuracy. This conclusion is significant in that it justifies the emerging UWB as a promising technology for accurate ranging and localization.

The above discussion assumes that the channel is a single-path AWGN

channel and the amplitude of the received signal is known. For most indoor propagation channels that contain multipath, the corresponding CRLB derivation needs to be modified. As shown in Appendix B, derivation of CRLB for TOA estimation in multipath channel reveals that when the multipath components do not overlap with the direct signal component, the CRLB for direct signal parameter estimation is not affected. However, if the multipath signal overlaps with the direct signal, the CRLB increases and potential estimation accuracy for the direct signal parameter is deteriorated.

2.4 *Introduction to UWB*

UWB is typically defined as radio signals having relative bandwidth greater than 20% or absolute bandwidth larger than 500 MHz [26]. Due to its extremely wide bandwidth, UWB is advantageous for accurate ranging and localization applications. The history of UWB can be traced back to 1897 when Guglielmo Marconi used impulse radio transmitter to conduct the first ever trans-ocean wireless communication experiment. The earlier applications of UWB are mainly in the RADAR field due to its fine time resolution. The pioneering work of Scholtz and Win [27] in 1998 gave rise to the growing attention on UWB from the academia, and substantial interest has been received since the FCC's First Report and Order [4] in 2002.

There are two common types of UWB systems: Multi-Carrier UWB (MC-

UWB) and Impulse-Radio UWB (IR-UWB). The former adopts multiple carriers occupying a wide bandwidth to satisfy the bandwidth regulation, while for IR-UWB, the broad bandwidth is achieved by generation of pulses of very short duration in time. Each of the UWB schemes has its own merits. MC-UWB is well suited for high-rate data communications while IR-UWB is ideal for localization. This thesis will focus on the IR-UWB systems due to its advantages such as low cost and multipath immunity, and unless otherwise stated, the term UWB will mean IR-UWB thereafter.

The broad spectrum of UWB inevitably overlays with that of existing communication systems like the GPS, and to avoid interference with current operative radio services, the emission power of UWB is limited by regulatory bodies such as the FCC in the United States, the European Communication Committee (ECC) in Europe, and the Infocomm Development Authority (IDA) in Singapore. An exemplary illustration of the emission limit for indoor UWB systems is shown in Fig. 2.8. The frequency band allocated to UWB devices ranges commonly from 3.1 GHz to 10.6 GHz. The upper and lower boundary frequencies are defined to be the frequencies where the radiated signal power spectrum is 10 dB below its peak value. The FCC regulation limits both the peak and average emission power of the signal. Within the allocated frequency band, a UWB device is allowed to emit a maximum average effective isotropic radiated power (EIRP) of -41.3 dBm when measured by a spectrum analyzer with resolution bandwidth of 1 MHz. The FCC average power limit mainly constraints high data rate UWB communication systems. For UWB localization systems, the pulse repetition frequency (PRF) is often very low (below 1 MHz),

and emission power of the UWB signal is limited by the peak power constraint instead, which is 0 dBm within 50 MHz bandwidth. It has been shown that an emission power of 1 W can satisfy both the average and peak power constraint with a PRF of 187.5 KHz and signal bandwidth of 2 GHz [28-30]. Hence by reducing the PRF, peak power can be exploited for accurate low-rate ranging and positioning applications.

Fig. 2.8 FCC UWB emission limit for indoor communication systems

[2].

Pulse shaping is often necessary in order to efficiently meet the spectrum requirement. UWB based on Gaussian pulses and their derivatives are widely adopted in current UWB research and development. A Gaussian pulse $p(t)$ is

defined as:

$$p(t) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{t^2}{2\sigma^2}} \quad (2.17)$$

and its x^{th} order derivative $p_x(t)$ is:

$$p_x(t) = \frac{d^x p(t)}{dt^x} . \quad (2.18)$$

The 5^{th} order derivative and beyond can satisfy the FCC emission mask [29]. The excessive bandwidth differentiates UWB from conventional narrowband communication systems by several distinctive features, the most significant of which is the extremely short pulse duration. The short pulse duration enables very fine time resolution, which brings advantages such as precise localization capability and robust multipath immunity. Due to its high time resolution, IR-UWB is an enabling technology for indoor localization applications where centimeter level accuracy is desired. Ranging with UWB radio is standardized by the IEEE 802.15.4a Task Group, which was formed in March 2004 to define the alternative physical layers (PHYs) able to provide precise ranging capability and adapt the medium access control (MAC) layer correspondingly. The IEEE 802.15.4a standard was finalized and approved in early 2007.

Other than precise ranging, UWB radio allows for several modulation schemes for data communication. Consider the transmitted signal:

$$s(t) = \sum_{i=-\infty}^{\infty} A_i(t) p(t - iT_f - d_i(t)) . \quad (2.19)$$

The data can be modulated onto the signal amplitude $A_i(t)$. This is known as Pulse Amplitude Modulation (PAM). PAM can be achieved by turning the transmitter on and off according to the data bits, or on-off keying (OOK). Alternatively, we can convey the data by changing the polarity of the pulse, or binary phase shift keying (BPSK). Besides pulse amplitude, data can also be modulated onto the pulse delay $d_i(t)$, which is called Pulse Position Modulation (PPM), where the pulse delay is dependant on the data bits.

2.5 *Relevant Works*

Leveraging on its accurate ranging capability, UWB has been integrated with GPS to provide reliable positioning result in areas such as forests and construction sites, where GPS alone degrades [31, 32]. For indoor applications, however, it is often not necessary to know the absolute coordinate of the target in longitude or latitude. Instead, it may be more meaningful to know the relative position of the target in the local coordinate system. Furthermore, as has also been pointed out in [32], GPS signal is significantly attenuated in indoor environment. Hence we are motivated to use UWB as a standalone technology for indoor localization.

Depending on the scale of deployment, indoor localization can be classified into network-based localization and single-cell localization. For large deployment (e.g. coverage of an entire building), localization is best achieved

via a network of locators. UWB for wireless sensor networks have been investigated in [33-36]. One of the distinct features of network localization is cooperation between the targets. Cooperation is especially important for cases where the number of targets is much larger than the number of locators to ensure sufficient coverage. The performance bound for cooperative localization has been derived and analyzed in [33]. A cooperative localization algorithm with quality of estimation has also been proposed for UWB sensor networks. A UWB sensor network for object positioning and imaging is presented in [34]. The proposed system is built on a mix of synchronous and asynchronous sensors. The synchronous sensors are first cooperatively located to extend the coverage of the system. The asynchronous sensor can then be located independently via the synchronous sensors to provide imaging information. UWB sensor network based localization in realistic environments has been examined in [35]. All the aforementioned studies focus on the physical layer of UWB sensor network. Design considerations with emphasis on MAC layer in the context of IEEE 802.15.4a standard have been presented in [36].

Networked localization requires inter-node communication. When the intended coverage is not large and the number of targets to be located is small, wireless sensor network may not be efficient and the targets can be located individually. In this thesis we will focus on the scenario of small-scale deployment where single-cell (one-hop) coverage is sufficient. One such system is presented in [37], where the distances are measured in a two-way ranging scheme as in [38]. Although absolute range can be estimated without synchronization, this type of two-way ranging schemes requires the master

device to address each responder in a round-robin fashion and creates redundant communication overhead. In our work on passive target ranging and positioning based on backscattering UWB range measurement [39-41] we have shown via simulation and measurement that conventional circular and hyperbolic positioning algorithms can be extended to locate passive target based on UWB backscattering range measurement. However, the backscattering range measurement may not provide sufficient coverage. Besides the works in [37] and [40], commercial indoor UWB positioning systems also exist. Time Domain developed a precision-location UWB system (PLUS) [42] that achieves sub-meter accuracy with TDOA range measurement. Combining TDOA with AOA measurement, Ubisense's precise location system [43] can achieve 15 cm accuracy. Recently, non-coherent UWB radar that is able to achieve millimeter accuracy was reported in [44]. However, the high accuracy was achieved in a much smaller coverage. Ranging accuracy was further improved by averaging the received signal. Other than UWB technology, indoor positioning systems may also adopt a combination of ultrasonic signal and radio-frequency (RF) signal. As RF signal travels much faster than ultrasound, it can be used as a triggering signal for synchronization. Positioning accuracy of 10 cm has been reported [45, 46]. Nevertheless, it is well-known that ultrasound has limitations due to multipath interference. Hence the system performance will deteriorate in a cluttered environment.

CHAPTER 3 HIGH-RESOLUTION TOA ESTIMATION

Estimation of the received signal TOA is the first step towards target localization. In indoor environment, the received signal often comprises several signal components due to multipath and/or multiple target transmitters. UWB pulses from multiple sources may overlap, which deteriorates the ranging accuracy, as discussed in Chapter 2. It is hence crucial to resolve the overlapping signal components. A high-resolution TOA estimation algorithm is then presented in this chapter. The TOA estimation techniques in the literature are also reviewed and compared. In particular the trade-off between performance and cost is addressed.

3.1 Review of TOA Estimation Techniques

Conventionally, TOA estimation is achieved via the so-called sliding correlator (Fig. 3.1) where the received buffered signal is first multiplied with a local template (a clean copy of the transmitted signal) and integrated within a correlation window, and this operation is repeated while sliding the correlator window over the receiver buffer. If the received buffered signal contains the transmitted signal and the correlator window matches its location in the buffer, a high correlation peak is produced at the correlator output, from the position of which the TOA can be recovered. To further reduce the noise, the received

signal can be accumulated and averaged before the correlator [14, 15].

Fig. 3.1 Illustration of sliding correlation

The sliding correlator is equivalent to a matched filter and is the optimum TOA estimator for a single deterministic known signal in the AWGN [10, 18]. However, it has one disadvantage: the width of the correlation peak is twice of the UWB pulse duration, hence limiting the time resolution of the correlator. For indoor environment with dense multipath, it is very likely that multiple overlapping signals are received. The overlapping signal components produce correlation peaks of comparable amplitudes in the adjacency of the true peak, as illustrated in the subsequent section. Due to the limited time resolution of the sliding correlator (which is twice of the UWB pulse duration), the overlapping signal components cannot be resolved, and the spurious peaks cause ambiguity

in correct peak selection and hence ranging error [19].

Resolution of overlapping multipath signal components will improve the ranging accuracy. An algorithm to detect the direct path pulse in a multipath channel based on generalized ML is proposed in [47]. The proposed algorithm does an exhaustive search to find the delay and amplitude of each signal component that minimizes the squared error. When the measurement noise is Gaussian, the least-square (LS) estimator is equivalent to the ML estimator. Several measures are taken to simplify the search process. Firstly, the search is constrained to the region where the DP signal could reside. Next, the number of paths searched is limited.

For UWB signals, ranging can also be achieved noncoherently via the analysis of power delay profile of the received signal [48]. The UWB signals are modeled as temporally correlated processes due to the transmitted waveform. Whether UWB pulses exist in the portion of the received signal affects the covariance of the received signal. Hence TOA estimation is equivalent to finding the break-point that segments the received signal into two processes with different covariance matrices. This is in fact an optimal classification problem. The major advantage of this ranging technique is that it only requires the power delay profile instead of detailed knowledge of the waveform, which may be distorted during propagation. However, the resolution of the algorithm is limited.

Fig. 3.2 UWB ranging based on power delay profile [48]

Another type of noncoherent UWB ranging technique is energy detection (ED) [16, 17], which may be the simplest ranging method in terms of hardware implementation. The architecture of an ED receiver is shown in Fig. 3.3. The TOA estimation is a leading edge or break-point detection problem, and the estimated TOA is the time instant when the ED receiver output first exceeds a threshold. Threshold selection for ED has been examined in [49], where the threshold is optimized based on the kurtosis of the received signal. The most significant advantage of ranging based on ED is that it does not require the Nyquist sampling rate and can be implemented easily. Furthermore, it does not require a local template or knowledge of the waveform either.

Fig. 3.3 The ED receiver architecture

The sliding correlator correlates the received signal with a clean local template, which needs to be generated online or stored in the receiver. Generation and storage of a template waveform can be costly. As an alternative, if the template is allowed to be noisy, it can be transmitted by the target and captured by the anchor. In other words, the template is embedded to be part of the received signal. This is the idea of the transmitted reference (TR) system [50]. Instead of transmitting a single pulse for ranging as in the sliding correlator or ED system, the target transmits two pulses with a known time separation D between them. The first pulse can be considered as the reference pulse that is used to build the correlation template at the receiver, and the second one is the ranging / data pulse. The receiver structure of a TR system is shown in Fig. 3.4, where the reference pulse is delayed by D and mixed with the second pulse. Conceptually the TR system is intriguing in that it eliminates the need to generate or store the template locally at the trade-off of using a noisy template which is embedded in the received signal waveform. As the reference pulse undergoes the similar channel as the ranging / data pulse, the received template matches more closely to the received signal. From an implementation perspective, the major challenge of TR system is realization of a reliable delay line for D of a few hundreds of nanoseconds.

Fig. 3.4 The TR receiver architecture

Other than time domain, estimation of the received signal TOA can also be achieved in the frequency domain by first Fourier transforming the signals. The received signal in the frequency domain comprises phase-shifted and attenuated versions of the transmitted signal and its multipath signals. The phase-shift is related to the delay in the time domain. Similar to the generalized ML technique in [47], a weighted relaxation based method is proposed in [51] to minimize a nonlinear least squares cost function that indicates the squared residual error between the received signal and its fitting function with estimated parameters. By relaxation, the multidimensional problem is decoupled into several one dimensional problems that can be optimized simply. The parameters (i.e. the phase and amplitude of each signal component) are iteratively estimated and refined.

The sliding correlator can also be implemented in frequency domain. The frequency domain correlation is derived from the Fourier property that convolution in time-domain is equivalent to frequency domain multiplication, and the sliding correlation can be performed in the frequency domain by

multiplying the received signal spectrum with the complex conjugate of the local template spectrum. Fig. 3.5 shows the structure of the frequency domain correlator. The Fast Fourier Transform (FFT) based correlator has been proposed for fast signal acquisition in software GPS receiver [52]. The frequency domain correlator output is identical to that of the sliding correlation in time-domain. Therefore, this algorithm is still vulnerable to multiple signal components arriving within one pulse duration.

Fig.3.5 Frequency-domain sliding correlator structure

Besides the frequency domain equivalent of a sliding correlator, ranging can also be achieved in the frequency domain by phase spectrum matching. The Phase-Only Correlator (POC) was first proposed and applied in the field of image alignment and pattern recognition [53, 54]. The POC is thus named because the FFT of both the received signal and local template are normalized by their respective spectral amplitudes, leaving only spectral phase information. The theoretical basis of POC is the Fourier shifting property, which states that a shift/delay in time produces phase change in frequency. As shown in Fig. 3.6, the normalized spectrums are then multiplied, which is equivalent to time-domain correlation. As a result of its flattened spectrum, the POC output is

impulse-like, with the correlation peak much narrower than that of the conventional correlator. Hence frequency-domain phase correlator is potentially suitable for precise timing recovery of wireless signals, as demonstrated in [55, 56].

Fig. 3.6 Structure of Phase-Only correlator

Despite its better correlator output characteristics, POC suffers from poor noise immunity when it is applied in noisy communication systems. In [57] and [58], a variation of the POC called Asymmetric Phase-Only Correlator (APOC) was proposed. Instead of normalization of both the signal and local template spectrums, APOC only normalizes the spectrum of the received signal while maintaining the local template spectrum as shown in Fig. 3.7. APOC has been shown to be beneficial for indoor ranging with narrowband signals processed at baseband, as it is more robust against noise with relatively narrow correlation peak. APOC not only inherits the advantage of POC as the upper portion of the correlation peak is much narrower than conventional correlation, but also precedes POC for better noise immunity. However, the performance of APOC has not been examined for ranging with UWB signals which are bandpass in nature.

Fig. 3.7 Structure of APOC

3.2 *Proposed method*

Motivated by the above phase correlators, a Modified Phase-Only Correlator (MPOC) is proposed in this chapter. The MPOC in its original form is identified to be an ill-posed frequency-domain deconvolution problem and it suffers from inherent noise amplification due to spectral nulls in the local template. Viewing the extremely amplified noise as outliers, we adopt a kurtosis-based amplified-noise identification and suppression strategy to enable the MPOC to resolve overlapping IR-UWB pulses without excessive noise amplification.

3.2.1 *System Model*

In a channel with multiple signal components arising from multiple sources or multipath, the received signal is commonly modeled as

$$r(t) = \sum_{l=1}^L \alpha_l \cdot s(t - \tau_l) + n(t) \quad (3.1)$$

where there are L UWB pulses with the shape $s(t)$. The l^{th} signal component is delayed by τ_l and attenuated by α_l . $n(t)$ is the AWGN. The total observation time is ensured to contain the entire signal region. The received analog signal is first sampled at a sampling frequency of F_s . To avoid aliasing, the sampling frequency should be at least the Nyquist frequency. As the bandwidth of UWB signal is in the order of GHz, current analog-to-digital conversion (ADC) technology may not support such high sampling rate. Hence the technique of equivalent time sampling, also known as stroboscopic sampling is commonly applied [59]. In this type sampling technique, the same signal frame is transmitted periodically. From each frame, only a few points are sampled. The sampled points are offset by a small amount in time between consecutive frames. The time offset corresponds to the sampling resolution. The interleaved sample points are then combined to re-construct one equivalent frame. The FFT of the samples of the received signal can be written as

$$R(k) = \sum_{l=1}^L \alpha_l \cdot S(k) \cdot e^{-j\omega_l k} + N(k) \quad (3.2)$$

where $\omega_l = 2\pi\tau_l / (KT_s)$ with K being the total number of points and $T_s = 1 / F_s$ being the sampling period. Equation (3.2) is a result of the linearity property of FFT. In MPOC, both $R(k)$ and the conjugate of $S(k)$ are normalized by the amplitude of $S(k)$ and multiplied to yield

$$Z(k) = \frac{R(k)}{|S(k)|} \cdot \frac{S^*(k)}{|S(k)|} = \frac{R(k)}{S(k)} \quad (3.3)$$

where $[\cdot]^*$ denotes complex conjugate. Substituting (3.2) into (3.3) yields

$$Z(k) = \sum_{l=1}^L \alpha_l \cdot e^{-j\omega_l k} + \frac{N(k)}{S(k)} = C(k) + N'(k). \quad (3.4)$$

The first term $C(k)$ in (3.4) is the frequency response of the channel. The delay τ_l (TOA to be estimated) can be found by performing the Inverse Fast Fourier Transform (IFFT) on $Z(k)$ to yield the time-domain correlator output. The second term in (3.4), $N'(k) = N(k)/S(k)$, adds noise to the correlator output. At frequencies outside the main UWB band where $S(k)$ is small, $N(k)/S(k)$ may be amplified by the spectral nulls, which then enhances the noise level in the time-domain MPOC output and increases the probability of false alarm.

3.2.2 *Suppression of Amplified Noise*

For high-resolution ranging, our objective is to estimate $C(k)$ based on the observed $Z(k)$, which may be contaminated by the amplified noise. This is equivalent to solving a frequency domain deconvolution problem, which is ill-posed and often involves subjective judgment [60]. To deal with the amplified noise $N'(k)$, several classes of frequency-domain filters have been suggested in [60] to modify $Z(k)$ before the IFFT. For bandpass IR-UWB, the filter that can lead to acceptable estimation is

$$F(k) = \frac{1}{1 + \frac{\lambda}{|S(k)|^2}} \quad (3.5)$$

where λ is a positive constant that has to be optimized heuristically such that

for small $|S(k)|$, $F(k)$ induces adequate attenuation to suppress the potential amplified noise. While the filter in (3.5) suppresses the amplified noise and preserves the passband information, it also filters $C(k)$, which is the frequency response of the channel and occupies the entire $Z(k)$ bandwidth. The filter $F(k)$ makes $C(k)$ a bandpass spectrum and causes its time-domain output to be widened with high sidelobes that exhibit as spurious peaks and cause false detection. Hence a good noise suppression strategy for MPOC should avoid unnecessary distortion to $C(k)$ and attenuate only the amplified noise components while maintaining as much $C(k)$ as possible. In [61], $Z(k)$ whose magnitude exceeds a pre-determined threshold was set to zero. However, the threshold is determined heuristically.

Noting the fact that the significantly amplified noise is produced when $N(k)$ is divided by near-zero $S(k)$ and has magnitude much larger than the maximum amplitude of $C(k)$, we can identify them using outlier detection techniques and suppress them by setting them to zero. Some common outlier detection approaches have been reviewed in [62] and [63]. Among them, a kurtosis-based statistical test is promising, as the kurtosis of a data set depends only on the distribution of the data and avoids the use of threshold. This is a significant advantage because threshold setting requires knowledge of the channel, which is supposed to be estimated in this case.

The kurtosis of a random variable X , defined as the normalized fourth central moment, can be written as:

$$Kurtosis = \frac{E\{(X - \mu)^4\}}{\sigma^4}$$

where μ and σ are the mean and standard deviation of X , respectively. For K sampled data with unknown mean and variance, the kurtosis can be estimated as:

$$Kurtosis = \frac{K \sum_{i=1}^K (x_i - \bar{x})^4}{\left[\sum_{i=1}^K (x_i - \bar{x})^2 \right]^2}$$

For complex $Z(k)$, the calculation is modified to be:

$$Kurtosis = \frac{K \sum_{k=1}^K |Z(k) - \bar{Z}|^4}{\left[\sum_{k=1}^K |Z(k) - \bar{Z}|^2 \right]^2} \quad (3.6)$$

The kurtosis can be interpreted as a measure of the peakedness and tailedness of a distribution and it can be applied as a discrepancy test to detect one or more outliers that have shifted mean (location-slippage) or shifted variance (dispersion-slippage) [63]. Distribution of data with high kurtosis tends to have a sharp peak near the mean and heavy tails. In the presence of noise amplification, the amplified noise components are much larger in amplitude than the in-band $Z(k)$ (i.e. $Z(k)$ that are within the main signal spectral lobe of UWB, defined by $S(k)$). These amplified noise components increase the concentration of large $Z(k)$. This leads to a heavy tail in the $Z(k)$ distribution and thus an increase in the kurtosis.

The effect of noise amplification on kurtosis is illustrated in Fig. 3.8 for a single path channel with normalized signal amplitude. Fig. 3.8(a) and Fig. 3.8(b)

show the magnitude and histogram of $Z(k)$ without noise amplification. For a normalized single path channel, when there is no noise amplification, most $|Z(k)|$ values are centered around 1. When noise amplification occurs, outliers or $|Z(k)|$ values much larger than 1 are produced, as the two spikes greater than 10 observed in Fig. 3.8(c). This leads to a corresponding increase in the concentration in the tail of $Z(k)$ histogram, as circled in Fig. 3.8(d). For the same channel, the kurtosis increases from 1.01 in the first case to 20.17 in the second case.

Fig. 3.8 Illustration of the effect of noise amplification on kurtosis

The minimum value, maximum value and mean value of kurtosis of $Z(k)$ for 6000 channel realizations with random number of signal components (up to 10), delays and amplitudes is plotted in Fig. 3.9 against the received signal-to-noise ratio (SNR). Also shown in the figure is the percentage of noise amplification, calculated based on the number of noise amplification occurrence in 6000 random channel realizations. Noise amplification is considered to occur when $|N'(k)| > \max |C(k)|$. Noise amplification has a higher probability of

occurrence at low SNR, where the noise variance is large and $N'(k)$ is more likely to be amplified by small $S(k)$. Due to the amplified noise, the kurtosis is relatively large at low SNR. It starts to decrease when the SNR increases and the relative strength of amplified noise reduces. When no noise amplification occurs, the kurtosis is less than 3. As the SNR increases further (e.g. SNR>35 dB), $N'(k)$ is very small and $Z(k) \approx C(k)$. In this case, the kurtosis is mainly determined by $C(k)$. It is noteworthy that the band formed by the maximum and minimum kurtosis for different channel realizations is very narrow and is close to the average value. This shows that the changes in delay and amplitude cause little variation in the kurtosis, and the kurtosis is almost independent of the channel. Hence, the kurtosis is a reliable indicator for noise amplification and can be used for noise suppression as discussed in the sequel.

The proposed MPOC block diagram is shown in Fig. 3.10, and the noise suppression procedure based on kurtosis is summarized as follows:

Step 1: Calculate the kurtosis of $Z(k)$ in the receiver buffer according to (3.6).

Step 2: If the kurtosis of $Z(k) < 3$, stop; otherwise, find the maximum value of the out-of-band $|Z(k)|$ (i.e. $Z(k)$ that are beyond the main signal spectral lobe of UWB, defined by $S(k)$) and its index $k_{\max}$;

Step 3: Set $Z(k_{\max}) = 0$;

Step 4: Repeat Step 1 for the remaining $Z(k)$ components.

Fig. 3.9 Percentage of noise amplification occurrence and kurtosis of $Z(k)$ against SNRs for 6000 different channel realizations.

Fig. 3.10 Proposed MPOC block diagram

It should be noted that no assumption on knowledge of SNR is made in the above noise suppression procedure. The SNR only relates to the kurtosis by the fact that noise amplification is more significant at low SNR, as shown in Fig.

3.9. These amplified noise components exhibit as outliers and change the shape of $Z(k)$ distribution. As the kurtosis depends only on the distribution of the data, we can use it as a measure to determine whether there is significant noise amplification.

It is also noteworthy that we only force selected spikes of the out-of-band $Z(k)$ to zero instead of suppressing the entire out-of-band $Z(k)$ (bandpass filtering) as done in (3.5) [60]. The time-domain outputs of MPOC based on these two noise suppression methods are compared in Fig. 3.11 for two signal sources at SNR = 10 dB. The SNR of 10 dB is calculated from the energy of the received pulse over the noise variance that is approximately estimated from noise only region. The proposed kurtosis-based noise suppression method largely maintains the bandwidth of $Z(k)$ and therefore virtually does not produce any sidelobes. The filtering method based on (3.5) gives a bandpass output with several adjacent high sidelobes that are undesirable for high-resolution ranging. The effectiveness of the proposed noise suppression method will be demonstrated by both simulation and experimental measurement.

Fig. 3.11 Comparison of MPOC outputs based on bandpass filtering and noise-spike suppression (proposed) methods.

3.3 Simulation Result

The block diagram of our simulation system is shown in Fig. 3.12. The clock signal periodically triggers the UWB pulse shaping circuit that generates the FCC-compliant 6th order Gaussian derivative pulses at regular intervals (longer than the maximum channel delay spread). The channel adds multipath signals with different delays, amplitudes and polarities, as well as AWGN to the signal. The received signal is sampled by 16 sampling points per pulse (as in [56]) and correlated with a local template using the conventional correlator [14, 15], POC [55, 56], APOC [57], and MPOC [61, 64]. The number of channel paths is fixed

at 4.

Fig. 3.12 Simulation block diagram

We first investigate the correlators' performance in ideal noiseless channels. Fig. 3.13(a) shows the 6th order Gaussian derivative pulse that is sent by the transmitter, and used as the local template at the receiver. Fig. 3.13(b)-(d) show the various correlator outputs in an ideal single-path noiseless channel. Both the conventional correlator and APOC outputs contain sidelobes, while the POC and MPOC outputs are impulse-like with no sidelobes. Fig. 3.13(e)-(h) show the correlator outputs in a noiseless two-path channel with the traveling distance difference of half a UWB pulse width. Both the conventional correlator and APOC outputs become wider and more cyclic, as they are made up of 2 slightly-displaced correlation patterns that merge. The MPOC output is still impulse-like without sidelobes, while sidelobes start to appear in the POC output due to its nonlinearity.

Fig. 3.13 Waveforms of: (a) Pulse template: 6th-order Gaussian derivative pulse; (b) 1-path noiseless channel: conventional correlator output; (c) 1-path noiseless channel: APOC output; (d) 1-path noiseless channel: POC and MPOC output; (e) 2-path noiseless channel: conventional correlator output; (f) 2-path noiseless channel: POC output; (g) 2-path noiseless channel: APOC output; (h) 2-path noiseless channel: MPOC output.

Next, we investigate the correlators' performance in noisy channels. Fig. 3.14 shows the correlator outputs for a noisy 4-path channel with path separation of $3/2$ UWB pulse width, at a receiver SNR of 20 dB. The 4 channel paths have amplitudes '+1, -1, +0.9, -0.8'. Multipath signals with similar strengths are chosen merely for illustration. It could happen when there are large metal objects around the propagation path. Signal strength has little impact on the performance of MPOC, as shown in Fig. 3.9. As expected, since no channel paths fall within one UWB pulse width, the 4 paths can be resolved and their arrival times can be correctly detected by all the correlators. However, the conventional correlator and APOC outputs contain significant sidelobes, which may cause false alarm if some sidelobes exceed the detection threshold. On the other hand, both the POC and MPOC produce correlation peaks with much lower sidelobes and narrower peak width.

Fig. 3.14 Normalized correlator outputs for a 4-path channel with path separation of $3/2$ UWB pulse width. The dotted vertical lines indicate the true peak positions.

For the same receiver SNR of 20dB, Fig. 3.15 shows the correlator outputs when the channel paths are separated by $1/4$ of a UWB pulse width. In other words, all the 4 paths arrive within one UWB pulse duration. The path amplitudes are still '+1, -1, +0.9, -0.8'. In this case, only the MPOC is still able to resolve and detect all the paths correctly, while all the other correlators fail due to their much wider correlation peak widths and/or higher sidelobes shown previously in Fig. 3.13.

Fig. 3.15 Normalized correlator outputs for a 4-path channel with path separation of $1/4$ UWB pulse width. The dotted vertical lines indicate the true peak positions.

The Correlation Peak to Highest Sidelobe Ratio (CPHSR) versus receiver SNR is shown in Fig. 3.16 for the 4-path channel with path separation of $3/2$ UWB pulse width. The CPHSR is calculated as the absolute value of the correct correlation peak magnitude divided by the absolute value of the second highest spurious sidelobe magnitude. Increasing the SNR represents decreasing the distance between the transmitter and receiver, though not linearly. The CPHSR curves of the conventional correlator and APOC are found to be almost invariant with respect to SNR, and lower than those of POC and MPOC. The CPHSR of both the POC and MPOC increases monotonically with SNR, with

the MPOC displaying a larger CPHSR slope. These are because both the conventional correlator and APOC outputs have significant sidelobes, while the sidelobes of POC output are much lower and the MPOC produces impulses with essentially no sidelobes (Fig. 3.13). A high CPHSR is desirable for precise ranging because it prevents misjudging a spurious sidelobe as a correlation peak for TOA detection.

Fig. 3.16 CPHSR vs. receiver SNR of conventional correlator, POC, APOC, and MPOC.

Also plotted in Fig. 3.16 are the POC and MPOC outputs when the channel paths are separated by 1/4 UWB pulse width (conventional correlator and APOC fail to distinguish them, hence are not shown). It can be seen that in this case, the performance of MPOC is not much affected because its peak width is

sufficiently narrow to separate the peaks. However, the performance of POC deteriorates, as observed earlier in Fig 3.15.

3.4 Measurement Result

The practical performance of MPOC for high-resolution multiple TOA estimation is examined in an experiment. The measurement is conducted in the Positioning and Wireless Technology Center (PWTC) of Nanyang Technological University (NTU), Singapore. The floor-plan and photo of the laboratory room have been shown in Fig. 1.1 and 1.2 respectively, and the setup for range measurement is shown in Fig. 3.17. The two signal sources (transmitters TX1 and TX2) are placed such that their waveforms overlap at the receiver (RX). Both the transmitting and receiving antennas are bi-conical antennas. The measurement setup is placed far away from walls, floors and large objects in order to segregate the environment-induced multipath from TX1 and TX2 signals. Therefore, the major signal components received are the two UWB pulses from TX1 and TX2, and their propagation paths are denoted as 'p1' and 'p2' in Fig. 3.17. When multipath signals from the environment are also included, more peaks corresponding to these signal components will be present in the MPOC output. The transmitter emits UWB pulses with duration of 1.2 ns every 100 ns. The SNR is estimated to be 15 to 30 dB.

Fig. 3.17 Measurement setup to verify the MPOC performance

Fig. 3.18 shows the actual waveforms of the local template (a single transmitted pulse: top waveform) and the received signal obtained from the measurement setup (bottom waveform). The waveforms are captured at an equivalent sampling rate of 20 GHz by an Agilent digital communication analyzer and post-processed in Matlab. The local template $s(t)$ is obtained by placing a single transmitter 1 meter away from the receiver with 512 times averaging. The received signal $r(t)$ is averaged 256 times. As the path difference between p1 and p2 is very small, the two received pulses merge and are hardly distinguishable from each other in the received waveform.

Fig. 3.18 Actual waveforms from measurement

Fig. 3.19 shows the resultant output of the conventional correlator, POC, APOC, and MPOC. The figure shows that the conventional correlator and APOC fail to resolve the ToAs of TX1 and TX2 due to their inherently wide correlation peaks and high sidelobes, while the output of POC contains spurious peaks when there are multiple signal components. Only the proposed MPOC is able to correctly resolve the two TOAs with low sidelobes. Note that the TOA separation of the two targets is only 0.4 ns while the UWB pulse duration is about 1.2 ns, which verifies that the proposed MPOC is able to resolve overlapping pulses. When the channel is not corrupted by noise, the output of MPOC is the channel impulse response represented by discrete sampling points. The time resolution of MPOC is equal to the peak width, which is twice the

sampling interval. Hence the time resolution of MPOC is inversely proportional to the sampling rate of the receiver.

Fig. 3.19 Normalized correlator outputs for measured signal. The dotted vertical lines indicate the true ToAs.

With the same measurement setup as in Fig. 3.17, the ranging error of MPOC and POC is measured and compared in Fig. 3.20. The error shown is the mean absolute error (MAE) for 60 measurements. As there is no synchronization between the transmitter and receiver during the measurement, absolute range cannot be measured directly. Hence calibration is first conducted with a single transmitter to estimate the time offset between the transmitter and the receiver. The second transmitter is then added to create the multipath. The ranging error refers to the error of the first transmitter, whose signal always arrives first. TOA of the first transmitter corresponds to the first correlation peak in the MPOC

output, as it is closer to the receiver. Fig. 3.20 shows that the MPOC consistently outperforms POC because POC tends to produce spurious peaks that cause false detection.

Fig. 3.20 Comparison of ranging performance of MPOC and POC.

3.5 Conclusion

In this chapter, TOA estimation techniques with UWB signal are studied. A high-resolution MPOC algorithm is proposed to resolve overlapping UWB pulses due to multipath, even when the TOAs of the signal components are separated by less than a UWB pulse width. A kurtosis-based noise suppression method is adopted to mitigate the noise amplification problem inherent in the MPOC detector. Compared with other high-resolution TOA estimation

algorithms such as the generalized ML [47] and WRELAX [51] (which are in fact least squares channel estimators in the time and frequency domain respectively), the MPOC is advantageous in that it is non-iterative and its processing time does not depend on the number of signal sources. No prior knowledge of the number of signals in the channel is required either.

As a concluding remark, the accuracy and resolution of a TOA estimator is related to its complexity. A more sophisticated estimator often demands more resources in computation and instrumentation such as higher sampling rate and FFT operation. To address the performance-cost trade off, the TOA estimation techniques discussed in Section 3.1 are summarized in Table 3.1 and compared in terms of their performance and cost. Choice of the most suitable TOA estimation technique depends largely on the application scenario.

Table 3.1 Comparison of TOA estimation techniques

	TOA estimator	Accuracy	Local template	Computation	Implementation
Time-domain techniques	Sliding correlator	Pulse-level resolution	Yes	Delay and multiplication	Hard to generate and store the template
	Generalized ML	Sub-pulse resolution	Yes	Iterative	Requires high-sampling rate
	Power delay profile	Limited	No	Simple square law	Requires high-sampling rate
	ED	Limited	No	Simple square law	Simple
	TR	Limited	No	Simple multiplication	Requires precise analog delay line
Frequency-domain Techniques	WRELAX	Sub-pulse level resolution	Yes	FFT, iterative	Requires high-sampling rate
	POC	Precise only in single path	Yes	FFT	Requires high-sampling rate
	APOC	Precise only in single path	Yes	FFT	Requires high-sampling rate
	MPOC (proposed)	Sub-pulse resolution	Yes	FFT	Requires high-sampling rate

CHAPTER 4 NLOS IDENTIFICATION

Apart from multipath, localization system also suffers from the NLOS problem, where the direct-path (DP) signal is obstructed and the system detects a subsequent multipath signal as the DP signal. This introduces a bias to the range measurement, and deteriorates the localization accuracy. Ranging error due to NLOS usually cannot be corrected unless prior knowledge of the propagation channel is available. A straightforward solution to the NLOS problem is to discard the NLOS measurement and use only LOS measurements for localization. Alternatively, as the NLOS error is always positive, it defines a region where the target could reside (in contrast to LOS range measurement that defines a locus of the target). Hence, we can impose the NLOS measurement as a region constraint in the optimization process to find the target position [24]. All the above solutions require that the NLOS path be detected. Therefore, NLOS identification is essential in a localization system and will be discussed in this chapter.

Our emphasis in this chapter is on hyperbolic and elliptical localization systems (to be discussed in Chapter 5) due to their advantage in implementation. In these systems the target to be located is a transmitter, and the anchors are deployed as synchronized receivers. It should be noted that they are also the more general and difficult cases to tackle. These two cases require receiver cooperation to eliminate range uncertainty due to lack of target-anchor synchronization. The proposed idea can be easily adapted and implemented in a

circular localization system.

The rest of this chapter is organized as follows: relevant works in the literature are first reviewed in Section 4.1. After that a new NLOS identification method based on hybrid RSS and TOA measurement is proposed. The RSS and TOA measurement and modeling as well as the impact of NLOS propagation are discussed in Section 4.2. The proposed method is then presented in Section 4.3. Performance analysis and result are shown in Section 4.4 and Section 4.5, respectively. The chapter is concluded in Section 4.6 with a comparison of various NLOS identification techniques.

4.1 Introduction

NLOS propagation can happen in several scenarios, in which the characteristics of the received signal as well as the NLOS error may differ. It is therefore necessary to classify the various NLOS mechanisms and tailor the NLOS identification and mitigation technique for each type of NLOS propagation.

For indoor localization, the received signal usually comprises the DP signal (if it is not obstructed) followed by environment-induced multipath components such as the signals reflected from furniture and walls, as shown earlier in Fig. 2.6. In UWB ranging, the TOA is often estimated from the leading edge of the received signal. Hence it is the first-detected signal component that is of

interest. Thus the multipath signal that is much weaker and arrives much later than the DP signal can be neglected, and the received signal can be described by a two-cluster model, where the DP signal cluster is followed by an influential multipath signal cluster. Depending on the resolution of the TOA estimator, each cluster may comprise one or several signal components. The influential multipath signal refers to the multipath signal that would be falsely detected as the leading signal if the DP signal were absent or severely attenuated.

The relative delays and amplitudes of the two signal clusters depend on the propagation mechanism and the channel nature. From these parameters of the two-cluster model, the corresponding TOA estimation error characteristics can be deduced. In LOS propagation, the DP signal cluster dominates the subsequent multipath signal cluster, and the major error sources are AWGN and unresolved overlapping multipath signals within the DP signal cluster. The multipath signal cluster only come into play in NLOS propagation where the DP signal is obstructed. If the obstruction is so strong that the DP signal diminishes and is undetectable, the bias in TOA estimation is equal to the relative delay of the multipath signal cluster with respect to the DP signal cluster. Hence the NLOS bias error is larger if the relative delay of the multipath signal cluster is longer. This happens when the multipath signal cluster source (e.g. furniture and wall) is separated from the target transmitter by a large distance. In contrast, when the multipath signal cluster source is adjacent to the target transmitter, the NLOS bias error is small.

In some situations where an optical LOS path does not exist, the DP signal

may still be detected [65, 66]. This could happen when the obstruction is weak and the DP signal is able to penetrate through the obstruction. Other than direct penetration, the DP signal may also be diffracted around the obstruction and be detected at the receiver [66]. In both cases, the TOA of the detected DP signal is slightly biased due to the different signal propagation speeds in two media or additional signal propagation distance.

From the above discussion, the NLOS scenarios can be classified as large-error cases and small-error cases based on the amount of NLOS bias error in TOA estimation. When the obstruction of the DP signal is strong and the relative delay of the multipath signal is large, the NLOS error is large. In this case, the NLOS bias error in TOA estimation is much greater than the TOA error in LOS. For small NLOS error cases, the NLOS bias error is usually a result of short multipath delay, weak obstruction, or diffraction, and the NLOS bias error ranges from 0.2 ns to 3 ns and is comparable to the standard deviation of TOA estimation error due to AWGN or unresolved multipath.

Most works on NLOS identification in the literature focus on the large-error case, and small-error NLOS cases are often treated as LOS cases [65, 67, 68]. NLOS identification can be based on variance test, channel characteristics, and prior knowledge [24, 69]. The NLOS propagation causes abnormality in the range measurement, and often increases the variance of range measurement. Hence, by testing the variance of multiple repetitive range measurements against some threshold, the NLOS propagation can be identified [70]. When NLOS range measurement is treated as a LOS, it introduces a range outlier and

causes the target to deviate from its true position significantly, especially if the NLOS bias is large. Hence, instead of detecting NLOS propagation from redundant range measurement at a single receiver, we can also exploit the redundancy in anchor-receiver combination for NLOS identification [71, 72]. Different combinations of LOS anchors produce similar positioning result. In contrast, when there is NLOS anchor involved in the anchor combination, the resulting position estimation deviates from that of the all-LOS anchor combination. Thus the NLOS anchor can also be detected from position variance. The key factor that affects the performance of variance-based NLOS identification techniques is that the abnormal measurement due to NLOS propagation should be large enough to cause significant deviation from normal LOS range measurement errors due to AWGN or unresolved multipath. Besides, reliable detection requires sufficient redundancy which either prolongs the measurement time or demands more anchors.

Instead of testing the effect of NLOS propagation on range and position estimation, a more fundamental approach is to examine the channel characteristics of the received signal. As the channel characteristics are different for LOS and NLOS propagation, NLOS can also be identified by evaluation of the metrics such as mean/excess delay, amplitude statistics, and higher-order statistics [67, 73-78]. However, it sometimes can be complicated to obtain the channel parameters. Rather than extraction of the propagation information from the received signal, prior knowledge such as distribution of NLOS bias and map of region of interest can also be used for NLOS identification [79]. It is also noteworthy that with prior knowledge such as the map of the region of interest,

correction of the NLOS errors is possible.

Although large NLOS error introduces large ranging bias and may be devastating for indoor localization systems, it can be identified easily, as the large deviation from normal LOS measurement exhibits as outliers. While for certain applications it is acceptable to ignore the small-error NLOS cases, it is still desirable to detect the small-error NLOS propagation for applications that require high accuracy. Small-error NLOS propagation occurs frequently in most personnel/object localization and tracking applications where the target transmitter is attached to the person or object to be located, and the transmitted signal is often weakly obstructed or diffracted [66, 80]. The small NLOS bias can be comparable to the standard deviation of the TOA error in LOS cases and is more challenging to identify. In the subsequent discussion, we will focus on identification of small NLOS error.

4.2 *Range Measurement and Modeling*

We consider the typical UWB localization system where the target emits UWB pulses. The transmitted pulse is captured by the anchor receivers. The receivers are synchronized either by explicit synchronization mechanism (as in hyperbolic localization [81]) or by implicit signaling (as in elliptical localization to be discussed in Chapter 5).

4.2.1 RSS Measurement and Modeling

In conventional narrowband systems and UWB communication systems, the RSS is measured based on the total power of the received signal including all the multipath components [2, 83]. For UWB ranging systems, however, it is more meaningful to measure the power of the DP signal as it describes the propagation distance more accurately [65, 84, 85]. In this chapter, RSS refers to the power of the first detected path signal.

We assume that the received signal power at a reference distance (say 1 m) between the transmitter and receiver is known, either by calibration or calculation. First we consider LOS propagation. At anchor receiver i , the RSS specified in decibel (dB) scale at distance u_i (m) is conventionally modeled as [10]:

$$\Omega(u_i) = \Omega_0 - 10\gamma \log_{10} u_i + w_{sh} \quad (4.1)$$

where Ω_0 is the average RSS at the reference distance (1m), γ is the path loss exponent, and w_{sh} is a zero-mean Gaussian random variable with standard deviation σ_{sh} . w_{sh} represents the log-normal channel shadowing effect. It is straightforward to obtain the maximum likelihood (ML) estimation of the propagation distance as:

$$\tilde{u}_i = 10^{\left(\frac{\Omega_0 - \Omega(u_i)}{10\gamma}\right)} = u_i + e_i. \quad (4.2)$$

where e_i is the estimation error indicating the amount of deviation of the

estimated range from its true value. The estimation accuracy of the above estimator is lower bounded by the Cramer-Rao Lower Bound (CRLB), which is the minimum variance of any unbiased estimator [18]. The ML estimator is asymptotically Gaussian distributed with its mean being the true value and its variance equal to the CRLB asymptotically. For a single snapshot, the variance of the above estimation in (4.2) is not known. Hence we approximate it by its CRLB [18] as :

$$\varsigma_i^2 = E[e_i^2] \approx \left(\frac{\ln 10}{10} \frac{\sigma_{sh}}{\gamma} u_i \right)^2 = \varsigma_0^2 u_i^2 \approx \varsigma_0^2 \tilde{u}_i^2 \quad (4.3)$$

where

$$\varsigma_0^2 = \left(\frac{\ln 10}{10} \frac{\sigma_{sh}}{\gamma} \right)^2$$

For a given σ_{sh} and γ , the CRLB increases with the distance between transmitter and receiver. In (4.3), the exact value of u_i is unknown, so we further replace it by the estimated value $\tilde{u}_i$ from (4.2).

If the propagation is NLOS, the RSS is attenuated further by the obstruction, and the estimated distance becomes:

$$\tilde{u}_i' = 10^{\left(\frac{\Omega_0 - \Omega(u_i')}{10\gamma} \right)} = 10^{\left(\frac{\Omega_0 - \Omega(u_i) + \Delta\Omega_i}{10\gamma} \right)} = k_i \cdot \tilde{u}_i \quad (4.4)$$

where

$$k_i = 10^{\Delta\Omega_i/10\gamma}.$$

In (4.4), $\Delta\Omega_i = \Omega(u_i) - \Omega(u_i')$ denotes the potential RSS attenuation caused by NLOS propagation. It is noteworthy that although the NLOS attenuation

changes with propagation condition, for a fixed target position, it can be treated as a deterministic variable that remains constant in the short measurement time [71, 72]. From (4.4) the weaker RSS due to additional attenuation is equivalent to longer travel distance under LOS situation, and hence u'_i is always larger than u_i . The ML estimation in (4.4) can be rewritten as:

$$\tilde{u}'_i = u'_i + e'_i = u_i + l_i + e'_i \quad (4.5)$$

where

$$l_i = (k_i - 1) \cdot u_i$$

$$e'_i = k_i \cdot e_i.$$

The additional travel distance l_i is the NLOS bias error and is considered to be a deterministic parameter rather than a random variable [86]. Hence in NLOS propagation, the estimated distance from attenuated RSS is still asymptotically Gaussian distributed with variance approximated as:

$$\varsigma_i'^2 = E[e_i'^2] \approx \varsigma_0^2 u_i'^2 \approx \varsigma_0^2 \tilde{u}_i'^2. \quad (4.6)$$

4.2.2 Time Measurement and Modeling

Due to its implementation advantage and the availability of hardware, the energy detection receiver [49] is used to measure the TOA τ_i of the signal at anchor i . The TOA can be estimated more accurately by more sophisticated algorithms discussed in Chapter 3. The TOA is estimated by finding the first time instant when the energy detector output exceeds a threshold [17]. From the

estimated TOA $\tilde{\tau}_i$, the LOS propagation distance can be calculated as

$$\begin{aligned}\tilde{\mu}_i &= c \cdot \tilde{\tau}_i \\ &= \mu_i + \varepsilon_i = u_i + \psi + \varepsilon_i\end{aligned}\tag{4.7}$$

where $\tilde{\mu}_i$ denotes the estimation of the true parameter μ_i from time measurement and ε_i is the estimation error denoting the amount of deviation of the estimated range from the true value. c is the UWB signal propagation speed. When the target transmitter and anchor receiver are not synchronized, μ_i is not the absolute range, but the pseudorange that has a constant offset ψ to the absolute range u_i . When the transmitter and receiver are synchronized, $\psi=0$. The variance of the pseudorange estimation $\tilde{\mu}_i$ is approximated by the CRLB as [10]:

$$\sigma_i^2 = E(\varepsilon_i^2) \approx \frac{c^2}{8\pi^2 F^2} \frac{1}{SNR_i}\tag{4.8}$$

where SNR_i is the signal-to-noise ratio, and F is the effective bandwidth of the signal as defined in (2.16). The SNR is related to the RSS as in (4.1), and hence is also related to the distance as:

$$SNR_i = \frac{\Omega(u_i)}{N_0} = \frac{\Omega_0}{N_0} u_i^{-\gamma}\tag{4.9}$$

with the power units in Watt and N_0 being the noise power. Hence the variance for pseudorange estimation is approximated as:

$$\sigma_i^2 = E(\varepsilon_i^2) \approx \frac{c^2}{8\pi^2 F^2} \frac{N_0}{\Omega_0} u_i^\gamma = \sigma_0^2 u_i^\gamma \quad (4.10)$$

where

$$\sigma_0^2 = \frac{c^2}{8\pi^2 F^2} \frac{N_0}{\Omega_0}.$$

When μ_i is the true absolute range, $\mu_i = u_i$, and the estimated $\tilde{\mu}_i$ is used to approximate u_i in (4.8). However, when μ_i is the pseudorange, the absolute range is not available from time measurement and is approximated by $\tilde{u}_i$ from the RSS measurement.

In NLOS propagation, the first detected path is always delayed with respect to the true TOA in LOS case. Hence the estimated pseudorange μ_i is positively biased as:

$$\tilde{\mu}_i' = \mu_i' + \varepsilon_i' = \mu_i + \ell_i + \varepsilon_i' \quad (4.11)$$

where ℓ_i is the bias error. The magnitude of ℓ_i determines whether the propagation is small-error NLOS or large-error NLOS. Similar to RSS case, the NLOS bias error during the short observation time is treated as a deterministic parameter rather than a random variable, and the pseudorange estimation is Gaussian distributed. Its variance increases in NLOS case as a result of attenuation in RSS and is approximated as:

$$\sigma_i'^2 = E(\varepsilon_i'^2) = \sigma_0^2 \mu_i'^2. \quad (4.12)$$

4.2.3 *Small-Error NLOS Propagation*

Experimental measurement has been conducted in the Positioning and Wireless Technology Centre, Nanyang Technological University, Singapore. The layout and photo of the laboratory room has been shown earlier in Fig. 1.1 and Fig. 1.2. The received signal waveform at various propagation conditions are illustrated in Fig. 4.1, where the receivers are mounted on the ceiling and a transmitter is attached to a person's body to mimic a personnel tracking scenario. The transmitted signal may be blocked by the person's body, thus causing NLOS.

The top plot in Fig 4.1 shows the received signal waveform (energy detector output) in LOS case. The transmitter is 3 m away from the receiver and there is no blockage of the DP signal. The centre plot in Fig. 4.1 is obtained when the transmitter is mounted on the shoulder of a person, and the DP signal path is blocked by the person's head partially. In the bottom plot of Fig. 4.1, the transmitter is mounted on the person's arm and the DP signal is obstructed by the torso. Fig. 4.1 shows three representative cases where the signal is unblocked, partially blocked, and totally blocked, and they correspond to LOS, NLOS with detectable DP (NLOS-DDP), and NLOS with undetectable DP (NLOS-UDP), respectively [65, 67]. During the measurement, the transmitter and receiver distance is kept identical, and the person stands close to a wall, which produces the subsequent multipath cluster.

Fig. 4.1 Measured waveform (energy detector output) for LOS propagation (top), NLOS propagation with detectable DP (centre), and NLOS propagation with undetectable DP (bottom). The waveforms are normalized by the maximum amplitude in LOS case.

In the LOS case (Fig. 4.1: top), we can find the DP signal TOA easily. In the NLOS-UDP case (Fig. 4.1: bottom), the DP cannot be detected and the subsequent multipath cluster TOA will be treated as the DP TOA. This can give rise to a TOA estimation bias of up to 3 ns, or a positive ranging error of almost 1 meter. If NLOS propagation at a receiver is identified, we can discard the range measurement or impose it as a constraint for target location to avoid degradation of localization accuracy [24]. For the case of NLOS-DDP (Fig. 4.1:

centre), if the threshold level is too high, the DP may be missed, which will severely degrade the ranging accuracy. On the other hand, by proper threshold setting, or search-back windowing [17], the DP can be detected. Identification of NLOS propagation will aid the design of better ranging technique to recover the DP. Furthermore, detailed examination of Fig. 4.1 reveals that the DP signal in NLOS-DDP case may be delayed with respect to the LOS case for up to 0.2 ns because such DP signal is a diffracted signal. This is equivalent to a ranging bias of 6 cm. For application where high ranging accuracy is required, this may not be tolerable and it is preferred to either discard the measurement or impose it as a constraint, instead of using it as a LOS measurement directly. Hence it is important to identify the NLOS propagation. Noting the y-axis scale difference in Fig. 4.1, we observe that the RSS under NLOS situation is generally much smaller than that of the corresponding LOS propagation. This attenuation creates a positive bias in the estimated range as in (4.4) and (4.5). This bias is especially significant if the transmitter-receiver separation is large and will dominate over the bias in time measurement.

Fig. 4.1 depicts the small-error NLOS scenarios and shows that the RSS of a NLOS signal is generally much weaker than that of a LOS signal, while the estimated TOA in NLOS case, although delayed by up to a few nanoseconds, is still close to the LOS signal. This is generally valid in a dense-multipath environment such as the indoor environment, where the immediate NLOS multipath signals can still be detected when the DP signal is obstructed (Fig. 4.1: bottom). The assumption is also valid when the DP signal is diffracted (Fig. 4.1: centre). While the time bias due to NLOS is small, the RSS of the signal is

attenuated significantly, and a large NLOS bias is induced in RSS based range measurement, as shown by (4.4) and (4.5). Neglecting the range uncertainty of time measurement due to lack of target-anchor synchronization (i.e. $\psi=0$), we have the following relationship between the range measurements in small-error NLOS cases:

$$u'_i > \mu'_i \approx \mu_i = u_i . \quad (4.13)$$

Due to strong attenuation, the weak RSS in NLOS yields a large range bias from the path loss model in (4.1), while the NLOS range error from time measurement is usually much smaller.

4.3 Proposed NLOS Identification Method

In this section we present the proposed NLOS identification method. It requires the RSS measurement and TOA measurement as described in 4.2. From these measurements, the range difference as well as their variance can be estimated, which forms the basis of our proposed algorithm. We assume that a LOS receiver always exists by careful system planning, and the LOS receiver is used as the reference receiver. Selection of the reference receiver will also be discussed.

4.3.1 Formulation of the Test Statistic

We adopt a statistical hypothesis testing framework to identify the NLOS

propagation. First we consider the case when the transmitter and receiver are synchronized ($\psi=0$). In this case, the absolute distance between the transmitter and receiver can be estimated from time measurement. For receiver i , the NLOS identification problem is cast into the following hypothesis as:

$$\begin{aligned} H_{LOS} : & \begin{cases} \tilde{u}_i = u_i + e_i \\ \tilde{\mu}_i = \mu_i + \varepsilon_i \end{cases} \\ H_{NLOS} : & \begin{cases} \tilde{u}'_i = u_i + l_i + e'_i \\ \tilde{\mu}'_i = \mu_i + \ell_i + \varepsilon'_i \end{cases} \end{aligned} \quad (4.14)$$

It should be noted that the differentiation between $\tilde{u}_i$ and $\tilde{u}'_i$ as well as between $\tilde{\mu}_i$ and $\tilde{\mu}'_i$ for LOS and NLOS cases are merely for the sake of discussion. In practical measurement, whether the measured quantity is LOS or NLOS is not known. Hence the RSS measurement and TOA measurement in general are represented by $\tilde{u}_i$ and $\tilde{\mu}_i$ respectively. The likelihoods of the two hypotheses are:

$$\begin{aligned} p(\tilde{u}_i, \tilde{\mu}_i; u_i, \mu_i, H_{LOS}) = & \frac{1}{\sqrt{2\pi\zeta_i^2}} \exp\left[-\frac{(\tilde{u}_i - u_i)^2}{2\zeta_i^2}\right] \cdot \frac{1}{\sqrt{2\pi\sigma_i^2}} \exp\left[-\frac{(\tilde{\mu}_i - \mu_i)^2}{2\sigma_i^2}\right] \\ & (4.15) \\ p(\tilde{u}_i, \tilde{\mu}_i; u_i + l_i, \mu_i + \ell_i, H_{NLOS}) = & \frac{1}{\sqrt{2\pi\zeta_i'^2}} \exp\left[-\frac{(\tilde{u}_i - l_i - u_i)^2}{2\zeta_i'^2}\right] \cdot \frac{1}{\sqrt{2\pi\sigma_i'^2}} \exp\left[-\frac{(\tilde{\mu}_i - \ell_i - \mu_i)^2}{2\sigma_i'^2}\right] \end{aligned}$$

The probability that H_{NLOS} is declared while H_{LOS} is true is usually called the false alarm probability (P_{FA}), and the probability that H_{NLOS} is declared while

H_{NLOS} is true is called the detection probability (P_D). For a given P_{FA} , the detector that maximizes P_D is the Neyman-Pearson (NP) detector [18]. The NP detector decides H_{NLOS} if:

$$\frac{p(\tilde{u}_i, \tilde{\mu}_i; u_i + l_i, \mu_i + \ell_i, H_{NLOS})}{p(\tilde{u}_i, \tilde{\mu}_i; u_i, \mu_i, H_{LOS})} > \gamma_i. \quad (4.16)$$

Substituting (4.15) into (4.16), taking the natural logarithm, and neglecting the constants, the likelihood ratio test becomes declaring H_{NLOS} if

$$\frac{(\tilde{u}_i - u_i)^2}{2\zeta_i^2} + \frac{(\tilde{\mu}_i - \mu_i)^2}{2\sigma_i^2} - \frac{(\tilde{u}_i - u_i - l_i)^2}{2\zeta_i'^2} - \frac{(\tilde{\mu}_i - \mu_i - \ell_i)^2}{2\sigma_i'^2} > \gamma_i'. \quad (4.17)$$

However, the test statistic in (4.17) above contains unknown parameters u_i, μ_i, l_i and ℓ_i . From the principle of generalized likelihood ratio test (GLRT) [18] and the relationship in (4.13), the unknown parameters u_i and μ_i in the first two terms of (4.17) are approximated by:

$$u_i = \mu_i \approx \tilde{\mu}_i \quad (4.18a)$$

and $(u_i + l_i)$ and $(\mu_i + \ell_i)$ are approximated by the corresponding measurements as:

$$\begin{aligned} u_i + l_i &\approx \tilde{u}_i \\ \mu_i + \ell_i &\approx \tilde{\mu}_i \end{aligned} \quad (4.18b)$$

Hence after some simplification, the test statistic is equivalent to deciding H_{NLOS} if

$$T(\tilde{u}_i, \tilde{\mu}_i) = \tilde{u}_i - \tilde{\mu}_i > \gamma_i'' . \quad (4.19)$$

The test statistic (4.19) shows that the RSS alone is not a fair indicator for the propagation condition, as a LOS signal may propagate a longer distance, which yields a weaker RSS than a NLOS signal. Hence to make a fair decision, we have to consider both the time measurement and RSS measurement jointly. Similar RSS ranging and TOA ranging results are expected if the propagation is LOS. On the other hand, if NLOS occurs, the estimated range from RSS deviates significantly from that of TOA.

The above test can be performed at each individual anchor receiver independently. When there is range uncertainty ($\psi \neq 0$) as in the hyperbolic and elliptical localization systems, it is impossible to infer directly from TOA measurement the absolute range that the signal has traveled. Nevertheless, in both of the above systems, the receivers can be synchronized. Hence, we are motivated to compare the range difference instead. As an example, consider two receivers (RX_i and RX_j) under test as illustrated in Fig. 4.2. From RSS measurement, we can estimate the absolute signal propagation distance to be $\tilde{u}_i$ and $\tilde{u}_j$ for RX_i and RX_j respectively. From time measurement, we are only able to estimate the pseudoranges $\tilde{\mu}_i$ and $\tilde{\mu}_j$. The pseudoranges are offset to the absolute range by a constant ψ , and taking their difference will eliminate the range offset. Hence we define the test variable:

$$T'(\tilde{u}_i, \tilde{u}_j, \tilde{\mu}_i, \tilde{\mu}_j) = (\tilde{u}_i - \tilde{u}_j) - (\tilde{\mu}_i - \tilde{\mu}_j) \quad (4.20)$$

which compares the range difference from RSS measurement with the range

difference from time measurement. We shall first assume that one of the receivers is known to be LOS. From the assumptions in (4.13) and letting $x_{ij} = T'(\tilde{u}_i, \tilde{u}_j, \tilde{\mu}_i, \tilde{\mu}_j)$ for notational convenience, the following decision can be made based on the test variable x_{ij} in noiseless case:

$$x_{ij} : \begin{cases} = 0 & \text{if both receivers are LOS} \\ > 0 & \text{if RX}_i \text{ is NLOS and RX}_j \text{ is LOS} \\ < 0 & \text{if RX}_i \text{ is LOS and RX}_j \text{ is NLOS} \end{cases} . \quad (4.21)$$

In (4.21), it is assumed that the NLOS bias in TOA is much smaller than the NLOS bias in RSS ranging, and large TOA NLOS bias can be identified by other techniques such as positioning variance based method [71]. When both receivers are NLOS, any of the above three cases could happen. However, as will be discussed in 4.3.3, we will always be able to identify a LOS receiver (by proper system design) as the reference receiver to remove this ambiguity.

Fig. 4.2 Illustration of the proposed NLOS identification method for pseudorange measurement.

4.3.2 Hypothesis Test

In practice, the test variable x_{ij} in (4.20) is corrupted by noise and is modeled as:

$$x_{ij} = A_{ij} + n_{ij} \quad (4.22)$$

where $A_{ij} = (u_i - u_j) - (\mu_i - \mu_j)$ is the true value of x_{ij} , and the noise term n_{ij} is a zero-mean Gaussian random variable. The Gaussian error assumption can be justified by the asymptotic property of ML estimator [18]. The variance of

n_{ij} is the sum of all the range measurement variance. Hence the variance of x_{ij} is given approximately by

$$\sigma_{ij}^2 \approx \varsigma_0^2 \tilde{u}_i^2 + \varsigma_0^2 \tilde{u}_j^2 + \sigma_0^2 \tilde{\mu}_i^2 + \sigma_0^2 \tilde{\mu}_j^2, \quad (4.23)$$

which is a function of the absolute distance approximated by the RSS measurement. When multiple measurements are conducted, the range estimation can be smoothed to reduce the variance σ_{ij}^2 [71]. Repetitive measurement improves performance, but is not a prerequisite. This is fundamentally different from range variance test [70] that must rely on repetitive range measurement.

We first assume that one of the receivers, say RX_j , is selected to be the reference LOS receiver. Selection of the LOS reference receiver will be discussed in 4.3.3. We are interested to find out whether RX_i is NLOS by formulating the following hypothesis test:

$$\begin{cases} H_{LOS} : A_{ij} = 0 \\ H_{NLOS} : A_{ij} > 0 \end{cases} \quad (4.24)$$

Under H_{LOS} (RX_i is LOS), x_{ij} is zero-mean Gaussian distributed. Under H_{NLOS} (RX_i is NLOS), the mean of x_{ij} is positive and is unknown. We can compare the test variable with a threshold λ_{ij} such that we declare H_{NLOS} is true when $x_{ij} > \lambda_{ij}$, and H_{LOS} is true otherwise. The threshold λ_{ij} can be determined from a given false alarm probability P_{FA} as:

$$\lambda_{ij} = \sqrt{\sigma_{ij}^2} Q^{-1}(P_{FA}) \quad (4.25)$$

where $Q^{-1}(\cdot)$ is the inverse of the Q function. Although the exact value of A_{ij} is not known, it can be seen from (4.25) that the false alarm probability and the threshold setting is independent of the value of A_{ij} . A_{ij} is of interest only in the calculation of the detection probability, which is given by:

$$P_{Dij} = Q \left(Q^{-1}(P_{FA}) - \sqrt{\frac{A_{ij}^2}{\sigma_{ij}^2}} \right). \quad (4.26)$$

4.3.3 Selection of the LOS Receiver

In the proposed method, we have assumed that one particular receiver is known to be LOS. In this section we will present a method to select the LOS receiver that will be used as the reference receiver.

When a pair of receivers (RX_i and RX_j) that could be LOS or NLOS are compared, there are four different LOS and NLOS combinations and three possible outcomes, as discussed in (4.21). Because of the NLOS-NLOS combination, the outcome is ambiguous. Even in noiseless case, it is impossible to determine the propagation condition. However, if one of the receivers, say, RX_j , is a LOS receiver, the number of possible outcomes reduces to two, and the attribute of RX_i can be determined. Hence, we can first assume a receiver to be LOS and test whether the assumption is supported or violated.

To illustrate, consider the noiseless case first, where $x_{ij} = A_{ij}$. We first

assume that RX_j is LOS and use it as the reference receiver to calculate all x_{ij} as in (4.20) for $i = 1, 2 \dots M$. If RX_j is indeed LOS, there are only two outcomes in the calculated x_{ij} : $x_{ij} > 0$ or $x_{ij} = 0$, which occurs if RX_i is NLOS or LOS, respectively. On the other hand, if RX_j is NLOS, there exists at least one negative x_{ij} , which occurs if RX_i under test is LOS. In summary, if all the calculated x_{ij} values for $i = 1, 2 \dots M$ are non-negative, our assumption that RX_j is LOS is supported. Otherwise the assumption is violated. When all the receiver pair combinations have been tested, there exists at least one RX_j such that $x_{ij} \geq 0$ for all x_{ij} ($i = 1, 2 \dots M$), and RX_j is a LOS receiver, corresponding to our assumption that at least one receiver is LOS.

In noisy case, the above test is no longer effective because the sign of x_{ij} could be corrupted by noise. Hence a more robust test should incorporate the x_{ij} values instead of merely the signs. Thus the proposed metric to select the reference LOS receiver is its probability of being LOS, and the reference LOS receiver RX_L is selected to be the one that is more probable to be LOS as:

$$L = \arg \max_j \Pr(RX_j \text{ is LOS}), j = 1, 2 \dots M. \quad (4.27)$$

For RX_j , given the test variables x_{ij} ($i = 1, 2 \dots M$), the probability that RX_j is LOS is:

$$\begin{aligned}
\Pr(\text{RX}_j \text{ is LOS}) &= \prod_{i=1}^{i=M} \Pr(A_{ij} \geq 0) \\
&= \prod_{i=1}^{i=M} \Pr(n_{ij} \leq x_{ij}) \quad . \\
&= \prod_{i=1}^{i=M} Q\left(-\frac{x_{ij}}{\sqrt{\sigma_{ij}^2}}\right)
\end{aligned} \tag{4.28}$$

The NLOS identification method is summarized as follows:

Step 1: conduct RSS measurement to obtain the distance estimation $\tilde{u}_i$ for $i =$

1, 2...M, where M is the total number of receivers.

Step 2: conduct time measurement to obtain the pseudorange estimation $\tilde{\mu}_i$

for $i = 1, 2 \dots M$.

Step 3: for all combinations of receiver pairs with RSS and time measurement,

calculate x_{ij} and σ_{ij}^2 as in (4.20) and (4.23).

Step 4: select the reference LOS receiver as (4.27), and denote it as RX_L .

Step 5: calculate x_{iL} and compare it against the threshold in (4.25) for $i = 1,$

2...M. If $x_{iL} > \lambda_{iL}$, RX_i is declared to be NLOS. Otherwise RX_i is declared to be LOS.

4.4 Analysis

The subsequent analysis relies on the small error assumption in (4.13) that the NLOS bias in time measurement is much smaller than that in RSS measurement, and the range estimation variance from time measurement is very

small compared to that of RSS measurement, which is readily justified by comparing their ranging CRLB. Hence, we can neglect the variance due to time measurement to simplify the analysis. The P_{Dij} given by (4.26) shows that it depends on A_{ij}^2/σ_{ij}^2 for a given P_{FA} . A_{ij} determines the separation of the two distributions under H_0 and H_1 , and σ_{ij} determines the width of the distribution. P_{Dij} increases with A_{ij}^2/σ_{ij}^2 . We let:

$$\beta_{ij} = \frac{A_{ij}^2}{\sigma_{ij}^2}. \quad (4.29)$$

The β_{ij} in (4.29) is often referred to as the deflection coefficient [18], which indicates the quality of the test statistic and solely affects the detection probability at a fixed P_{FA} as shown by (4.26). The detection probability P_{Dij} against the deflection coefficient β_{ij} at various P_{FA} is plotted in Fig. 4.3. The detection probability increases with deflection coefficient β_{ij} . Fig. 4.3 also shows that for a fixed β_{ij} , if we allow higher P_{FA} , the corresponding threshold is reduced, and P_{Dij} increases.

Fig. 4.3 Probability of NLOS detection against deflection coefficient at various false alarm probabilities.

Without loss of generality, assume RX_j is the LOS receiver. From (4.4) and (4.13), neglecting the NLOS bias in time measurement, we have the approximation of A_{ij} as:

$$A_{ij} \approx u'_i - u_i = (k_i - 1)u_i. \quad (4.30)$$

From (4.29) and (4.30), we have:

$$\beta_{ij} = \frac{A_{ij}^2}{\sigma_{ij}^2} = \frac{(k_i - 1)^2 \cdot u_i^2}{\varsigma_0^2 u_j^2 + \varsigma_0^2 k_i^2 u_i^2}. \quad (4.31)$$

The deflection coefficient increases with decreasing u_j , as shown in (4.31).

Therefore the reference LOS receiver is preferred to be close to the transmitter.

Although the separation between transmitter and receiver is beyond our control,

when several receivers are potentially eligible to be LOS, we can use the one that has the shortest propagation distance as our reference receiver.

The effect of distance between the transmitter and receiver under test on deflection coefficient is shown in Fig. 4.4, where $\sigma_{sh}=1$ dB, $\gamma=2$, and $u_j=10$ m. The metric β_{ij} increases with u_i , and will eventually reach the limit:

$$\lim_{u_i \rightarrow \infty} \beta_{ij} = \frac{(k_i - 1)^2}{k_i^2 \zeta_0^2}. \quad (4.32)$$

Fig. 4.4 Deflection coefficient as a function of distance between transmitter and receiver under test.

Another parameter that affects the detection metric is RSS attenuation in NLOS propagation, which is reflected in k_i as in (4.4). Taking the derivative of β_{ij} with respect to k_i we obtain:

$$\frac{\partial \beta_{ij}}{\partial k_i} = \frac{2C_2 k_i^2 + 2(C_1 - C_2)k_i - 2C_1}{(C_1 + C_2 k_i^2)^2} \quad (4.33)$$

where $C_1 = \varsigma_0^2 \left(\frac{u_j}{u_i} \right)^2$ and $C_2 = \varsigma_0^2$. The derivative is positive when $k_i \leq -\frac{C_1}{C_2}$

or $k_i \geq 1$. Except for some special cases, $k_i \geq 1$ in general, and thus β_{ij} also increases with the attenuation of multipath. The effect of NLOS attenuation on deflection coefficient is shown in Fig. 4.5. From Fig. 4.4 and Fig. 4.5, the proposed method works best if the NLOS attenuation is strong and the transmitter-receiver distance is large.

Fig. 4.5 Deflection coefficient as a function of multipath attenuation

4.5 Performance Evaluation

The modeling parameters have been extracted from our measurement conducted in the Positioning and Wireless Technology Centre. From our measurement, the standard deviation of shadowing σ_{sh} is 0.5 dB, the path loss exponent γ is 2 for LOS propagation, and σ_0^2 is 1 cm². Unless otherwise stated, the above empirical system parameters are used as the default simulation parameters to evaluate the performance of the proposed NLOS identification method. In the simulation, the ranging result is generated from the RSS measurement model and time measurement model.

First we show the probability of detection against the false alarm probability, or the operating curve of the detector for different σ_{sh} values in Fig. 4.6. Both the reference receiver and the test receiver are 3m away from the transmitter. The test receiver is NLOS with RSS attenuated by 6 dB compared to LOS. The detection performance improves as σ_{sh} decreases, which improves the accuracy of RSS measurement. For typical indoor coverage less than 10m, σ_{sh} is usually less than 2 dB [2], and detection probability of 0.7 can be achieved at a false alarm probability of 0.1.

Fig. 4.6 Operating curve for different shadowing variances.

The simulation result with variance of x_{ij} approximated by CRLB as in (4.23) is shown in Fig. 4.7. The standard deviation of shadowing σ_{sh} is assumed to be 1 dB, which is more pessimistic than our measured result, and path loss exponent is assumed to be 2. The false alarm probability is set to 0.01. The reference LOS receiver is 3m away from the transmitter. The distance value represents the true transmitter-receiver separation. As discussed in the previous section, the deflection coefficient decreases with distance, and the proposed method is more effective to identify NLOS receivers that are far from the transmitter. When the transmitter is close to the receiver under test, NLOS propagation is hardly identified by the proposed method, because the equivalent increase in propagation distance due to NLOS attenuation is largely offset by

the NLOS bias in TOA measurement and the distributions of the test statistic under LOS and NLOS cases overlap. This situation can be avoided by careful placement of the anchor receivers to ensure that every receiver has a clear LOS region around it.

Fig.4.7 Simulation result with variance approximated by CRLB

Fig. 4.7 also shows that when the NLOS attenuation factor reduces, the NLOS detection probability will decrease as expected, because the received signal appears more like a LOS signal. The divergence of the simulated detection probability from the theoretical result in (4.26) is due to the variance approximation by CRLB in simulation. As the exact variance used to generate the simulated range measurement is not known, it is approximated by CRLB as in (4.3) and (4.6). The theoretical result in (4.26), however, uses the exact variance. When the CRLB approximation is replaced by the true variance, the

result plot is plotted in Fig. 4.8 for the same setup. Now the simulation result agrees with theory. However, the true value of the variance is generally not available, unless prior calibration is feasible.

Fig. 4.8 Simulation result with exact variance

Our proposed NLOS identification is next compared with the NLOS identification technique by Ma *et al.* in [71]. There are 8 receivers located at (0, 10), (10, 10), (10, 0), (10, -10), (0, -10), (-10, -10), (-10, 0), and (-10, 10) with units in meters. The target position varies randomly inside the square formed by the receivers. First we use the IEEE 802.15.4a channel model [87] to generate the RSS of the received signal. There are four types of channel models corresponding to residential, office, outdoor, and industrial environments. In each of the environments the RSS is modeled as in (4.1) with different

parameters for LOS and NLOS propagations. These parameters are available in [87] and are summarized in Table 4.1. It should be noted that NLOS RSS is also generated based on (4.1), where the attenuation in RSS is implied in the NLOS channel parameters as shown in Table 4.1.

Table 4.1 Model parameters to generate RSS of received signal [87]

Channel Model		Reference RSS Ω_0 [dB]	Path loss exponent γ	Standard deviation of shadowing σ_{sh} [dB]
Residential	CM1: LOS	-43.9	1.79	2.22
	CM2: NLOS	-48.7	4.58	3.51
Office	CM3: LOS	-35.4	1.63	1.9
	CM4: NLOS	-59.9	3.07	3.9
Outdoor	CM5: LOS	-45.6	1.76	0.83
	CM6: NLOS	-73.0	2.5	2
Industrial	CM8: LOS	-56.7	1.2	6
	CM9: NLOS	-56.7	2.15	6

The NLOS identification error probability of our proposed method and the method of Ma *et al.* [71] is first compared in Fig. 4.9 for indoor residential environment (CM1 and CM2). 30000 random target positions were tested with

the NLOS TOA varying between 10 ns and 100 ns (3m to 30m). The number of NLOS receivers was set to be 1, 4, as well as a random number between 0 and 7 in the simulation. The false alarm probability P_{FA} is set to 0.01. The detection error includes deciding any LOS receiver to be NLOS and deciding any NLOS receiver to be LOS. From Fig. 4.9, Ma *et al.*'s method is more effective when the NLOS TOA bias is large, because the estimated target position with NLOS measurement behaves more like outlier and can be identified easily. Due to the strong RSS attenuation in NLOS, k_i is large and the NLOS receivers can be identified reliably by our proposed method, as discussed in (4.33) in 4.4.

Fig. 4.9 Error probability of proposed method and positioning variance based method against TOA NLOS bias for residential channel.

The error probabilities of our proposed method and positioning variance

based method for the four types of channel models in [87] are shown in Fig. 4.10. The number of NLOS receivers varies randomly between 0 and 7, and the TOA bias varies between 5 ns to 30 ns. For residential, office, and outdoor environments, the NLOS RSS attenuation is strong as implied in Table 4.1, and hence the NLOS identification error probability for our proposed method is very small. On the other hand, our proposed method fails in the industrial environment, as NLOS propagation only causes small attenuation in RSS, making it hard to detect the divergence between RSS-based range difference and time-based range difference. The method by Ma *et al.* is in general less effective to detect the small NLOS TOA bias.

Fig. 4.10 Error probability of proposed method and positioning variance based method against TOA NLOS bias for residential, office, outdoor and industrial environments.

In the subsequent discussion we will use realistic modeling parameters extracted from our measurement. The NLOS attenuation in RSS is fixed at 6 dB, which doubles the RSS range estimation. The NLOS TOA bias is assumed to be 1 m, which is considered pessimistic for small-error NLOS cases. The detection error probability against the standard deviation of shadowing σ_{sh} is shown in Fig. 4.11. σ_{sh} affects the RSS measurement quality as shown in (4.4). Fig. 4.11 shows that the NLOS identification performance of Ma *et al.* is independent of σ_{sh} , because it only uses time measurement. The method of Ma *et al.* relies on redundancy created by different LOS receiver combinations and its performance is mainly affected by the number of NLOS receivers. As expected, when the number of NLOS receivers increases, the redundancy diminishes and its performance deteriorates considerably. Our proposed method does not rely on redundancy, and the NLOS only affects its performance by increasing the variance of range measurement. For σ_{sh} smaller than 2 dB, our proposed method consistently outperforms the redundancy-based method. The improvement is especially significant when the number of NLOS receivers is large.

Fig. 4.11 Error probabilities of proposed method and positioning variance based method against σ_{sh} based on modeling parameters extracted from measurement.

The performance comparison between our proposed method and the ranging variance based method [70] is shown in Fig. 4.12. The false alarm probability remains at 0.01. The ranging variance in LOS and NLOS cases are assumed to be known in the derivation of the threshold for variance test. NLOS identification based on ranging variance assumes that the target is stationary and requires multiple repetitive measurements. For 10 repetitive measurements with constant NLOS bias and random TOA error (due to AWGN and multipath) and RSS error (due to log-normal shadowing), the error probability of our

proposed method and the ranging variance based method is plotted in Fig. 4.12 against σ_{sh} for $k_i=2$ and $k_i=3$ (corresponding to 6 dB and 10 dB NLOS attenuation respectively). For the proposed method, the averaged RSS and TOA measurements are used. The performance of both methods improves as k_i increases. As the method in [70] only uses time measurement, its performance is independent of σ_{sh} . When σ_{sh} is smaller than 2 dB, our proposed method has a smaller error probability than the method in [70]. When σ_{sh} increases, the RSS measurement becomes less accurate, and the error probability of our proposed method increases.

Fig. 4.12 Error probabilities of proposed method and TOA variance based method against σ_{sh} .

Finally, the performance of our proposed method is evaluated with

measurement data and compared with kurtosis-based channel identification technique [75], as shown in Fig. 4.13. The data were collected from the measurement at the Positioning and Wireless Technology Centre with transmitter-receiver separation of 1 to 5 meters. Two types of thresholds were used in the kurtosis based method to classify the channel to be LOS or NLOS. For adaptive threshold, the threshold is optimized based on the measurement at each distance to give the minimum error probability. Similar to the result in [49], it was found that the kurtosis depends on the SNR of the received signal. Hence the adaptive threshold is distance-dependent, which limits the applicability of the method in [75] for practical systems. In contrast, the fixed threshold is optimized based on the measurement data at 3 m only and is more realistic. The error probability for kurtosis-based method with adaptive threshold increases with distance, because as the distance increases, the SNR reduces, and it becomes harder to differentiate between low-SNR LOS propagation and NLOS propagation. For the fixed threshold kurtosis based method, its error probability increases significantly for distance beyond 3m (where the threshold is optimized) because of the kurtosis ambiguity between high-SNR NLOS propagation and low-SNR LOS propagation.

From previous discussion, we expect the performance of our proposed method improves with the distance. While this is true for distance smaller than 3m, the error probability starts to increase for distance beyond 3m. A closer examination of the received signal reveals for distance larger than 3m, large-error NLOS cases occur. To mitigate the large NLOS error, the search-back windowing technique [88] is applied in the TOA estimation instead of simple

thresholding. With the improved TOA estimation technique, small-error NLOS cases dominate, and the error probability reduces as distance increases.

Fig. 4.13 Error probability of proposed method and kurtosis based method against distance.

4.6 Conclusion

In this chapter, we address the issue of NLOS propagation, the other major source of error in a localization system. NLOS identification helps the design of more accurate TOA estimation methods. Identification of NLOS anchor also enables us to reject or underweight the corresponding range measurement to avoid fusion of erroneous information in the target position calculation step. Various NLOS identification methods have been summarized in Table 4.2. We

propose a NLOS identification technique based on hybrid RSS and TOA measurement. Making use of receiver cooperation, the technique is applied to hyperbolic and elliptical localization system. The proposed method is simple to implement, as it does not require channel estimation. It only requires at least one receiver to be LOS. Although exchange of information among receiver is needed, the overhead is small. The major limitation of the proposed method is knowledge of RSS measurement and propagation model. The propagation parameters such as the path loss exponent γ are assumed to be obtained from prior calibration or some well-established channel models. Admittedly the performance of the detector is affected by mismatch in parameters. However, for small-error NLOS case, the impact of parameter mismatch is small as long as the attenuation of the NLOS signal is strong and absorbs parameter mismatch error. Each NLOS identification technique in Table 4.2 has its own merits and drawbacks, and may be effective for a particular NLOS scenario. From the practical implementation point of view, several techniques may be selected, tailored, and integrated to cater for the specific application. For example, in an indoor personnel tracking application, the variance-based technique may be first applied to remove the large-error NLOS influence due to other people or furniture. The proposed technique can then follow to reject the NLOS measurement due to the person being located.

Table 4.2 Comparison of NLOS identification techniques

	Method	Assumption	Comments
Range measurement variance test (e.g. [70])	Conduct multiple repetitive measurements; Detect abnormal range measurement by running variance test.	NLOS propagation increases the variance of range measurement.	Effective for large NLOS error; Requires redundant measurement.
Positioning variance test (e.g. [71])	Calculate target positions from different anchor combinations; Detect abnormal range measurement from position outliers.	NLOS propagation causes a large deviation in target position estimation.	Effective for large NLOS error; Requires redundancy; the number of anchors needed depends on NLOS number
Channel parameter (e.g. [67, 73-77])	Test NLOS propagation from channel parameters such as the mean/excess delay, amplitude statistics, and higher-order statistics.	Knowledge of channel parameters in LOS and NLOS.	Fundamental approach; Requires perfect channel knowledge; certain parameters may be hard to extract.
Proposed	Test NLOS propagation by hybrid RSS and TOA measurement.	NLOS propagation causes attenuation of RSS.	Requires simple information exchange among the receivers; Requires RSS propagation model and measurement.

CHAPTER 5 ASYNCHRONOUS ELLIPTICAL LOCALIZATION

5.1 *Introduction*

As discussed in Chapter 2, localization commonly involves two steps. Range measurement is first conducted between the target and the anchor. In time-based range measurement, we need to estimate the TOA τ of the signal at the receiver, which has been discussed in Chapter 3. The estimated TOA alone does not imply TOF and is not meaningful unless it conveys range information. Extraction of range information from TOA measurement requires the other aspect of ranging: synchronization. Different levels of synchronization require different ranging protocols and define different target locus. In this chapter, we focus on the issue of synchronization and propose a new indoor localization system that does not implement costly synchronization mechanism but is able to estimate the absolute range from measurement of the differential TOA (DTOA) between the direct coupling (DC) signal and the target signal. In the second step of localization, range measurements are combined and target position is estimated. The positioning step is basically an optimization process that makes use of the target locus information from range measurement to find the optimum target position.

This chapter is organized as follows. Related works are first reviewed in

Section 5.2. We then present the system architecture and possible range measurement schemes with different levels of synchronization requirement in Section 5.3. The impact of these schemes on the accuracy of position measurement is evaluated in Section 5.4 via the CRLB. Comparison of CRLB also provides insight for our system design and choice of synchronization scheme. The concept of elliptical localization is illustrated and we also show that least squares (LS) based positioning algorithms can be extended to our proposed elliptical localization in Section 5.5. Positioning results from both our measurement prototype and simulation are shown in Section 5.6. The chapter is concluded in Section 5.7.

5.2 *Literature Review*

5.2.1 *Synchronization Mechanisms and Ranging Protocols*

Synchronization is vital to almost every communication system. For localization, the synchronization requirement can be more stringent, as it affects how TOA can be estimated and the estimated TOA accuracy that is directly pertinent to the range accuracy. There are various synchronization mechanisms. These synchronization mechanisms, together with the corresponding ranging protocol, generate the target range information. The target range can be relative or absolute, and enables hyperbolic and circular localization respectively, as in Fig. 2.4 and Fig. 2.5. As shown later in this chapter, absolute range conveys

more information than relative one, and localization based on absolute range is potentially more accurately.

Synchronization can be achieved by hardware. For example GPS uses precise atomic oscillator to synchronize the satellites' clocks [3]. For low-cost localization systems, however, the precise oscillator is an unaffordable luxury. Most indoor localization systems have coverage of up to 100 meters, and wired synchronization can be implemented for such small coverage. The anchor can share a common clock [89], and synchronization among them enables hyperbolic localization. Synchronization via hard wiring is accurate. However, for localization applications that are ad-hoc, it may be troublesome.

Rather than hardware, synchronization and ranging can also be achieved via extra signaling. Ultrasound localization systems such as Active Bat [45] and Cricket [46] use RF signals to synchronize the target and anchor, leveraging on the property that RF signal travels much faster than ultrasound. However, it is well-known that ultrasound has limitations due to multipath interference, and the system may not perform well in a cluttered environment. Furthermore, if the ranging signal is RF and travels at the speed of light, no other signal can propagate faster and be used for synchronization.

An alternative to extra signaling is redundant measurement for single type of wireless signal. For UWB signals, a two-way ranging (TWR) scheme between a pair of nodes, say node A and node B has been proposed [38, 90]. After establishing ranging session, node A first sends a ranging packet to node B. Upon receipt of the ranging packet, node B responds a reply packet to node A.

The receipt-reply process at node B involves a processing delay, and this delay is time-stamped in node B's reply packet. At node A, the round-trip time is measured. Together with the time-stamped processing delay, node A is able to estimate the TOF. As the processing delay is usually much longer than the TOF, TWR suffers from the issue of clock drift. To mitigate clock drift, symmetric double-sided TWR, or SDS-TWR has been proposed[91, 92]. SDS-TWR requires an additional ranging session that has a similar procedure as above but is initiated by node B. TWR aims to find the absolute range between the target and anchor. However at each ranging session, the range between the target and only one anchor is found. From a system efficiency point of view, it is more desirable to eliminate the communication overhead and find the ranges between the target and all the anchors simultaneously. Besides, it remains questionable how to control and measure the processing delay reliably.

Recently, signal parameter estimation technique has been applied to range and locate a moving target asynchronously [93]. Conventional hyperbolic localization systems measure the range difference *across the synchronized anchors*. In contrast, the method in [93] eliminates the requirement for anchor synchronization and measures the range difference at each individual anchor *across different time frames*. While implementation-wise is intriguing and efficient, the accuracy of the method is limited, and it is not effective for slow-moving target.

5.2.2 *Position Estimation Algorithms*

From the first step of localization, we are able to establish the range relation between the target and the anchors. Based on the range measurement, together with knowledge of the anchor positions, we can then calculate the target position in the positioning step. The range equations linking the measurements and the unknown target position are generally nonlinear. A straightforward but computationally intensive method is to solve them directly [94]. As an alternative to solving nonlinear equations, one may linearize them first and solve the equations iteratively [95, 96]. However, only local convergence can be achieved in this technique. Hence it is critical to have a good initial guess of the position to ensure convergence to the correct solution. The range relation can be relaxed to convert the positioning problem into a convex optimization problem, where efficient solvers readily exist and global convergence is guaranteed [97, 98].

For real-time positioning, the nonlinear equations are first transformed into linear ones by the introduction of an intermediate variable and then solved via the least squares (LS). One closed-form solution termed spherical interpolation (SI) is given in [99]. Although computationally simple, the SI algorithm neglects the relation between the unknown position and the intermediate variable and the positioning accuracy may not be satisfactory. To improve the positioning accuracy, Chan and Ho proposed a two stage weighted LS in [81], where a second stage LS is applied to refine the unconstrained LS solution (which is equivalent to SI as claimed in [100]). The problem with the weighted

LS is the approximation involved in the weighting matrix might degrade the system performance. Another approach to exploit the relation between the unknown target position and the intermediate variable is to incorporate the constraint into the LS objective function via Lagrange multipliers [100, 101].

5.3 *System Design*

5.3.1 *System Architecture*

For a typical indoor localization scenario, our proposed localization system architecture is shown in Fig. 5.1. The localization system has $(M+1)$ anchors. One of the anchors is a transmitter. In addition to being an anchor node to provide position reference, the anchor transmitter can also function as a coordinator that transmits commands from the central processing unit to the target. This is a notable advantage compared to hyperbolic systems, where the targets are uncoordinated and collisions could occur. The remaining M anchors are receivers. The target to be located in our measurement prototype is a semi-passive tag which has two antennas, one for reception and the other for transmission. With the transmission and reception capability of the anchors, the central processing unit can communicate with the target and multiple targets can be supported. The anchors are mounted on the ceiling and distributed around the region of interest to detect and localize the target. As evidenced in [40], the distributed geometry of the receivers improves the geometric dilution

of precision (GDOP), which is a measure of the amount of range measurement error amplification onto position estimation error due to anchor geometry [96, 102]. The positions of the anchor transmitter and receivers are known. For localization in 2D and 3D, a minimum of 3 and 4 receivers are needed respectively.

The ranging process is as follows. A UWB pulse is first transmitted from the anchor transmitter and it travels a distance d_t to the target. The pulse is captured by the target receiver. Upon receiving the pulse, the target is illuminated, and it amplifies and re-transmits the pulse. The re-transmitted pulse from the target travels d_i towards the anchor receiver i . Multiple targets can be supported by modulating the pulse at the target. For example, a BPSK switch can be added after the amplifier to control the polarity of the re-transmitted signal. It is also noteworthy that the target amplifies its received signal and returns it to the anchor receivers directly. In other words, the target only processes the signal at the analog front-end circuit in contrast to conventional round-trip range measurement systems that involve imprecise timing logic to re-generate the return signal.

The system architecture in Fig. 5.1 allows various range measurement schemes at different levels of synchronization. For all these ranging schemes, same TOA estimation technique can be applied and they should have the same target TOA estimation accuracy. The difference between these schemes only lies in the level of synchronization and it is the synchronization level that determines the positioning accuracy. Conventional absolute range measurement

demands the highest level of synchronization, where both the transmitter and the receivers need to be synchronized. The requirement is less stringent for relative range measurement, which only requires receiver synchronization. We also propose in this chapter an asynchronous absolute range measurement scheme. Various range measurement schemes are described in the following.

Fig. 5.1 Proposed position measurement system architecture.

5.3.2 Range Measurement Schemes and Modeling

We shall first model the range measurement. Letting r_i denote the absolute range measured at the i^{th} receiver, we have

$$r_i = \|\mathbf{p} - \mathbf{p}_t\| + \|\mathbf{p} - \mathbf{p}_i\| + n_i = R_i + n_i \quad (5.1)$$

where $\mathbf{p}$, $\mathbf{p}_t$ and $\mathbf{p}_i$ denote the position vector of the target, the transmitter and

the i^{th} receiver, respectively. $R_i = \|\mathbf{p} - \mathbf{p}_t\| + \|\mathbf{p} - \mathbf{p}_i\|$ is the true range and n_i is range measurement error which is assumed to be Gaussian distributed as $n_i \sim \mathcal{N}(0, \sigma_i^2)$ and is independent for different receivers. The Gaussian error assumption is supported by [102] and is also justified by our measurement. In general, (5.1) is a valid model when the range measurement is under LOS conditions. We will focus on LOS conditions in this chapter to demonstrate the working principle of the asynchronous elliptical localization system and assume NLOS errors can be corrected by mitigation techniques such as those presented in Chapter 4. The ranging schemes at various synchronization levels are then presented.

Global-Synchronous Absolute Range Measurement

In global-synchronous (GS) range measurement, the anchor transmitter and anchor receivers are synchronized and the absolute distance the target signal travels is available directly from the target signal TOA as

$$r_i = c \times \tau_i \text{ .}$$

Stacking all the measured range into a vector $\mathbf{r}_{GS} = [r_1 \ r_2 \ \dots \ r_M]^T$, we have the range measurement distribution as $\mathbf{r}_{GS} \sim \mathcal{N}(\mathbf{R}_{GS}, \mathbf{C}_{GS})$ with $\mathbf{R}_{GS}$ being the true absolute range vector and the error covariance $\mathbf{C}_{GS}$ is

$$\mathbf{C}_{GS} = \begin{bmatrix} \sigma_1^2 & 0 & \cdots & 0 \\ 0 & \sigma_2^2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \sigma_M^2 \end{bmatrix}.$$

Receiver-Synchronous Relative Range Measurement

In receiver-synchronous (RS) range measurement, only the anchor receivers are synchronized. Due to the clock offset between the anchor transmitter and anchor receivers, absolute range cannot be obtained from the target signal directly as in GS case. Hence we have to measure the TDOA and use range difference for localization. Without loss of generality, assume that receiver 1 is used as our reference. The relative range measurements are $\mathbf{r}_{RS} = [r_2 - r_1 \ r_3 - r_1 \dots \ r_M - r_1]^T$. The range difference vector can also be expressed as:

$$\mathbf{r}_{RS} = \mathbf{H}\mathbf{r}_{GS}$$

where $\mathbf{H} = \begin{bmatrix} -\mathbf{1}_{M-1} & \mathbf{I}_{M-1} \end{bmatrix}$. $\mathbf{1}_m$ indicates the $m \times 1$ vector of all ones and $\mathbf{I}_m$ indicates the $m \times m$ identity matrix. The relative range measurement distribution is:

$$\mathbf{r}_{RS} \sim \mathcal{N}(\mathbf{R}_{RS}, \mathbf{C}_{RS}) = \mathcal{N}(\mathbf{H}\mathbf{R}_{GS}, \mathbf{H}\mathbf{C}_{GS}\mathbf{H}^T).$$

Proposed Asynchronous Absolute Range Measurement

In our proposed asynchronous localization, no synchronization mechanism is implemented. Instead it leverages on the broadcast nature of wireless signal. It is noteworthy that anchor receiver i also receives from the anchor transmitter the DC signal that propagates a distance $L_i = \|\mathbf{p}_t - \mathbf{p}_i\|$. Hence from the TOA relation between the DC signal and the target signal, we can estimate the absolute distance that the target signal travels as:

$$r'_i = L_i + c \times \Delta_i \quad (5.2)$$

where Δ_i is the difference between the target signal TOA and the DC signal TOA at receiver i and is referred to as differential TOA or DTOA. When the range measurement is contaminated by noise, the error of our proposed range measurement scheme is caused not only by the error in the target signal TOA estimation, but also in the DC signal TOA estimation. For the range measurement vector $\mathbf{r}_{Asyn} = [r'_1 \ r'_2 \ \dots \ r'_M]^T$, we have $\mathbf{r}_{Asyn} \sim \mathcal{N}(\mathbf{R}_{GS}, \mathbf{C}_{Asyn})$. The error covariance matrix is $\mathbf{C}_{Asyn} = \mathbf{C}_{GS} + \mathbf{C}_{DC}$, where $\mathbf{C}_{DC}$ is due to the error of DC signal TOA estimation. The increase in range measurement error due to the latter is the trade-off for elimination of global synchronization. Nevertheless, the DC signal TOA estimation error is almost negligible, as for most applications the DC signal is much stronger. We can also improve the DC signal ranging based on knowledge acquired during calibration phase, where multiple measurements are conducted to obtain the statistical knowledge of the channel. The knowledge can then be used (e.g. for threshold selection) to

improve the ranging accuracy in measurement phase.

5.4 Positioning Error Bound

We will evaluate the performance of the aforementioned localization systems with different levels of synchronization via the CRLB, which is useful because it not only gives us a performance benchmark, but also provides us insight into the system design. Following the definition of CRLB in (2.4), the positioning CRLB is repeated here as:

$$\text{var}(\mathbf{p}) \geq \text{CRLB} = \mathbf{J}^{-1}(\mathbf{p}) \quad (5.3)$$

where $\text{var}(\mathbf{p})$ is the covariance matrix of the position estimation. $\mathbf{J}(\mathbf{p})$ is the FIM:

$$\mathbf{J}(\mathbf{p}) = E \left[\left(\frac{\partial \ln \Lambda(\mathbf{r}; \mathbf{p})}{\partial \mathbf{p}} \right) \left(\frac{\partial \ln \Lambda(\mathbf{r}; \mathbf{p})}{\partial \mathbf{p}} \right)^T \right] \quad (5.4)$$

where $\Lambda(\mathbf{r}; \mathbf{p})$ is the likelihood of range measurement. When the range measurement is Gaussian distributed as $N(\mathbf{R}, \mathbf{C})$, $\mathbf{J}(\mathbf{p})$ can also be written as :

$$\mathbf{J}(\mathbf{p}) = \left(\frac{\partial \mathbf{R}}{\partial \mathbf{p}} \right)^T \mathbf{C}^{-1} \left(\frac{\partial \mathbf{R}}{\partial \mathbf{p}} \right). \quad (5.5)$$

We first let

$$\mathbf{F} = \frac{\partial \mathbf{R}_{GS}}{\partial \mathbf{p}}.$$

In GS localization, localization is based on TOA measurement and we have the FIM for this case as:

$$\mathbf{J}_{GS} = \left(\frac{\partial \mathbf{R}_{GS}}{\partial \mathbf{p}} \right)^T \mathbf{C}_{GS}^{-1} \left(\frac{\partial \mathbf{R}_{GS}}{\partial \mathbf{p}} \right) = \mathbf{F}^T \mathbf{C}_{GS}^{-1} \mathbf{F}. \quad (5.6)$$

The FIM is a function of the target position vector, which is dropped for the simplicity of presentation. The FIM for TDOA-based RS localization is

$$\begin{aligned} \mathbf{J}_{RS} &= \left(\frac{\partial \mathbf{R}_{RS}}{\partial \mathbf{p}} \right)^T \mathbf{C}_{RS}^{-1} \left(\frac{\partial \mathbf{R}_{RS}}{\partial \mathbf{p}} \right) \\ &= \mathbf{F}^T \mathbf{H}^T \left(\mathbf{H} \mathbf{C}_{GS} \mathbf{H}^T \right)^{-1} \mathbf{H} \mathbf{F} \end{aligned} \quad (5.7)$$

For asynchronous DTOA based localization, only the range measurement error covariance matrix increases by $\mathbf{C}_{DC}$ compared to the GS case, and the FIM is given by

$$\mathbf{J}_{Asyn} = \left(\frac{\partial \mathbf{R}_{GS}}{\partial \mathbf{p}} \right)^T \mathbf{C}_{Asyn}^{-1} \left(\frac{\partial \mathbf{R}_{GS}}{\partial \mathbf{p}} \right) = \mathbf{F}^T \mathbf{C}_{Asyn}^{-1} \mathbf{F}. \quad (5.8)$$

Equations (5.6), (5.7) and (5.8) are the FIM for different ranging schemes. The inverse of the FIM is the CRLB. When the range measurement is more accurate or contains more information, the FIM increases and the CRLB decreases correspondingly. Hence, to compare the positioning CRLB, it is equivalent to evaluate the FIM, which is more convenient. Therefore we are going to

compare the FIMs $\mathbf{J}_{GS}$, $\mathbf{J}_{RS}$ and $\mathbf{J}_{Asyn}$ given by (5.6), (5.7) and (5.8) respectively. In the subsequent discussion, $\mathbf{A} \geq \mathbf{B}$ means the matrix $\mathbf{A} - \mathbf{B}$ is semi-positive definite. From matrix inversion formula,

$$\mathbf{J}_{Asyn} = \mathbf{F}^T \mathbf{C}_{GS}^{-1} \mathbf{F} - \mathbf{F}^T (\mathbf{C}_{GS} + \mathbf{C}_{DC})^{-1} \mathbf{C}_{DC} \mathbf{C}_{GS}^{-1} \mathbf{F}. \quad (5.9)$$

The first term is in fact $\mathbf{J}_{GS}$. It is obvious that

$$\mathbf{F}^T (\mathbf{C}_{GS} + \mathbf{C}_{DC})^{-1} \mathbf{C}_{DC} \mathbf{C}_{GS}^{-1} \mathbf{F} \geq 0,$$

or positive semi-definite. Hence

$$\mathbf{J}_{GS} \geq \mathbf{J}_{GS} - \mathbf{F}^T (\mathbf{C}_{GS} + \mathbf{C}_{DC})^{-1} \mathbf{C}_{DC} \mathbf{C}_{GS}^{-1} \mathbf{F} = \mathbf{J}_{Asyn}. \quad (5.10)$$

However, the error caused by the DC signal TOA estimation is generally negligible (i.e. $\mathbf{C}_{DC} \approx \mathbf{0}$). Hence $\mathbf{C}_{Asyn} \approx \mathbf{C}_{GS}$ and $\mathbf{J}_{Asyn} \approx \mathbf{J}_{GS}$. For relative range measurement, it has been shown in [103] that

$$\mathbf{J}_{RS} = \mathbf{F}^T \mathbf{C}_{GS}^{-1} \mathbf{F} - \mathbf{F}^T \frac{\mathbf{C}_{GS}^{-1} \mathbf{1}_M \mathbf{1}_M^T \mathbf{C}_{GS}^{-1}}{\mathbf{1}_M^T \mathbf{C}_{GS}^{-1} \mathbf{1}_M} \mathbf{F}. \quad (5.11)$$

Hence we have

$$\mathbf{J}_{GS} \geq \mathbf{J}_{GS} - \mathbf{F}^T \frac{\mathbf{C}_{GS}^{-1} \mathbf{1}_M \mathbf{1}_M^T \mathbf{C}_{GS}^{-1}}{\mathbf{1}_M^T \mathbf{C}_{GS}^{-1} \mathbf{1}_M} \mathbf{F} = \mathbf{J}_{RS}. \quad (5.12)$$

In other words, there is a loss of information in relative range measurement due to the relaxation on synchronization requirement. Hence localization based on

relative range measurement has a higher positioning CRLB. This is shown in Fig. 5.2 for the system architecture in Fig.5.1. The z-coordinate of the target is assumed to be known by measurement and does not require estimation. The range measurement error is assumed to be 0.1 m. In Fig. 5.2, the unit dBm^2 is defined as $10\log(\sigma^2)$ where σ^2 is the error variance in m^2 . As illustrated in Fig. 5.2, the CRLB based on absolute range measurement is less than -16 dBm^2 (0.025 m^2) and is generally smaller than relative range measurement based positioning CRLB. This is especially obvious when the GDOP is poor (i.e. around the edges of the region of interest). Hence, we can potentially achieve much better positioning accuracy using absolute range measurement.

Fig. 5.2 Comparison of CRLB for absolute range based localization and relative range based localization.

The average CRLB against the range measurement schemes is shown in Fig. 5.3. As all ranging schemes have the same target signal TOA estimation accuracy, Fig. 5.3 mainly depicts the effect of synchronization on the positioning accuracy. The average positioning CRLB in GS scenario is about 13 dB below the CRLB in RS scenario. CRLB for our proposed asynchronous ranging scheme is larger than GS due to additional DC signal TOA estimation error. Although the TOA estimation error of the DC signal is usually much smaller than that of the target signal, in Fig. 5.3 it is assumed to be equal to the error in target signal TOA estimation. Even with this worst-case assumption, the CRLB for our proposed system without any hardware synchronization mechanism is still 10 dB better than the CRLB in RS.

Fig. 5.3 Comparison of average positioning CRLB for different range measurement schemes.

5.5 Positioning Algorithms

As absolute range measurement reduces CRLB and potentially produces more accurate positioning result, we will focus on absolute range based localization, where the sum of transmitter-target range and target-receiver range can be estimated from measurement. The range sum defines an ellipse where the target resides, and hence the name elliptical localization. As illustrated in Fig. 5.4, the target is located at the intersections of the ellipses with the anchor transmitter

and anchor receivers being the foci. Next we will show that the conventional circular and hyperbolic localization algorithms can be extended to elliptical localization. Neglecting noise and rearranging the term, we can re-arrange (5.1) as:

$$r_i' - \|\mathbf{p} - \mathbf{p}_t\| = \|\mathbf{p} - \mathbf{p}_i\| \quad (5.13)$$

Letting $d_t = \|\mathbf{p} - \mathbf{p}_t\|$ and squaring both sides of (13) and stacking all the ranges gives:

$$\mathbf{b} = \mathbf{A}\boldsymbol{\theta} \quad (5.14)$$

where

$$\mathbf{b} = [b_1 \ b_2 \ \dots \ b_M]^T$$

$$b_i = r_i'^2 + \mathbf{p}_t^T \mathbf{p}_t - \mathbf{p}_i^T \mathbf{p}_i$$

$$\mathbf{A} = [\mathbf{A}_1 \ \mathbf{A}_2 \ \dots \ \mathbf{A}_M]^T$$

$$\mathbf{A}_i = 2 \begin{bmatrix} (\mathbf{p}_t - \mathbf{p}_i)^T & r_i' \end{bmatrix}$$

$$\boldsymbol{\theta} = \begin{bmatrix} \mathbf{p}^T & d_t \end{bmatrix}^T$$

Fig. 5.4 Illustration of elliptical localization

The actual measurement is corrupted by noise. A straightforward least-squares (LS) solution to (5.14) is:

$$\hat{\mathbf{\theta}} = (\mathbf{A}^T \mathbf{A})^{-1} \mathbf{A}^T \mathbf{b} \quad (5.15)$$

which is equivalent to the spherical interpolation (SI) algorithm in conventional hyperbolic localization [99]. However, in obtaining (5.15) we have assumed that $\mathbf{p}$ and d_t are independent and neglected the relationship

$$d_t^2 = (\mathbf{p} - \mathbf{p}_t)^T (\mathbf{p} - \mathbf{p}_t).$$

Imposing the constraint explicitly we can formulate the following problem:

$$\begin{aligned}\hat{\boldsymbol{\theta}} &= \arg \min_{\boldsymbol{\theta}} (\mathbf{b} - \mathbf{A}\boldsymbol{\theta})^T (\mathbf{b} - \mathbf{A}\boldsymbol{\theta}) \\ \text{subject to: } &\boldsymbol{\theta}^T \boldsymbol{\Sigma} \boldsymbol{\theta} = 0\end{aligned}\tag{5.16}$$

where the transmitter is assumed to be at the origin, and $\boldsymbol{\Sigma} = \text{diag}(1, 1, -1)$ for 2D and $\boldsymbol{\Sigma} = \text{diag}(1, 1, 1, -1)$ for 3D. The constrained LS problem in (5.16) can be solved by the technique of Lagrange multiplier. The problem (5.16) is equivalent to minimize the following Lagrange function:

$$L(\boldsymbol{\theta}, \lambda) = (\mathbf{b} - \mathbf{A}\boldsymbol{\theta})^T (\mathbf{b} - \mathbf{A}\boldsymbol{\theta}) + \lambda(\boldsymbol{\theta} - \boldsymbol{\theta}_t)^T \boldsymbol{\Sigma}(\boldsymbol{\theta} - \boldsymbol{\theta}_t).$$

We first let $\frac{\delta L(\boldsymbol{\theta}, \lambda)}{\delta \boldsymbol{\theta}} = 0$, which gives the optimum $\hat{\boldsymbol{\theta}}$:

$$\hat{\boldsymbol{\theta}} = (\mathbf{A}^T \mathbf{A} + \lambda \boldsymbol{\Sigma})^{-1} \mathbf{A}^T \mathbf{b}\tag{5.17}$$

The Lagrange multiplier λ can then be solved iteratively by substituting (5.17) into the constraint in (5.16) as in [100].

The above position estimation in (5.15) or (5.17) can be further refined when we minimize the squared range measurement error as

$$\hat{\mathbf{p}} = \arg \min_{\mathbf{p}} \left[\sum_{i=1}^M (r'_i - \|\mathbf{p} - \mathbf{p}_t\| - \|\mathbf{p} - \mathbf{p}_i\|)^2 \right].\tag{5.18}$$

For the k^{th} iteration, from the Gauss-Newton method we have

$$\mathbf{p}^{k+1} = \mathbf{p}^k + \mathbf{W}^k (\mathbf{r}_{async} - \|\mathbf{p}^k - \mathbf{p}_t\| - \|\mathbf{p}^k - \mathbf{p}_i\|)\tag{5.19}$$

where

$$\mathbf{W}^k = (\mathbf{H}_k^T \mathbf{H}_k)^{-1} \mathbf{H}_k^T$$

$$[\mathbf{H}_k]_{ij} = \frac{\partial(\|\mathbf{p}^k - \mathbf{p}_t\| + \|\mathbf{p}^k - \mathbf{p}_i\|)}{\partial p_j}.$$

Generally, it is desirable to initiate (5.18) with a point as close to the true position as possible to avoid convergence to local minima. Our extensive simulation shows that both (5.15) and (5.17) give one such initial point. Other starting solutions could also be considered. The average positioning performance of the above three solutions in (5.15), (5.17) and (5.19) is evaluated in Section 5.6.

5.6 Result

The principle of asynchronous elliptical localization has been demonstrated by a localization system prototype. The measurement set-up is shown in Fig. 5.1. The measurement was conducted in the RF room of the Positioning and Wireless Technology Centre, Nanyang Technological University. The RF room is a typical lab room with tables, chairs and equipment to mimic a typical indoor environment. The anchor transmitter is mounted on the ceiling (2.76 m above the floor) and is the origin of our coordinate system (i.e. $\mathbf{p}_t = [0 \ 0 \ 0]^T$). The transmitter emits UWB pulses centered at 4 GHz periodically at a pulse repetition frequency of 3.2 MHz. The pulse duration is about 1 ns. Four ED receivers are also mounted on the ceiling and distributed around the transmitter. The received signal is sampled by a LeCroy WaveMaster 8420A digital

sampling oscilloscope at 20 GSamples/s. The digital oscilloscope is used merely for illustration of the received waveform. In a practical system we can either use a low-rate ADC to sample the ED receiver output [29] or sample the received waveform directly by stroboscopic sampling [59]. The position vectors of the receivers are $\mathbf{p}_1 = [0 \ 1.87 \ 0]^T$, $\mathbf{p}_2 = [-3.04 \ 0 \ 0]^T$, $\mathbf{p}_3 = [0 \ -2.96 \ 0]^T$, and $\mathbf{p}_4 = [3.04 \ 0 \ 0]^T$. No synchronization mechanism is imposed on the receivers. The spacing of the reception and transmission antennas of the target is much smaller than the signal propagation distance so that the target can be treated as a single location point. When a UWB pulse is captured by the target, it is amplified 12 dB by a Mini-Circuit ZX60-14012L amplifier and re-transmitted. Except for amplification, the target does not further process the pulse (e.g. time-stamp it) to avoid clock non-idealities. The amplifier circuitry introduces an additional internal delay, which can be treated as an unknown and jointly estimated in the position estimation step [104]. However, this degrades the absolute range based localization to a relative one as shown in the Appendix C. To preserve the position measurement accuracy, we measure the delay during system calibration and subtract it from our DTOA measurement. All the antennas used in our measurement are bi-conical and have omni-directional radiation pattern.

5.6.1 Range Measurement

As discussed previously, to find the absolute range asynchronously, we need

to estimate the TOA of the DC signal and the TOA of the target signal. TOA is estimated by finding the first time instant when the signal energy exceeds a threshold. Similar to [49], the threshold γ is defined adaptively as:

$$\gamma = z_{\min} + \varepsilon(z_{\max} - z_{\min}) \quad (5.20)$$

where $z_{\min}$ and $z_{\max}$ are the minimum and maximum value of the signal energy. ε is a normalization factor between 0 and 1 and is closely related to the signal SNR. Based on our extensive measurement, ε is taken to be 0.6 for DC signal and $\varepsilon=0.3$ for target signal.

For a typical indoor environment, the target signal is often buried in the DC signal or its multipath. Assuming the channel is stationary, we adopt the technique of empty-room measurement. First we measure and store the waveform at each receiver with the target amplifier switched off. The stored waveform contains the DC signal and its multipath and serves as a reference waveform. When the target amplifier is switched on, the received signal at each receiver is compared with the stored reference waveform by taking their difference. This is shown in Fig. 5.5, where the top figure shows the ED receiver output that contains the DC signal, target signal, and multipath that lasts about 60 ns. The anchor transmitter is mounted on the centre of the ceiling at (0, 0, 0). The anchor receiver is at (-3.04, 0, 0). The target is at (-1.5, 0, -0.66) with all units in meters. The DC signal TOA is 7.8 ns and the target signal arrives at 12 ns. However, the target signal is buried in the DC signal multipath and is not discernable. The energy difference between the reference signal and

the received signal with target amplifier on is shown in the bottom plot. There is an obvious change at the target signal TOA. Subtracting the DC signal TOA from the target signal TOA and adjust for the internal delay (which is known from calibration), we can obtain the final DTOA used for positioning. Fig. 5.6 shows the DTOA distribution of 300 range measurements for the same setup. The measured DTOA has a mean of 4.21 ns, which is almost equal to the true DTOA (4.2 ns). The standard deviation of DTOA measurements is 0.36 ns, which corresponds to a range uncertainty of 10.8 cm. The measurement histogram fits well into a Gaussian distribution and justifies our Gaussian range error assumption. The final range sum estimation is given by (5.2).

It is noteworthy that in our measurement, the reference waveform was obtained once during calibration. The reference waveform is relatively stable, as the transmitter and receivers are placed on the ceiling and are less disturbed by the environment. In a dynamic environment, the reference waveform can also be obtained by coding the re-transmitted signal from the target. For example, the target may be triggered to transmit only on the second frame, where the first frame is used as the reference.

Fig. 5.5 Waveform of DTOA measurement

Fig. 5.6 Histogram of measured DTOA for 300 independent trials

5.6.2 Position Measurement Result

There are three factors determining the position estimation result: the quality of range measurement, the GDOP, and the position estimation algorithm. Simply speaking, the range measurement quality infers the width of uncertainty of the target locus, and the GDOP and the positioning algorithm determine how the locus will intersect.

Based on the localization system prototype, the scatter plots of position measurement result are shown in Fig. 5.7 and Fig. 5.8 for two representative target locations $\mathbf{p} = [0.8 \ -0.8 \ -0.76]^T$ and $\mathbf{p} = [-3.64 \ 2.5 \ -0.76]^T$. These two positions correspond to good GDOP and poor GDOP, respectively. If SI estimation is used, larger error distribution will be observed. To improve the positioning accuracy, we refine the SI position estimation recursively by the Gauss-Newton algorithm. We have also assumed that we know the z -coordinate of the target for the simplicity of presentation. For the target at $\mathbf{p} = [0.8 \ -0.8 \ -0.76]^T$ its position estimations have almost equal spread along the x and y direction. Due to poor GDOP, the target located at $\mathbf{p} = [-3.64 \ 2.5 \ -0.76]^T$ has a larger error distribution. The spread of the position estimations also agrees with the intersection area of the ellipses. The mean and variance of the measurement result for these two locations are summarized in Table 5.1 and compared with the true target position and CRLB, respectively. The mean of the position measurement is almost equal to the true position, which shows that the estimated position is unbiased. The MSE of the estimated

target position also approaches the CRLB in both cases.

Fig. 5.7 Position measurement result for target location with good GDOP. True target location is indicated by the cross. The dots indicate the position estimations. The lines are drawn based on the target locus $\pm$ standard deviation of range measurement.

Fig. 5.8 Position measurement result for target location with poor GDOP. True target location is indicated by the cross. The dots indicate the position estimations. The lines are drawn based on the target locus $\pm$ standard deviation of range measurement.

Table 5.1 Statistics of measurement data

	Good GDOP	Poor GDOP
Mean of measured data (cm)	(79.8, -80.1)	(-362.9, 251.3)
True position (cm)	(80, -80)	(-364, 250)
Variance of measured data (cm ²)	13.9	142.1
CRLB (cm ²)	12.4	133.4

5.6.3 Average Positioning Result

The average positioning accuracy is further evaluated in simulation. The locator geometry is identical to our measurement setup and the range measurement error varies between -60 dBm^2 and 0 dBm^2 . For each error variance, 100000 independent target locations are randomly chosen within the area $-4 \text{ m} \leq x \leq 4 \text{ m}$ and $-4 \text{ m} \leq y \leq 4 \text{ m}$. The positioning MSE of three LS position estimation algorithms are compared, namely, the ordinary LS (OLS) in (5.15), the constrained LS (CLS) in (5.17), and the recursive LS (RLS) in (5.19). The positioning MSE of the three algorithms is shown in Fig. 5.9. Also shown in Fig. 5.9 is the average CRLB. Although the OLS has the largest MSE, it is the simplest in terms of computation. The RLS can achieve the CRLB but it is iterative. The positioning MSE of OLS and CLS is about 4 dB and 2 dB above the CRLB.

Fig. 5.9 Average positioning MSE for different positioning algorithms by simulation

5.7 Conclusion

We present an elliptical position measurement system based on asynchronous absolute range measurement in this paper. Absolute range measurement helps to improve the position accuracy, as shown by both theory and simulation. Exploiting the locator geometry and the differential TOA between the direct signal from the transmitter and the target signal, we are able to infer the absolute range and eliminate the cost of synchronization. This is advantageous in that the system can be setup easily without using cables for synchronization. Measurement from our low-cost prototype shows the effectiveness of the

proposed system for applications such as warehouse management, equipment and personnel tracking and monitoring. The major limitations of the proposed system are the complexity to enable the target to re-transmit the received signal and the need to measure the DTOA between the anchor signal and target signal.

The proposed system is also compared with existing solutions in terms of synchronization, implementation, computation and accuracy. The comparison is summarized in Table 5.2. Except Ubisense's system that requires AOA, all systems have similar computational complexity, regardless of the type of localization (circular, hyperbolic, or elliptical). As shown in Table 5.2, these systems mainly differ in their synchronization level and implementation. For indoor channel with dense multipaths, similar positioning accuracy is achieved in both [37] and our proposed system. However, our system does not require transmission scheduling/coordination and is more efficient for the same range measurement time.

Table 5.2 Comparison with Existing Positioning Systems

System	Synchronization level	Implementation	Computation	Accuracy in good GDOP
Ultrasonic [45, 46]	Asynchronous	Separate detection of RF and ultrasound signals.	Circular	~ 10 cm in good channel condition
Zhang <i>et al.</i> [44]	Receiver synchronization	Simple energy detection	Hyperbolic	mm level in small coverage
Angelis <i>et al.</i> [37]	Asynchronous	Scheduling / coordination for round-trip ranging	Circular	~10 cm indoor
Time Domain [42]	Receiver synchronization	Not available	Hyperbolic	Sub-meter level
Ubisense [43]	Receiver synchronization	Not available	AOA + Hyperbolic	~15 cm indoor
Proposed [82]	Asynchronous	Differential TOA estimation based on simple ED	Elliptical	< 10 cm indoor

Chapter 6 Construction of Local Anchor Map

6.1 *Introduction*

As discussed previously, target localization usually requires some sensors known as anchors to provide position references. A prerequisite for target localization is therefore the availability of the anchor positions. For fixed localization infrastructure, obtaining the anchor position is a trivial problem, as the set-up is once and for all, and time is not a major concern. In this case the anchor positions can be obtained by techniques such as GPS, ruler measurement, and map of the region of interest. However, many indoor localization applications such as emergency rescue team tracking and home interactive gaming are ad-hoc. These ad-hoc localization systems demand quick and easy setup, and it is often a challenging task to obtain the anchor positions by the aforementioned methods. In this case, an additional calibration phase is needed prior to target localization to find the position of the anchors that are often placed arbitrarily.

Although anchor position calibration is critical for ad-hoc localization systems, this problem has not been well-studied. Most works assume that such information is available with positioning devices such as GPS. However, precision GPS increases the cost of the system. Furthermore it is not available in indoor environment. The goal of GPS is to find the global coordinate in

longitude and latitude. For most indoor applications, on the other hand, it suffices to know the relative position of the target with respect to the anchors. In fact, if a local coordinate system can be established, it is more meaningful to know the target position in the local coordinate rather than its longitude and latitude. Therefore it is of practical significance to find the relative position of the anchors (relative map) and use it as a basis for construction of the local coordinate system. The constructed local anchor map can be rotated, reflected and translated in the global coordinate system, but the relative positions of the anchors should be preserved.

In this chapter we study the problem of local anchor map construction. When we consider all the anchors as sensors to be located, some related works can be found in wireless sensor network localization, where coordinates of the sensors are commonly obtained from techniques such as multi-dimensional scaling (MDS) [105-108]. As shown later, MDS requires inter-anchor range information, be it absolute or relative. Once pair-wise ranges between the anchors are obtained, the local anchor map can be constructed. High-fidelity construction of anchor map requires accurate range information, and hence, precise time measurement. It is worth mentioning that the work presented in this chapter differs from conventional works on localization such as those presented in [5, 10, 81, 100] in that we aim to find a local map of the anchors without any position references. In other words, the local anchor map construction is a process independent of and prior to the target localization process.

The rest of the chapter is organized as follows. The MDS technique is briefly introduced first in 6.2. The MDS requires either absolute or relative inter-anchor range in order to construct the local anchor map. When the measured range is absolute, metric MDS or classical MDS can be applied, which is discussed in 6.3. When only relative range, or the ranking of the range is available, nonmetric or ordinal MDS can be applied, as discussed in 6.4. The measurement of the inter-anchor ranges includes two types of errors: the pseudorange error and the measurement error, and the performance of both classical MDS and ordinal MDS against these two types of errors is shown in 6.5. The chapter is concluded in 6.6 with a comparison of various techniques to construct the local anchor map.

6.2 *Multidimensional Scaling*

The MDS is a dimension reduction technique that reveals the hidden structure of data in low-dimensional space based on the observation of data proximity measured in high-dimensional space [109, 110]. The aim of MDS is to find a configuration of points in the low-dimensional space such that the distance d_{rs} between any point r and s represents the proximity between the objects in the high-dimensional space. Proximity is a measure of how close different locations are in the physical space. The proximity between two point r and point s is reflected in the dissimilarity δ_{rs} , which is a measure of how close two observations are in the variable space, or on the configuration to be constructed.

A small dissimilarity value indicates that the objects are close in proximity. There are many MDS methods, and they can be classified into two categories: metric MDS and non-metric MDS, depending on how proximities in the high-dimensional space are transformed into dissimilarities in the low dimensional space. Euclidean distance is both a proximity measure and a dissimilarity measure.

6.2.1 *Metric MDS*

Metric MDS assumes that for any two points r and s , the proximity δ_{rs} and distance d_{rs} are related by some continuous monotonic function $f(\cdot)$, i.e.

$$d_{rs} = f(\delta_{rs}).$$

There are many forms of the function that maps proximity with distance, giving rise to numerous MDS models and solutions. If the proximity measure (dissimilarity) and the distance measure are both Euclidean, as in the localization context, closed-form solution to find the configuration in low-dimensional space exists, and this approach is called classical MDS. We will focus on the representative metric MDS approach in this section.

For M points, the classical MDS starts with construction of the matrix of squared dissimilarities:

$$\mathbf{D} = \begin{bmatrix} 0 & \delta_{12}^2 & \delta_{13}^2 & \cdots & \delta_{1M}^2 \\ \delta_{21}^2 & 0 & \delta_{23}^2 & \cdots & \delta_{2M}^2 \\ \delta_{31}^2 & \delta_{32}^2 & 0 & \cdots & \delta_{3M}^2 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \delta_{M1}^2 & \delta_{M2}^2 & \delta_{M3}^2 & \cdots & 0 \end{bmatrix} \quad (6.1)$$

where the $(i, j)^{th}$ entry of $\mathbf{D}$ in error-free case is given by:

$$[\mathbf{D}]_{ij} = \delta_{ij}^2 = d_{ij}^2 = (\mathbf{p}_i - \mathbf{p}_j)^T (\mathbf{p}_i - \mathbf{p}_j) \quad (6.2)$$

where $\mathbf{p}_i$ is the position vector of the i^{th} point. The position vectors of all points are not known. Hence in actual implementation, δ_{ij} is obtained from measurement and is corrupted by noise.

Next the origin of the configuration is shifted to the centroid of the coordinates such that:

$$\sum_{i=1}^M \mathbf{p}_i = \mathbf{0}. \quad (6.3)$$

To achieve this, double centering is applied to $\mathbf{D}$ as:

$$\mathbf{B} = -\frac{1}{2} \mathbf{\Omega} \mathbf{D} \mathbf{\Omega} \quad (6.4)$$

where $\mathbf{\Omega}$ is the centering matrix defined as:

$$\mathbf{\Omega} = \mathbf{I}_M - \frac{1}{M} \mathbf{1}_M \mathbf{1}_M^T. \quad (6.5)$$

The resultant matrix $\mathbf{B}$ after double centering is a scalar product matrix, and in

the absence of noise it is shown to be:

$$\mathbf{B} = \mathbf{P}\mathbf{P}^T, \quad (6.6)$$

where $\mathbf{P} = [\mathbf{p}_1 \ \mathbf{p}_2 \ \cdots \ \mathbf{p}_M]^T$ is the matrix of coordinates with origin at the centroid. We can then solve $\mathbf{P}$ by eigendecomposition of $\mathbf{B}$ as

$$\mathbf{B} = \mathbf{V}\mathbf{\Lambda}\mathbf{V}^T \quad (6.7)$$

The final solution is given by:

$$\mathbf{P} = \mathbf{V}_D\mathbf{\Lambda}_D^{1/2}, \quad (6.8)$$

where $\mathbf{\Lambda}_D$ is the diagonal matrix of the D largest eigenvalues, and $\mathbf{V}_D$ contains the eigenvectors corresponding to the D largest eigenvalues. D denotes the dimension of the position vector.

6.2.2 Non-Metric MDS

In contrast to metric MDS, non-metric MDS does not require the mapping between the dissimilarity δ_{rs} and distance d_{rs} to be some explicit function. Instead, it only stipulates that the rank order of the proximity be preserved, i.e.

$$\delta_{rs} < \delta_{ab} \Rightarrow d_{rs} \leq d_{ab}.$$

Therefore, non-metric MDS is also called ordinal MDS.

In ordinal MDS, once we have acquired the order of the dissimilarities, we can search for the configuration of points by minimizing a loss function. A common approach is the Kruskal's algorithm [10-12], which minimizes the loss function

$$L = \sqrt{\frac{\sum_{r,s} (d_{rs} - \rho_{rs})^2}{\sum_{r,s} d_{rs}^2}} \quad (6.9)$$

where the summation is taken over $1 = r < s = M$ due to the symmetry of $\delta_{ij} = \delta_{ji}$. In (6.9), d_{ij} is the distance between the point i and j in the constructed configuration and ρ_{ij} is called the disparity, which is viewed as a monotonic function of the distance $\rho_{ij} = f(d_{ij})$. The disparity indicates how closely the distance in the constructed configuration matches the originally measured dissimilarity. The measured dissimilarity δ_{ij} enters the loss function by defining the order for the disparities as:

$$\delta_{ij} < \delta_{mn} \Rightarrow \rho_{ij} \leq \rho_{mn}.$$

In other words, the disparity preserves the order of the measured dissimilarity. Kruskal's algorithm minimizes the loss function with respect to the coordinates of the configuration of points as well as the disparity using isotonic regression. Detailed algorithm and its implementation can be found in [111].

6.2.3 MDS in the Context of Localization

In the context of sensor localization, given M sensors with unknown positions

and range measurement δ_{ij} between sensor i and sensor j , $i, j \in \{1, 2, \dots, M\}$, classical MDS aims to find a configuration of points representing the sensors such that any distance d_{ij} between the point i and point j match the measured inter-sensor range δ_{ij} as closely as possible. As the goal of classical MDS is to preserve the inter-sensor ranges, it requires absolute range measurement to ensure an accurate configuration.

In contrast to classical MDS, ordinal MDS attempts to configure the points such that the order of their distances reflects the order of the original range measurement. Preservation of the range ranking is less stringent a requirement and this is significant for practical measurement systems because we only need to sort the inter-sensor ranges to find their rank. The sorting does not necessarily require the exact values of the ranges and can be achieved via rotational TDOA measurement discussed in the sequel.

6.3 *Local Anchor Map Construction via Classical MDS*

From the previous discussion, when the ranges between every anchor pairs are available, it is straightforward that the relative anchor positions can be found. For ad-hoc applications, the anchors are expected to conduct the range measurement among themselves. To facilitate the self-configuration of the anchors, we shall assume in the subsequent discussion that each anchor is capable of both transmitting and receiving UWB pulses. The transmitter may

not need to be a dedicated hardware on the anchor. For example, a transmitting target may be placed near a receiving-only anchor to act as an asynchronous anchor transmitter.

We first assume that all the anchors are synchronized. Besides, the transmitter and receiver on each anchor are also synchronized. The two aspects of synchronization demands different implementations. The inter-anchor synchronization depends largely on the localization system architecture, whereas synchronization within each anchor is mainly a hardware design issue. In this illustrative case, each anchor transmits in turns, and by measuring the TOA of the signal at rest of the anchors, we can directly obtain the range between each anchor pairs. The measured ranges are then used as dissimilarities to construct the matrix of squared dissimilarities $\mathbf{D}$, and the anchor configuration can be solved subsequently. Although the range measurement protocol is simple and straightforward, it poses the most stringent requirement on implementation of the synchronization mechanism in that not only anchors but also the transmitter and receiver on each anchor need to be synchronized.

Next we relax the synchronization constraint such that we only require the transmitter and receiver on each anchor to be synchronized. In this case, we will rely on two-way ranging (TWR) to find the inter-anchor ranges. The idea of TWR is illustrated in Fig. 6.1.

Fig. 6.1 Illustration of TWR [83]

In TWR between a pair of anchors (anchor A and anchor B), anchor A first initiates the ranging process by sending a packet to anchor B. Upon receiving the signal from anchor A, anchor B sends a reply packet back to anchor A. The reply packet from anchor B contains the local processing time t_{replyB} between its reception of anchor A's signal and transmission of the signal back to anchor A. Meanwhile, anchor A also counts the time between transmission of the initial ranging packet and reception of anchor B's reply packet. The TOF of the signal between anchor A and anchor B can then be calculated as:

$$\begin{aligned}
 2t_p &= (\tau_{BR} - \tau_{AT}) + (\tau_{AR} - \tau_{BT}) \\
 &= (\tau_{AR} - \tau_{AT}) - (\tau_{BR} - \tau_{BT}) \quad . \\
 &= (\tau_{AR} - \tau_{AT}) - t_{replyB}
 \end{aligned} \tag{6.10}$$

Repeating the above TWR process for each pair of anchors, we can measure all the inter-anchor ranges.

The above TWR protocol assumes the anchor clocks are perfect. For low-cost UWB systems this is usually not the case. The anchor clocks are hardly ideal. The clock drift issue surfaces when the processing time is much longer than propagation time, and the effect of clock drift is shown in the following. When the clocks at node A and node B are drifted by e_A and e_B respectively, the estimated erroneous TOF becomes:

$$2\hat{t}_p = (\tau_{AR} - \tau_{AT}) \times (1 + e_A) + (\tau_{BR} - \tau_{BT}) \times (1 + e_B) \quad (6.11)$$

Compared with the true TOF, the error is:

$$\hat{t}_p - \tau_P = \frac{1}{2} (t_{replyB} \times e_A - t_{replyB} \times e_B + 2t_p \times e_A) \approx \frac{1}{2} t_{replyB} \times (e_A - e_B) \quad (6.12)$$

From the above equation, the timing error caused by clock drift depends on the processing time at node B and the rate of the drift. For typical clock frequency drift, say 20 ppm, 100 μ s processing time will introduce a 1 ns error in TOF estimation.

There are several techniques to eliminate the clock drift such as extra range measurement and repetitive signaling. The symmetric double sided (SDS)-TWR technique uses extra range measurement to eliminate the clock drift, as illustrated in Fig. 6.2.

Fig. 6.2 Illustration of SDS-TWR [83]

In the SDS-TWR between anchor A and anchor B, an additional TWR process similar to above is involved, but this TWR session is initiated by anchor B.

From Fig. 6.2, the following relationship can be established:

$$\begin{aligned} t_{roundA} &= 2t_p + t_{replyB} \\ t_{roundB} &= 2t_p + t_{replyA} \end{aligned} \quad (6.13)$$

Summing the above two relations and rearranging the terms we obtain:

$$4t_p = t_{roundA} - t_{replyA} + t_{roundB} - t_{replyB}. \quad (6.14)$$

When there is clock drift, the estimated TOF becomes:

$$4\hat{t}_p = (t_{roundA} - t_{replyA}) \times (1 + e_A) + (t_{roundB} - t_{replyB}) \times (1 + e_B), \quad (6.15)$$

and the TOF error is:

$$\hat{t}_p - t_p = \frac{1}{2} \times t_p \times (e_A + e_B) + \frac{1}{4} (t_{replyB} - t_{replyA}) \times (e_A - e_B) \quad (6.16)$$

Assuming that $t_p \ll t_{replyA}, t_{replyB}$, which is usually the case, the error can be simplified to be

$$\hat{t}_p - t_p = \frac{1}{4} (t_{replyB} - t_{replyA}) \times (e_A - e_B), \quad (6.17)$$

which, apart from being dependent on the clock drift rate, is now a function of the difference in reply time at node A and node B, and can be eliminated when $t_{replyB} = t_{replyA}$. However, it is generally hard to control the reply time precisely. Hence the clock drift error almost always exists in TWR. The SDS-TWR only reduces the clock drift error but in general cannot eliminate it.

We can also estimate the drift by repetitive signaling, as in [59, 112]. Instead of transmitting a single ranging signal, anchor A transmits a sequent of pulses at some known interval. These pulses are then captured by anchor B to estimate the time drift over the entire pulse train. This technique assumes linear drift model, the validity of which needs further investigation.

From (6.12), the range error due to clock drift is proportional to the processing time, which is largely affected by the poor stability of controller clocks. Hence we can cut the local processing time and eliminate the time-stamping process to obtain a more precise ranging result. TWR is more precise if it is implemented only in the analog domain, which significantly shortens the processing time. The analog circuit delay is always fixed and can be calibrated.

6.4 *Local Anchor Map Construction via Ordinal MDS*

From the above discussion, it is sometimes still a challenging task to estimate the pair-wise ranges accurately, largely due to the clock drift issue. Range finding based on TOA measurement requires either expensive synchronization between the transmitting sensor and the receiving sensor for one-way measurement or round-trip measurement that suffers from clock non-idealities.

Although it is hard to synchronize the transmitter and the receivers, for TDOA based localization system such as [81] and [100], all the anchors are synchronized as receivers. Even if they are not, it is still possible to synchronize them during system calibration. It is also simple to make an anchor transmit asynchronously, for example, by placing a transmitting target very close to the anchor or switching the anchor antenna to a transmission circuit during calibration. Leveraging on the availability of receiver synchronization and the simplicity of asynchronous transmission, we will next show our proposed

anchor position calibration method. The proposed method is based on ordinal MDS and rotational TDOA measurement, and is able to produce accurate result if the number of anchors is sufficiently large.

6.4.1 Rotational TDOA Measurement

As discussed previously, ordinal MDS requires the rank of the dissimilarities. The rank of the inter-anchor ranges can be obtained from TDOA measurement in a round-robin fashion as follows. For M anchors, there are $M(M-1)$ inter-anchor range measurements. Let the range between anchor i and anchor j be δ_{ij} . It is obvious $\delta_{ij} = \delta_{ji}$ and $\delta_{ii} = 0$. Due to aforementioned reasons, absolute range measurement is not feasible and we do not know the exact value of δ_{ij} . However with anchor i and anchor j being synchronous receivers, we can measure the TDOA of the signal transmitted from anchor k and received by anchor i and anchor j as

$$TDOA_{ij}^k = TOA_i^k - TOA_j^k$$

and their range difference is

$$r_{ij}^k = \delta_{ki} - \delta_{kj} = c \times TDOA_{ij}^k$$

where c is the signal propagation speed. Without loss of generality, first let anchor 1 be the transmitting anchor and assume δ_{21} is known. It will be shown later that it is not necessary to know δ_{21} for our proposed method. We can then express the range between anchor i and anchor 1 as

$$\delta_{i1} = \delta_{21} + r_{i2}^1.$$

Next, let anchor 2 be the transmitter. As $\delta_{12} = \delta_{21}$ is assumed known, we can express the range between anchor i and anchor 2 as

$$\delta_{i2} = \delta_{21} + r_{i1}^2.$$

Similarly, letting each anchor be the transmitter, we can obtain all the inter-anchor ranges using δ_{21} and relative range measurement as

$$\delta_{ij} = \delta_{j1} + r_{i1}^j = \delta_{21} + r_{j2}^1 + r_{i1}^j. \quad (6.18)$$

From (6.18) all the anchor-pair ranges share the same δ_{21} . As the value of δ_{21} does not affect the range order, it is not necessary for δ_{21} to be known. Treating δ_{21} as an arbitrary constant, we can rank all the dissimilarities.

6.4.2 Relative Anchor Map Construction

Once we have acquired the order of the inter-anchor ranges, we can then search for the configuration of points via the Kruskal's algorithm. Detailed algorithm and its implementation can be found in [109-111]. There are several points to note when applying Kruskal's algorithm. The algorithm is iterative and its output depends on the initial configuration. To increase the probability that it approaches the global minimum more closely, different initial configurations should be attempted and the configuration that yields the minimum L in (6.9) should be chosen. Besides, as ordinal MDS only preserves the order of the range measurement, the output of Kruskal's algorithm is dilated

and should be properly scaled. The scaling constant can be obtained by comparing the distance difference of the output with the measured range difference.

6.5 *Results*

For the simplicity of illustration, we assume that the anchors are co-planar for 2-D position measurement. There are two types of range errors: pseudorange error and measurement error. The former refers to the range offset due to asynchronous transmission and reception. The latter error is caused by the range measurement noise. When all the receivers are synchronized, the pseudorange error caused by the clock offset between the transmitter and receivers is a bias error common to all the anchors. In TWR, the clock drift error can be considered as a large measurement error that is unique to each anchor. We first investigate the effect of pseudorange error on the localization performance. Fig. 6.3 shows the result obtained from classical MDS and our proposed approach for 10 anchors randomly distributed in a 30m by 30m area. There is an offset of 4 m between the true range and pseudorange obtained from (6.18) with a nominal δ_{21} . The 4 m offset corresponds to 13.33 ns of clock drift that could result from a 20 ppm clock over a 1.33 ms processing time in TWR, as discussed in Section 6.3. It is chosen mainly to illustrate the detrimental effect of pseudorange error due to clock non-idealities. Fig. 6.3 shows that ordinal MDS provides a better fit than classical MDS, as the range ordering is not

affected by the offset.

Fig. 6.3 Positioning result of random anchor geometry

The effect of number of anchors on the mean squared error (MSE) of anchor position is shown in Fig. 6.4 for 10000 trials with random anchor positions within the same area and random range offset uniformly distributed between -3m and 3m. It should be noted that when there is pseudorange error, the constructed matrix of squared dissimilarities $\mathbf{D}$ may not be a valid dissimilarity matrix (e.g. due to some negative distance). In this case the classical MDS will not work. This situation is rejected and is replaced by a new pseudorange simulation. Both algorithms produce more accurate positioning result when the number of anchors increases. Ordinal MDS is sensitive to the number of anchors, as can be seen from the sharp reduction in positioning MSE when the

number of sensors increases from 4 to 10. As the number of anchors increases, the solution space for ordinal MDS shrinks rapidly and the positioning result is more accurate [113]. When the number of anchors exceeds 10, ordinal MDS consistently outperforms classical MDS, due to its robustness against pseudorange error. For 10 anchors, the positioning MSE for classical MDS and ordinal MDS is 0.08m^2 and 0.02 m^2 respectively.

Fig. 6.4 Positioning MSE for anchor localization based on classical MDS and ordinal MDS against the number of anchors. The range measurement error is 0.

For 10 randomly distributed sensors, the performance of our proposed method under random measurement error is shown in Fig. 6.5. The pseudorange

error is uniformly distributed between -3m and 3m and the measurement error is Gaussian distributed with zero mean. The standard deviation ranges from 0 to 0.3m, which is typical for UWB ranging. Although the performance of ordinal MDS is robust against pseudorange error, it deteriorates with increasing measurement error, which causes wrong ranking of the inter-anchor ranges. This degradation is especially serious when the measurement error exceeds 0.1m. However, as anchor map construction usually occurs during system calibration phase, we can afford to conduct multiple range measurements and average the result to improve the ranging accuracy into centimeter level. Hence in general we can assume that the effect of measurement error can be alleviated. Also shown in Fig. 6.5 is the positioning MSE for classical MDS without pseudorange error. As expected, when the pseudorange error can be mitigated (e.g. by perfect synchronization mechanism), classical MDS outperforms ordinal MDS.

Fig. 6.5 Positioning MSE for anchor localization based on classical MDS and ordinal MDS against range measurement error. Also shown is the positioning MSE for classical MDS without pseudorange error.

6.6 Conclusion

We studied the problem of anchor map construction in this chapter. An ordinal MDS based local anchor map construction method is also proposed. The method possesses several advantages. Its implementation is simple and low-cost. Moreover, it is more robust to pseudorange error when the number of anchors is more than 10, as it does not require the exact value of the inter-anchor range but only their relative order. The proposed method is especially

suitable for ad-hoc indoor position measurement systems. The major limitation of the proposed ordinal MDS based method is the requirement for receiver synchronization. However, synchronization of the receivers is relatively easy during the calibration phase. Moreover, for systems using hyperbolic localization architecture, the receivers are synchronous and no extra effort is needed. To summarize, the anchor position calibration techniques discussed in this chapter are summarized and compared in Table 6.1.

Table 6.1 Comparison of anchor position calibration techniques

MDS	Ranging protocol	Synchronization across anchor	Synchronization within anchor	Remarks
Classical	One way ranging	Synchronous TX and RX	Asynchronous TX and RX	Accurate; Complex/expensive implementation
Classical	Two-way ranging	Asynchronous TX and RX	Synchronous TX and RX	Low-cost implementation; Suffers clock drift
Ordinal	Rotational TDOA	Synchronous RX	Asynchronous TX;	Robust to pseudorange error; Needs sufficient number of receivers; Need receiver synchronization.

CHAPTER 7 CONCLUSION AND RECOMMENDATIONS

7.1 *Conclusion*

Location-information is important for many services and applications, and has both commercial value and practical significance. The recent emerging UWB technology enables many potential new applications capable of locating people and object in indoor environment, where conventional localization systems such as the GPS are denied. The indoor environment poses several measurement challenges and application requirement. In this thesis we have reviewed and proposed solutions to tackles these challenges. Some indoor localization applications are ad-hoc in nature and require easy set-up and flexibility rather than fixed-infrastructure deployment. These factors are also accounted for in the thesis. A summary of the thesis with contributions from each chapter is shown in Fig. 7.1. This thesis adopts the two-step localization approach, where the range measurement is first conducted to estimate the TOA. The target position is then calculated by combining the measurement result and the reference positions of the anchors. It is noteworthy that although several localization techniques have been proposed, the final choice of methods depends largely on the application scenario. Hence Fig 7.1 merely shows the general framework for localization and its relevance to each chapter in this thesis.

As shown in Fig. 7.1, the work done in Chapter 3 to Chapter 6 contributes to

the critical building blocks of an indoor localization system. Derivation of CRLB in Chapter 2 reveals that the positioning accuracy is related to both the quality of TOA estimation and the localization system architecture. To improve the quality of TOA estimation, it is important to first discard the NLOS range measurement that conveys no useful Fisher information. This is the focus of the work in Chapter 4. For the LOS range measurements that can be used for localization, resolving the direct path signal TOA from the overlapping multipath components improves the TOA estimation accuracy. Hence the high-resolution MPOC algorithm is proposed in Chapter 3. The ranging protocol determines how the estimated TOA can be converted to the target locus, which is then combined for target position calculation. Ranging protocol and position calculation are studied in Chapter 5. The elliptical localization system architecture proposed does not require anchor synchronization but is able to measure the absolute range, which has been shown to convey more information than relative range measurement. Knowledge of anchor positions is necessary as they provide the position references. The problem of anchor map construction is investigated in Chapter 6, where techniques based on MDS have been studied. The technical merits and limitations of the proposed techniques have also been summarized at the end of each chapter.

Fig. 7.1 Summary of the thesis with contributions from each chapter

The most distinguishing feature of radio propagation in indoor environment is the dense multipath. The optimum TOA detector in AWGN channel no longer performs well when the received signal comprises overlapping signal component, either due to multipath or multiple targets. It is therefore critical to resolve the overlapping signal components when accuracy is priority. In Chapter 3 of the thesis, we have demonstrated a high-resolution TOA estimation algorithm to improve system accuracy. Similar to most high-resolution algorithms, the proposed algorithm requires a local template, which is a clean copy of the transmitted signal. The channel impulse response can then be deconvolved in the frequency domain by dividing the spectrum of the received signal with the spectrum of the local template signal. Such division, however, gives rise to noise amplification problem, where the noise in the

received signal is enhanced by the spectral nulls of the local template. A kurtosis-based method is proposed to suppress the amplified noise while minimizing the impact on channel estimation due to such noise suppression. The major advantage of the proposed algorithm is that it is non-iterative, and the processing time does not depend on the number of parameters to be estimated. There is often a trade-off between the algorithm performance and complexity, and choice of a proper ranging algorithm should weigh and balance both factors.

Another non-negligible source of error in indoor localization is NLOS propagation. Detection of NLOS error will improve the system robustness. Although it is relatively easy to detect and mitigate the devastating large NLOS errors, the NLOS error that is comparable to range measurement noise is also detrimental. To deal with the ‘small NLOS error’, we have proposed a simple NLOS identification technique based on hybrid RSS and TOA information in Chapter 4. Assuming that both RSS-based and time-based range measurements are available, NLOS propagation creates divergence between these two types of measurements, and the proposed method identifies such divergence in a NP detection framework. The proposed method is also extended to hyperbolic and elliptical localization systems via receiver cooperation.

Some indoor applications require quick set-up. Deployment of anchors quickly without the tedious cable work will reduce the set-up time as well as system cost. In Chapter 5, we have developed an elliptical localization system that does not require hardware synchronization. In the proposed system, the

anchors comprise a transmitter and several receivers, and the target to be located is capable of both reception and transmission. The localization process starts with the anchor transmitter emits a UWB pulse, which is captured by the target as well as the anchor receivers. The target, upon reception of the pulse, also broadcasts a UWB pulse to the anchor receivers. By measuring the time interval between the anchor transmitted pulse and target transmitted pulse, the anchor receivers are able to deduce the sum of ranges from the anchor transmitter to the target and from the target to the anchor receiver. The range sum defines an ellipse, and in error-free case, the intersection of several such ellipses is the target location. When the ranging measurement contains error, the position calculation will optimize some objective function over the target position. The most commonly used metric is the sum of squared error. In Chapter 5, we have shown that the existing least-squares solutions for target position can be extended to the elliptical localization system.

An often overlooked issue in localization is system calibration before the target localization. In particular, it is beneficial if the anchors can calibrate their position and construct their local map to facilitate ad-hoc applications. In Chapter 6, we have presented techniques for anchor self-calibration. In particular, we focus on the MDS framework. Various MDS techniques exist, and which technique to use depends on the application scenario and given problem input. When absolute ranges between the anchors can be measured, techniques such as classical MDS can be applied to construct the anchor map. When only the relative ranges are available, the ranking of the ranges can be obtained, and ordinal MDS can be applied. The solution space of ordinal MDS

shrinks rapidly with increasing number of anchors. In fact, ordinal MDS can be more robust than classical MDS when the absolute range measurement is deteriorated by large errors such as clock drift.

7.2 *Recommendations*

The work in this thesis focuses on single target localization. Higher layer (e.g. MAC layer) implementation to support multi-user should be investigated in the future. Multi-user interference management has been extensively studied in conventional wireless communication systems. However, the unique feature of IR-UWB technology may require new techniques such as PPM and bring new perspectives.

The work is also limited to localization within a single cell. For large and scalable deployment, multiple cells are deployed. While using as many anchors as possible for target localization is optimum from the information theory perspective, there may exist a threshold such that adding additional anchor measurement only provides marginal benefit. Hence how to select the optimum set of anchors and balance the benefit and cost of additional anchor measurement should be studied.

From information theory, localization needs to exploit every piece of information. This thesis focuses on the measurement information between anchor and target. Besides that, information from target motion model and information measured among targets can also be helpful to improve the

positioning accuracy. The former involves investigation of the tracking of dynamic target. It is especially important to track the target that maneuvers. To make use of the information measured among targets, cooperative localization is needed, which is another interesting research direction. It is well-known that measurement among different users carries additional information, which results in more accurate position estimation. It seems challenging, though, to efficiently combine these measurements. Hence, practical implementation of the cooperative localization needs to be studied.

Recent advances of signal processing techniques also open other interesting research topics including high-resolution ranging by compressed sensing, secure and robust ranging and localization, and cognitive localization with machine learning. For example, high-rate sampling of UWB pulses in real time seems formidable even with current state-of-the-art ADC technology. Compressive sensing, however, only requires a few signal samples, but is able to achieve fine time resolution. Hence it is a promising direction to solve the sampling problem. Furthermore, it may also be interesting to apply compressive sensing techniques only to signals within the main UWB band where there is less noise.

While much progress has been made in the localization algorithms and techniques, development of an integrated localization system will help to realize the value of the research. Hence more focus may be placed on implementation and evaluation of various algorithms over practical localization platforms. Insight into localization hardware development is also helpful. Potential

research problems and directions may also be unveiled when there is a specific application scenario. For example, when the sensors are mounted on the human body or embedded in concrete walls, the signal propagation characteristics are different, and the channel condition has to be accounted for.

AUTHOR'S PUBLICATIONS

Journal papers:

1. **Y. Zhou**, C. L. Law, and J. Xia, "Ultra Low-Power UWB-RFID System for Precision Location-Aware Ambient Intelligence", *to be submitted*.
2. **Y. Zhou**, C. L. Law, Y. L. Guan, and F. Chin, "Cooperative NLOS identification based on RSS and TOA measurement for indoor UWB localization", *to be submitted*.
3. J. Xia, C. L. Law, **Y. Zhou**, and K. S. Koh, "3-5 GHz UWB impulse radio transmitter and receiver MMIC optimized for long range precision wireless sensor networks", *IEEE Transactions on Microwave Theory and Techniques*, vol. 58, no. 12, pp. 4040-4051, Dec 2010.
4. **Y. Zhou**, C. L. Law, Y. L. Guan, and F. Chin, "Indoor elliptical localization based on asynchronous UWB range measurement", *IEEE Transactions on Instrumentation and Measurement*, vol. 60, no. 1, pp. 248-257, Jan 2011.
5. **Y. Zhou**, Y. L. Guan, and C. L. Law, "Modified phase-only correlator with kurtosis-based amplified-noise suppression", *IEEE Transactions on Wireless Communications*, vol.9, no. 11, pp.3341-3345, Nov 2010.
6. **Y. Zhou**, C. L. Law, and F. Chin, "Construction of local anchor map for indoor position measurement system", *IEEE Transactions on Instrumentation and Measurement*, vol. 59, no. 7, pp.1986-1988, July 2010.
7. S. Hu, **Y. Zhou**, C. L. Law, and W. Dou, "Study of a uniplanar monopole antenna for passive chipless UWB-RFID localization system", *IEEE Transactions on Antennas & Propagation*, vol. 58, no. 2, pp.271-278, Feb 2010.

Journal paper 1, 3, and 7 describe the measurement hardware and prototypes.

Journal paper 5, 2, 4, and 6 correspond to the discussions in Chapter 3, 4, 5, and 6, respectively.

Conference papers:

1. **Y. Zhou**, C. L. Law, and J. Xia, “Ultra Low-Power RFID Tag with Precision Localization using IR-UWB”, *Proceedings of IEEE International Microwave Symposium (IMS)* 2011, pp. 1-4, May, 2011, Baltimore, US.
2. **Y. Zhou**, C. L. Law, J. Xia, and K. S. Koh, “Long range UWB localization system: from design to measurement”, *Proceedings of IEEE International Conference on Ultra-Wideband*, vol. 2, pp. 505-508, 20-23 Sept, 2010, Nanjing, China.
3. J. Xia, C. L. Law, K. S. Koh, **Y. Zhou**, and C. Fang, “A 3-5 GHz impulse radio UWB transceiver IC optimized for precision localization at longer ranges”, *Proceedings of IEEE International Microwave Symposium (IMS)* 2010, pp. 169-172, 23-28 May, 2010, Anaheim, US.
4. **Y. Zhou**, C. L. Law, Y. L. Guan, and F. Chin, “Localization of Passive Target Based on UWB Backscattering Range Measurement”, *Proceedings of IEEE International Conference on Ultra-Wideband*, pp. 145-149, 9-11 Sept, 2009, Vancouver, Canada.
5. **Y. Zhou**, C. L. Law, Y. L. Guan, and F. Chin, “Multi-Target UWB Passive Ranging with Local Template Uncertainty”, *Proceedings of IEEE International Conference on Ultra-Wideband*, vol.1, pp. 233-246, 10-12 Sept, 2008, Hannover, Germany.
6. **Y. Zhou**, Y. L. Guan, C. L. Law, and C. Xu, “High resolution UWB ranging based on Phase-Only Correlator”, *Proceedings of IEEE International Conference on Ultra-Wideband*, pp. 100-104, 24-26 Sept 2007, Singapore.

Conference paper 1, 2, and 3 describes the measurement hardware and prototypes.

Conference paper 4 is related to the discussion in Chapter 5.

Conference paper 5 and 6 are related to the discussion in Chapter 3.

APPENDIX A: DERIVATION OF CRLB FOR TOA ESTIMATION IN AWGN CHANNEL

For the received signal model:

$$r(t) = \sqrt{E_p} s(t - \tau) + n(t) \quad (\text{A.1})$$

where $s(t)$ has unit energy, the variance of the TOA estimation $\hat{\tau}$ is bounded by:

$$\text{Var}(\hat{\tau}) = E\{(\hat{\tau} - \tau)^2\} \geq \text{CRLB} = J(\tau)^{-1}. \quad (\text{A.2})$$

Here the amplitude of the received signal $\sqrt{E_p}$ is assumed to be known. It is straightforward to extend the derivation for unknown signal amplitude. The Fisher information $J(\tau)$ is:

$$J(\tau) = E \left[\frac{\partial^2 \Lambda(r(t); \tau)}{\partial \tau^2} \right]. \quad (\text{A.3})$$

For AWGN channel, the log-likelihood function is:

$$\Lambda(r(t); \tau) = C - \frac{1}{N_o} \int_0^T \left(r(t) - \sqrt{E_p} s(t - \tau) \right)^2 dt. \quad (\text{A.4})$$

where C is a constant independent of τ and the signal lies in the interval $[0, T]$.

The second derivative of the log-likelihood function is:

$$\frac{\partial^2 \Lambda(r(t); \tau)}{\partial \tau^2} = -\frac{2E_p}{N_o} \int_0^T \left(\frac{ds(t)}{dt} \right)^2 dt. \quad (\text{A.5})$$

Hence, the CRLB for TOA estimation is:

$$CRLB = J(\tau)^{-1} = \frac{1}{-E \left[\frac{\partial^2 \Lambda(r(t); \tau)}{\partial \tau^2} \right]} = \frac{\frac{N_o}{2}}{E_p \int_0^T \left(\frac{ds(t)}{dt} \right)^2 dt}. \quad (\text{A.6})$$

Equation (A.6) can be rewritten as:

$$CRLB = \frac{1}{2} \frac{N_o}{E_p \int_0^T s(t)^2 dt} \frac{\int_0^T s(t)^2 dt}{\int_0^T \left(\frac{ds(t)}{dt} \right)^2 dt} = \frac{1}{8\pi^2 \cdot SNR \cdot F^2} \quad (\text{A.7})$$

where the SNR is:

$$SNR = \frac{E_p \int_0^T s(t)^2 dt}{N_o} = \frac{E_p}{N_o} \quad (\text{A.8})$$

and making use of the Fourier transform, the effective bandwidth F is [18]:

$$F = \sqrt{\frac{\int_{-\infty}^{\infty} f^2 |S(f)|^2 df}{\int_{-\infty}^{\infty} |S(f)|^2 df}} = \frac{1}{2\pi} \sqrt{\frac{\int_0^T s(t)^2 dt}{\int_{t=0}^T \left(\frac{ds(t)}{dt} \right)^2 dt}}. \quad (\text{A.9})$$

Equation (A.7) gives the CRLB for TOA estimation in (2.14).

APPENDIX B: DERIVATION OF CRLB FOR TOA

ESTIMATION IN MULTIPATH CHANNEL

The model of the received signal in multipath channel is:

$$r(t) = \sum_{l=1}^L \alpha_l \cdot s(t - \tau_l) + n(t) \quad (\text{B.1})$$

where there are L signal components with amplitude α_l and TOA τ_l for the l^{th} component. Without loss of generality, we assume that $\tau_1 \leq \tau_2 \leq \dots \leq \tau_{L-1} \leq \tau_L$, and we are interest to find the TOA of the first component τ_1 . The vector of parameters to be estimated is:

$$\boldsymbol{\theta} = [\tau_1 \quad \alpha_1 \quad \tau_2 \quad \alpha_2 \quad \dots \quad \tau_L \quad \alpha_L]^T. \quad (\text{B.2})$$

If the noise is AWGN, the log-likelihood function of the received signal is:

$$\Lambda(r(t); \boldsymbol{\theta}) = C - \frac{1}{N_o} \int_0^T \left(r(t) - \sum_{l=1}^L \alpha_l s(t - \tau_l) \right)^2 dt. \quad (\text{B.3})$$

where C is a constant independent of τ and the signal lies in the interval $[0, T]$.

The $(i, j)^{th}$ entry of the FIM $\mathbf{J}(\boldsymbol{\theta})$ is given by:

$$[\mathbf{J}(\boldsymbol{\theta})]_{ij} = -E \left[\frac{\partial^2 \Lambda(r(t); \boldsymbol{\theta})}{\partial \theta_i \partial \theta_j} \right]. \quad (\text{B.4})$$

Taking the first derivative of $\Lambda(r(t); \boldsymbol{\theta})$ with respect to τ_i and α_i yields:

$$\begin{aligned}
\frac{\partial \Lambda(r(t); \boldsymbol{\theta})}{\partial \tau_i} &= \frac{2\alpha_i}{N_o} \int_0^T \left(r(t) - \sum_{l=1}^L \alpha_l s(t-\tau_l) \right) \frac{\partial s(t-\tau_i)}{\partial \tau_i} dt \\
\frac{\partial \Lambda(r(t); \boldsymbol{\theta})}{\partial \alpha_i} &= \frac{2}{N_o} \int_0^T \left(r(t) - \sum_{l=1}^L \alpha_l s(t-\tau_l) \right) s(t-\tau_i) dt
\end{aligned} \tag{B.5}$$

Again, taking the derivative of (B.4) and (B.5) with respect to τ_i and α_i yields:

$$\begin{aligned}
\frac{\partial^2 \Lambda(r(t); \boldsymbol{\theta})}{\partial \tau_i \partial \tau_j} &= -\frac{2}{N_o} \alpha_i \alpha_j \int_0^T \frac{\partial s(t-\tau_i)}{\partial \tau_i} \frac{\partial s(t-\tau_j)}{\partial \tau_j} dt \\
&= -\frac{2}{N_o} \alpha_i \alpha_j \langle \dot{s}_i, \dot{s}_j \rangle \\
\frac{\partial^2 \Lambda(r(t); \boldsymbol{\theta})}{\partial \alpha_i \partial \tau_j} &= \frac{\partial^2 \Lambda(r(t); \boldsymbol{\theta})}{\partial \tau_j \partial \alpha_i} = -\frac{2}{N_o} \alpha_j \int_0^T s(t-\tau_i) \frac{\partial s(t-\tau_j)}{\partial \tau_j} dt \\
&= -\frac{2}{N_o} \alpha_j \langle s_i, \dot{s}_j \rangle \\
\frac{\partial^2 \Lambda(r(t); \boldsymbol{\theta})}{\partial \alpha_i \partial \alpha_j} &= -\frac{2}{N_o} \int_0^T s(t-\tau_i) s(t-\tau_j) dt = -\frac{2}{N_o} \langle s_i, s_j \rangle
\end{aligned} \tag{B.6}$$

where $\langle f, g \rangle = \int_0^T f(t)g(t)dt$, $s_i = s(t-\tau_i)$, and $\dot{s}_i = \frac{\partial s(t-\tau_i)}{\partial \tau_i}$. It can be

observed from (B.6) that when the received signal components are non-overlapping,

$$\langle \dot{s}_i, \dot{s}_j \rangle = \langle s_i, \dot{s}_j \rangle = \langle s_i, s_j \rangle = 0 \tag{B.7}$$

and the FIM is of the form:

$$\mathbf{J}(\boldsymbol{\theta}) = \begin{bmatrix} \mathbf{J}_1 & 0 & \cdots & 0 \\ 0 & \mathbf{J}_2 & & \vdots \\ \vdots & & \ddots & 0 \\ 0 & \cdots & 0 & \mathbf{J}_L \end{bmatrix}. \tag{B.8}$$

In other words, the FIM for each signal component (each 2×2 block matrix in the diagonal) is decoupled from one another if the signal components are non-overlapping. Hence the TOA estimation for the direct signal component is not affected by the subsequent multipath components if the multipath signal is well separated from the direct signal,

When the direct signal overlaps with the subsequent multipath signal components, the FIM is no longer a block diagonal form and has the form:

$$\mathbf{J}(\boldsymbol{\theta}) = \begin{bmatrix} \mathbf{J}_1 & \boldsymbol{\rho}^T \\ \boldsymbol{\rho} & \mathbf{J}_M \end{bmatrix} \quad (\text{B.9})$$

where $\boldsymbol{\rho}$ is the correlation matrix that depends on the signal waveform and the amount of overlapping. The CRLB for TOA estimation is now:

$$\text{CRLB} = [\mathbf{J}(\boldsymbol{\theta})]_{2 \times 2}^{-1} = [\mathbf{J}_1 - \boldsymbol{\rho}^T \mathbf{J}_M \boldsymbol{\rho}]^{-1} \geq \mathbf{J}_1^{-1}. \quad (\text{B.10})$$

Hence, the overlapping multipath interferes with the direct signal component and increases the CRLB.

APPENDIX C: EFFECT OF A COMMON UNKNOWN BIAS IN RANGE MEASUREMENT

We will show in this Appendix that if there is a common unknown bias in the range measurement, the absolute range based localization degenerates to relative range based localization. The bias could be due to NLOS propagation in anchor transmitter – target path, or the clock bias between target and anchors. The range measurement is no longer absolute when the internal delay of the target is treated as an unknown parameter to be estimated instead of being obtained from calibration. Neglecting DC signal TOA estimation error, the measured range at the i^{th} receiver is

$$r_i = \|\mathbf{p} - \mathbf{p}_t\| + \|\mathbf{p} - \mathbf{p}_i\| + b + n_i = R_i + n_i \quad (\text{C.1})$$

where $b = c \times \Gamma$ represents the distance uncertainty due to target internal delay Γ . The parameter vector to be estimated in this case is

$\boldsymbol{\theta} = [\mathbf{p}^T \ b]^T$. Letting $\mathbf{G} = \frac{\partial \mathbf{R}}{\partial \boldsymbol{\theta}} = [\mathbf{F} \ \mathbf{1}_M]$, under Gaussian error assumption, the

FIM is

$$\mathbf{J}_{delay} = \mathbf{G}^T \mathbf{C}_{GS}^{-1} \mathbf{G} = \begin{bmatrix} \mathbf{F}^T \mathbf{C}_{GS}^{-1} \mathbf{F} & \mathbf{F}^T \mathbf{C}_{GS}^{-1} \mathbf{1}_M \\ \mathbf{1}_M^T \mathbf{C}_{GS}^{-1} \mathbf{F} & \mathbf{1}_M^T \mathbf{C}_{GS}^{-1} \mathbf{1}_M \end{bmatrix}. \quad (\text{C.2})$$

The positioning CRLB corresponds to the 2×2 sub-matrix on the top left corner of $\mathbf{J}_{delay}^{-1}$. From matrix inversion formula [43], the equivalent FIM for position

estimation is

$$\mathbf{J}_{delay-p} = \left(\mathbf{F}^T \mathbf{C}_{GS}^{-1} \mathbf{F} - \frac{\mathbf{F}^T \mathbf{C}_{GS}^{-1} \mathbf{1}_M \mathbf{1}_M^T \mathbf{C}_{GS}^{-1} \mathbf{F}}{\mathbf{1}_M^T \mathbf{C}_{GS}^{-1} \mathbf{1}_M} \right) \quad (\text{C.3})$$

and is equal to the relative positioning FIM $\mathbf{J}_{RS}$ in (6.11).

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