Direction finding for UWB RFID system in dense cluttered environments

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**Direction Finding for UWB RFID System in
Dense Cluttered Environments**

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A thesis submitted to the Nanyang Technological University
in fulfillment of the requirement for the degree of
Doctor of Philosophy

2014

Statement of Originality

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

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Date

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LUO Yanjia

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Summary

Source direction finding with an antenna array is a major topic in radar-related applications. Typically, an incident radio wave can be detected by measuring the difference of arrival time or phase between spatially spaced sensors of the antenna array. It becomes challenging due to abundant multipath and obstacles in dense cluttered environments, such as enclosed areas, tunnels or under-ground. Ultra-wide band (UWB) radio frequency identification (RFID) system provides a promising solution in these global-positioning-system (GPS-) denied environments due to a number of advantages such as low duty cycle, multipath immunity and low cost. However, the system susceptibility to dense cluttered environments is not well studied, and the potential of UWB signals for direction finding is not well investigated.

In this thesis, the performance limits in dense cluttered environments are firstly studied in detail. A channel model of plane waves from far-field reflectors or scatterers superimposed with near-field interferences is proposed, and the Cramér-Rao bounds for ranging and direction finding are derived to analyze the channel effects. Based on the insights into path-overlapping effects in the first cluster, a joint time-of-arrival (TOA) and angle-of-arrival (AOA) estimator with improved performance

is then designed. Secondly, various channel effects, including the signal-to-noise ratio (SNR), the near-field perturbation level, the far-field reflector spatial spacing and uncertain number of plane waves, on the robustness of UWB RFID system for direction finding are addressed. A robust solution for UWB impulse radio signals employing the alternating projection (AP) strategy in the presence of interference is investigated. Detection of the number of planewaves prior to AOA estimation is considered to improve the processing efficiency of AP strategy. Finally, channel identification that includes the line-of-sight (LOS), the non-line-of-sight (NLOS) with detected direct path (DDP) and the NLOS with undetected direct path (UDP) is studied. Measurements of three channel features are modeled as the log-normal random variables with site-specific distribution parameters. Joint log-likelihood ratio test with an empirical threshold selection is designed to make the decision. Accurate AOA estimation is helpful to measure the rise time, the kurtosis of signal envelope and the excess attenuation of the first detected path.

Table of Contents

Statement of Originality	i
Acknowledgements	ii
Summary	iii
List of Figures	ix
List of Tables	ix
List of Abbreviations	xiii
List of Symbols	xvii
1 Introduction	1
1.1 Background	1
1.2 Motivation	7
1.3 Objectives	10
1.4 Major Contributions of the Thesis	11
1.5 Organization of the Thesis	13

2	Literature Review	15
2.1	Introduction	15
2.2	Channel Estimation Methods	18
2.2.1	TOA Estimation	19
2.2.2	AOA Estimation	30
2.2.3	RSS Estimation	36
2.3	UWB Channel Characterization	37
2.3.1	Frequency-Dependent Path Loss	37
2.3.2	Power Delay Profile	38
2.3.3	NLOS Problems	39
2.4	AOA Resolution	40
3	Indoor Positioning in Presence of Dense Multipath with Path Over-	
	lapping	42
3.1	Introduction	42
3.2	Theoretical Bound Derivation	44
3.2.1	Well-separated LOS Path	50
3.2.2	Overlapped LOS Path	52
3.3	Joint TOA and AOA Estimation of the Direct Path	55
3.4	Simulation Results	63
3.5	Measurement Results	70
3.6	Conclusion	75

4	Robust Ultra-wideband Direction Finding in Dense Cluttered Environments	76
4.1	Introduction	76
4.2	System Model	80
4.3	UWB Plane Waves Detection	85
4.4	AOA Estimation	88
4.5	Simulation Scenarios	95
4.5.1	Effects of SNR	98
4.5.2	Effects of Near-field Perturbations	100
4.5.3	Effects of Far-field Reflector Spatial Spacing	101
4.5.4	Effects of Number of Interfering Plane Waves	103
4.5.5	Effects on Detection Performance	104
4.6	Concluding Remarks	106
5	NLOS Identification Using Empirical Threshold Selection for UWB Indoor Positioning	108
5.1	Introduction	108
5.2	Channel Estimation	111
5.3	Channel Detection	121
5.4	Detection Performance	129
5.5	Concluding Remarks	130
6	Conclusions and Recommendations	132
6.1	Conclusions	132

6.2 Recommendations for Future Work	133
Author's Publications	135
Bibliography	137
Appendix A Derivation of the Zero Entries in Eqn (3.10)	156
Appendix B Derivation of Multipath Gain in Eqn(3.13)	158
Appendix C Derivation of Lower Error Bound of ADOA	158

List of Figures

1.1	Block diagram of pulse radar.	3
1.2	Architecture of GNSS receivers.	4
1.3	EIRP limits of UWB radio.	7
2.1	General framework of UWB RFID navigation systems.	16
2.2	Block diagram of RFID tag and reader.	17
2.3	Positioning via RSS/TOA, TDOA and AOA.	17
2.4	Multipath propagation of UWB radio.	21
2.5	Low sampling scheme based on UWB signal envelope.	22
2.6	Input and output of low-sampling scheme.	23
2.7	Energy detector for TOA estimation.	24
2.8	TOA estimation using energy detector.	25
2.9	Matched filter for TOA estimation.	26
2.10	Cross correlator with dirty template.	29
2.11	Cross correlation between two consecutive symbols.	29
2.12	Direction finding with an antenna array.	31
2.13	CLEAN Beam-former contour.	34

2.14	An example of sub-arrays selection.	35
2.15	Power delay profile of UWB signals.	39
3.1	Antenna array: ULA and UAA.	51
3.2	Received signals at a 4-element UAA.	56
3.3	Beam-former output in normalized magnitude.	57
3.4	SNR effects on AOA estimations.	64
3.5	SNR effects on TOA estimations.	65
3.6	AOA errors versus path arrival rates.	67
3.7	TOA errors versus path arrival rates.	68
3.8	Measurement instruments setup.	72
3.9	AOA error versus range in real measurement.	73
3.10	TOA error versus range in real measurement.	74
4.1	Propagation model in dense cluttered environments.	80
4.2	Iterative processes of sensor CLEAN. The signal beams $B^{(0)}$, $B^{(1)}$, $B^{(2)}$ and $B^{(3)}$ are respectively shown in the top left, top right, bottom left and bottom right subplots.	87
4.3	(a) The AOA spectrum for SNR=13dB (solid line) and SNR=14dB (dashed line). (b) Received signal and the matched filter output for SNR=30dB.	93
4.4	Near-field multipath captured energy.	98
4.5	Standard deviation of ADOA $\Delta\theta$ versus SNR in a two closely spaced plane waves scenario free of near-field perturbations.	99

4.6	Standard deviation of AOA θ_1 versus SNR in a two closely spaced plane waves scenario free of near-field perturbations.	100
4.7	Standard deviation of ADOA and AOA versus near-field perturbation level in a dense cluttered scenario with SNR=25dB.	102
4.8	Standard deviation of ADOA and AOA versus temporal spacing between plane waves in a scenario of SNR=25dB and $\alpha=0.3$	103
4.9	AOA resolution of multiple coherent plane waves.	105
4.10	Channel effects on detection probability and false alarm.	106
5.1	The first detected path in LOS scenario.	118
5.2	The first detected path in NLOS with DDP scenario.	120
5.3	The first detected path in NLOS with UDP scenario.	121
5.4	CDFs of TOA and AOA errors.	124
5.5	CDF of rise time t_{rise} for $\mathcal{H}_i$	125
5.6	CDF of the first detected path excess attenuation $ \Delta a_1 $ for $\mathcal{H}_i$	126
5.7	CDF of kurtosis κ for $\mathcal{H}_i$	127
5.8	Threshold decision based on LLR test.	128

List of Tables

3.1	The multipath number in the first cluster versus path arrival rate. . .	66
3.2	Channel profile estimated in the measurement environment.	71
4.1	Channel Delay Spread Corresponding to $\Delta\tau_{min}$ and α	97
5.1	Simulation Parameters.	122
5.2	Log-normal Distribution Parameter for Channel Recognition.	125
5.3	Detection probability $P\{\mathcal{D} = \mathcal{H}_i \mathcal{H}_j\}$ using $\{t_{rise}\}$ (1^{st} row), $\{ \Delta a_1 \}$ (2^{nd} row), $\{\kappa\}$ (3^{rd} row), $\{t_{rise}, \Delta a_1 \}$ (4^{th} row), $\{t_{rise}, \kappa\}$ (5^{th} row), $\{ \Delta a_1 , \kappa\}$ (6^{th} row) and $\{t_{rise}, \Delta a_1 , \kappa\}$ (7^{th} row).	130

List of Abbreviations

Acronyms

ADC	Analog digital converter
ADOA	Angle difference of arrival
AOA	Angle of arrival
AP	Alternating projection
AWGN	Additive white Gaussian noise
CD	Coordinate descent
CIR	Channel impulse response
CML	Conditional maximum likelihood
CRB	Cramer-Rao bound
DDP	Detected direct path
DS-UWB	Direct sequence ultra-wide band
ED	Energy detection
EFIM	Equivalent Fisher matrix
EIRP	Effective isotropic radiated power
EM	Expectation maximization

ESPRIT	Estimation of signal parameters via rotation invariance techniques
FCC	Federal communications commission
FIM	Fisher matrix
GDOP	Geometrical dilution of precision
GML	Generalized maximum likelihood
GNSS	Global navigation satellite system
GPS	Global positioning system
IDA	Infocomm development authority of Singapore
IF	Intermediate frequency
IQML	Iterative quadratic maximum likelihood
IR	Impulse radio
ISI	Inter-symbol interference
JBSF	Jump back and search forward
LLT	Log-likelihood ratio test
LOS	Line of sight
LRT	Likelihood ratio test
LS	Least squares
MAP	Maximum a-posteriori
MF	Matched filter
ML	Maximum likelihood
MPCs	Multipath components
MUSIC	Multiple signal classification

MVDR	Minimum variance distortion-less response
NLOS	Non line of sight
<i>pdf</i>	Probability density function
PHY	Physical layer
PL	Path loss
PRI	Pulse repetitive interval
RF	Radio frequency
RFID	Radio frequency identification
RMSE	Root mean square error
RSS	Received signal strength
RSSI	Received signal strength indication
SBS MC	Serial backward search for multiple clusters
SBS SC	Serial backward search for single cluster
SF	Subspace fitting
SNR	Signal to noise ratio
TDOA	Time difference of arrival
TH-UWB	Time hopping ultra-wide band
TNR	Threshold to noise ratio
TOA	Time of arrival
UCA	Uniform circular array
UDP	Undetected direct path
ULA	Uniform linear array

UWB	Ultra-wide band
WLAN	Wireless local area network
WPAN	Wireless personal area network
WSF	Weighted subspace fitting
WSN	Wireless sensor network
ZZLB	Ziv-Zakai lower bound

List of Symbols

$E(\cdot)$	Expectation operation
$\text{var}(\cdot)$	Variance operation
$(\cdot)^T$	Matrix transposition
$(\cdot)^H$	Matrix conjugate transposition
$\text{Cov}(\cdot)$	Convolution operation
$\mathcal{F}(\cdot)$	Fast Fourier transform
$\mathcal{F}^{-1}(\cdot)$	Inverse Fourier transform
$\text{tr}(\cdot)$	Matrix trace
$(\cdot)^\dagger$	Moore-Penrose pseudo matrix inverse
$\ \cdot\ $	Euclidean norm
$\det(\cdot)$	Matrix determinant
$\text{diag}(\cdot)$	Diagonal matrix

Chapter 1

Introduction

1.1 Background

Since radars were first introduced to the military usage in World War II, various positioning and navigation systems with radio or satellite have been deployed or scheduled to be operational all over the world. In a radar system [1], the radar antenna transmits electromagnetic energy into the space and listens to the echo reflected from aircrafts within the radar range. Then the range and direction measurements can be used by the navigator to monitor and control the aircraft path. Sonar systems [2] having much in common with radars can track vessels and submarines using acoustic signals. A block diagram of typical pulse radar [1] is taken as an example in Fig. 1.1.

In Fig. 1.1, the phased array [1–3] can be employed to acquire the effective beam pattern in desired direction. The timer with modulator is used to trigger pulses at the pulse repetitive frequency that can be clock-synchronized with the indicator. The radio frequency (RF) signal generated by transmitter is radiated into space by the antenna. The duplexer is employed to provide sufficient isolation between transmitter

1.1 Background

and receiver while permitting them to share a common antenna [1]. The received RF signal is converted into the intermediate frequency (IF) band and amplified, and then characteristics related to the reflection objects can be extracted and shown in the indicator. The commonly used techniques to detect whether an echo signal is present or not in the noise background include the matched filter, the correlation receiver and the likelihood ratio test [4]. Three basic characteristics concerning the target object are range, velocity and angle-of-arrival (AOA) in elevation and azimuth. The range is usually calculated by measuring the signal propagation time in space Δt .

$$R = \frac{c \cdot \Delta t}{2} \quad (1.1)$$

The velocity v can be calculated straightforwardly using the change of continuous range observation divided by the time interval, or can be estimated by measuring the frequency shift Δf due to the Doppler effects [5],

$$\Delta f = \frac{2v}{c} f_0 \quad (1.2)$$

where f_0 is emitted frequency at the transmitter, and c is the speed of light. The AOA is indicated simply by the maximum amplitude from beam-forming but with directional ambiguity due to the beam width [6]. They can also be treated as unknown parameters that are solved by maximum likelihood estimation based on the statistical model of observed signals [6]. Compared to radars, sonar systems need to consider the propagation of acoustic signal under the water surface that is much

1.1 Background

more complicated than the propagation of RF signal in space [2]. These propagation characteristics have a major influence on the design of sonar systems.

Figure 1.1: Block diagram of pulse radar.

Global navigation satellite system (GNSS) plays important roles to provide geographic coordinates for civilian usage. It allows autonomous positioning and tracking accomplished by a small receiver end, and is widely deployed in cellular networks and in outdoor applications, such as Emergency-911 (E-911) services, traffic control, personal navigation and aviation navigation. Current systems in operation or in development include global positioning system (GPS) of United States, GLONASS of Russian, COMPASS of China and Galileo of European [7]. Generally, the architecture of GNSS consists of three segments: control stations, the satellites constellation and GNSS receivers. A GPS receiver can correct its clock and localize itself in longitude, latitude and altitude with the aid of four or more satellites. The positioning principle is based on the estimation of propagation time Δt_i at the GNSS receiver [8, 9],

$$c \cdot (\Delta t_i + \delta t) = \sqrt{(x - x_i)^2 + (y - y_i)^2 + (z - z_i)^2} \quad (1.3)$$

1.1 Background

where the four variables, i.e., the GNSS user position (x, y, z) and small difference δt between the satellite clock and the receiver clock, can be solved using at least four equations. A brief of the GNSS receiver architecture [9] is shown in Fig. 1.2.

In the first part, the received RF signal at the antenna is amplified, filtered and down-converted by the RF front, and is then digitalized by the analog-to-digital converter (ADC). In the second part, visible satellites can be targeted by estimating and tracking the code phase and the carrier frequency. In the third part, the navigation data is decoded and clock-synchronized, and the ranging is processed to find the receiver's own position. However, the navigation performance of GNSS users is limited due to many error sources such as multipath and signal masking, especially in dense urban areas or indoor environments [10, 11]. Because the GNSS transmission characteristics are known in public, the potential jamming by an adversary limits its usage in military applications [11]. Besides, the GNSS performance might suffer from the problem of poor geometrical dilution of precision (GDOP) [9].

Figure 1.2: Architecture of GNSS receivers.

Wireless local area network (WLAN), wireless sensor network (WSN) and wire-

1.1 Background

less personal area network (WPAN) are a few radio techniques used for navigation in indoor applications. The indoor applications often have higher requirements of accuracy and precision than the outdoor applications that may range from the order of meters to the order of centimeters [8, 12]. Moreover, the propagation characteristics in indoor environments are different from those in outdoor environments due to rich multipath and obstructions. Similar to cellular network, WLAN can provide diverse services for local users through base stations, such as internet access, location-sensitive advertisements and guided tours [13]. Received signal strength indication (RSSI) used in IEEE 802.11 implementations (that is a set of physical layers for WLAN) is not suitable for accurate sub-meter level positioning. WPAN for short-range purposes is used to interconnect personal devices around individual workspace and body area with accuracy requirements from a few centimeters to a few meters. WSN is developed to detect sensor data (e.g., location information, temperature, pressure, animals and human presence, etc.), and usually is a multi-hop network with numerous sensor nodes [14]. Detection of low data-rate signals in a short-range can be implemented at each sensor node. Ultra-wideband (UWB) impulse radio is considered as a promising alternative physical layer for WPAN and WSN due to relative immunity to multipath fading, material-penetration capability, and low duty cycle [15, 16]. UWB is defined as a radio technology with a -10dB bandwidth ($B_{-10\text{dB}} = f_H - f_L$) of at least 500MHz, or a fractional bandwidth ($B_{\text{frac}} = 2B_{-10\text{dB}}/(f_H + f_L)$) exceeding 20%. In February 2002, U.S. Federal Communications Commission (FCC) authorized the unlicensed use of UWB in the

frequency band from 3.1 to 10.6 GHz [17]. In December 2007, the Infocomm Development Authority (IDA) of Singapore specified the technical requirements of UWB devices [18]. According to FCC and IDA, effective isotropic radiated power (EIRP) of UWB systems indicated by power spectral density is limited by both the mean emission mask in Fig. 1.3 and the peak emission level of 0dBm/50MHz. Compared to narrowband systems, UWB applications benefiting from large bandwidths can significantly improve the resolution of channel characteristics in dense cluttered environments. This feature makes UWB highly suitable for navigation and imaging in short and medium range. UWB radio-frequency identification (RFID) systems allow a tag that is attached to an object to be detected and tracked by a reader, where a passive reader receives the UWB signal transmitted from an active tag, or an active reader triggers UWB pulses and receives authentication responses from a passive tag [19, 20]. It is useful in military surveillance, assets management and rescue in emergency.

Tracking performance or positioning accuracy is mainly concerned with the channel state recognition, such as whether a line-of-sight (LOS) path exists, and the precision of channel parameter estimations [12]. The commonly used parameters for ranging are received signal strength (RSS) and time-of-arrival (TOA) of the direct path, while angle-of-arrival (AOA) of the direct path is for direction finding. The estimation performances can be analyzed theoretically by the estimation error bounds, such as Cramér-Rao bound (CRB) and Ziv-Zakai lower bound (ZZLB), and be evaluated by Monte Carlo experiments or by the mean measurement error in a real

Figure 1.3: EIRP limits of UWB radio.

system. Channel state recognition can make decision on the switch among different estimators of complexities. The recognition performance is usually indicated by the probability of correct detection or wrong detection.

1.2 Motivation

There is an increasing demand for reliable navigation systems in indoor applications. In August 2007, direct sequence UWB was included into low-rate alternative physical layer for WPAN according to IEEE 802.15.4a [21]. UWB channel modeling helps to gain insight into the system design, and is useful to set effective positioning tech-

niques. UWB channel measurement campaigns were conducted in the frequency band from 2 to 10GHz to implement statistical characterization of UWB channels with site-specific key channel parameters [22]. Different from in outdoor environments, the signal propagation in indoor environments experiences clustering of multipath arrivals, obstructed LOS, traversal delay through materials and distorted signal shape. Compared to the flat fading in narrowband systems, the frequency-selective fading in ultra-wideband systems [12] is due to antenna efficiencies as well as frequency-dependence properties of reflecting and scattering materials. These channel effects in dense cluttered environments result in a major difference from navigation systems design in outdoors.

Firstly, the positioning performance degradation due to multipath-induced errors has not been well investigated. Most studies are under assumption that the multipath components (MPCs) absolutely have no impact on TOA and AOA estimations of the LOS path. This assumption is impractical when the LOS path is not clearly resolved due to the clustering of MPC closely-spaced with the direct path, especially for received signals in indoor environments. The positioning limits can be theoretically analyzed by the CRB of TOA and AOA estimations based on UWB antenna array responses. But there are few works on how these estimation errors are induced by MPC and what method can be used to mitigate these errors.

Secondly, conventional techniques used respectively for TOA-based or RSS-based ranging in GPS receivers cannot reach the accuracy requirements in most indoor applications. TOA-based ranging is preferred for UWB systems because the large

bandwidth is effective to increase the temporal accuracies. Maximum likelihood estimator (MLE) is typically used to approximate to the best performance suggested in the CRB, but usually suffers from high computational cost due to a high number of unknown parameters. A low-complex implementation of MLE is expected in practice.

Thirdly, direction finding based on narrowband array processing techniques in radar receivers are ineffective to UWB systems. The spatial and temporal resolution of beam-forming method is constrained by the beam width of the main lobe, and is susceptible to the multipath fading in dense cluttered environments. There are few studies on the robustness of source direction finding in a realistic channel model including coherent multiple plane waves and multipath rays due to far-field and near-field scattering or reflecting. Moreover, parameters estimation and detection with UWB antenna array needs to be developed and integrated into optimum array processing theory.

Finally, channel pattern recognition can be used to differentiate the non-line-of-sight (NLOS) from the LOS scenarios. NLOS estimation bias as a major error source in dense cluttered environments should be mitigated to improve the positioning efficiency. Generally, with the aid of a priori knowledge from the training, Neyman-Pearson lemma can be designed to detect the channel state. Complete channel pattern recognition consists of the channel features extraction, the probability density function (*pdf*) estimation of channel features, a priori knowledge of empirical threshold from the training, and the numerical analysis of correct and wrong recognition. However, most design experiments of channel pattern recognition using

UWB signals are incomplete.

From the above discussions, it is understood that although navigation techniques in outdoors using narrowband signals have been developed for a few decades, the design theory of UWB radio for indoor navigation is still new and not well established. There are still many challenges from the channel complications and the accuracy requirement in the design of ranging and direction finding algorithms. This thesis aims to develop error-bound theory and channel recognition criterion for UWB indoor positioning, and design some ranging and direction finding algorithms that can adapt to the harsh environments, which is the main motivation of this Ph.D. thesis.

1.3 Objectives

In regarding to the aforementioned motivations, the following tasks are envisaged.

- i*) A comprehensive literature review is conducted about state-of-the-art ranging and direction finding techniques using narrowband and wideband signals. IEEE 802.15.4a channel characteristics are summarized to explore their effects on the UWB system design.
- ii*) For the purpose of performance improvement, a theoretical analysis about the positioning errors in dense cluttered environments makes useful suggestions on what measures are more effective. Given the closed-form expressions of the positioning errors, the performance degradations due to transmitted signal characteristics, antenna geometry of receiver array, path-overlapping in the first

cluster, and received signal-to-noise ratio (SNR) are clarified.

- iii*) Based on the theoretical derivation of positioning error bounds, we proceed to mitigate the beam diffusion due to the bias in TOA and AOA induced by the clustering of multipath arrivals. Multipath-aided acquisition for the steering beam is designed to approximate to the theoretical error bound from derivations. Low computational cost can benefit from the usage of in-band energy spectrum, and spatial and temporal resolution of UWB beams.
- iv*) Alternating projection as a well-known MLE strategy for direction finding of narrowband sources can be extended to the received UWB signals in dense cluttered environments. The robustness to dense far-field coherent sources spacing, near-field perturbation, an uncertain number of plane waves and low SNR is comprehensively studied.
- v*) The NLOS scenario with detected direct path (DDP) or undetected direct path (UDP) is identified from the LOS scenario by a joint likelihood ratio test (LLT) of key channel parameters. The empirical threshold used for LLT is obtained from channel pattern training.

1.4 Major Contributions of the Thesis

The outcomes of our research result in multi-fold original contributions and developments over the existing works. They are outlined as follows.

- i*) The CRBs of TOA and AOA estimations are first jointly derived from the *pdf*

of received signals at a UWB planar antenna array. We extend the multipath channel model to directional plane-wave model with near-field perturbations. New insights into the effects of the antenna number within array and incident directions of plane waves overlapped with the direct path plane-wave are thus gained. The steering beam that is diffused by path-overlapping effects can raise the resolution ambiguities in AOA and TOA. A joint AOA and TOA least-squares estimator is proposed to efficiently mitigate this path-overlapping effects using multipath-aided acquisition. The computational load is lowered using in-band spectral samples and accurate initial estimations. Accuracy improvement for IEEE 802.15.4a CM3 channel model is 2.4cm and 13.1° respectively, while the error in a realistic environment is controlled within 0.5m² in a measured range of 20m.

- ii*) A robust UWB direction finding solution in dense cluttered environments is designed. The efficiency is improved by introducing detection of a number of plane-wave sources prior to AOA estimation. This saves computational time in the joint AOA detection and estimation processing. Robustness to multiple correlated plane waves and near-field perturbations is solved using a novel alternating projection strategy, and is demonstrated in various densely cluttered indoor environments. High angular resolution achieved by this strategy leads to temporal-separated plane waves, which greatly simplify the TOA estimation by a matched filter. Monte Carlo experiments show that the mean AOA error is 2.32° while the angular resolution error is 6.31° when the sampling rate is

20GHz.

iii) Channel characteristics in dense cluttered environments are extracted using ranging and direction finding techniques. Three features consisting of the channel rise time, the first detected path attenuation and the kurtosis of received signal shape are chosen to differentiate three scenarios: LOS, NLOS with UDP, and NLOS with DDP. Training is used to show that each feature can be modeled as the log-normal random variable with distribution parameters dependent on the site-specific environment. Empirical threshold used for the Neyman-Pearson lemma can be also generated by minimizing the detection error probability in the training phase. The performance based on 10000 times shows that the correct detection probability in LOS scenarios achieves 93.1%, while those in NLOS scenarios are 71.9% for UDP and 70.1% for DDP. Compared to the existing works, our innovative research integrates the processes of channel characteristics extraction and threshold decision making, because the direct use of channel impulse responses (CIR) is impractical for a site-specific environment most of the time.

1.5 Organization of the Thesis

The rest of the thesis is organized as follows. Chapter 2 presents a literature review of the commonly-used techniques for direction finding and TOA-based or RSS-based ranging. A brief description of IEEE 802.15.4a channel model is also included.

In Chapter 3, the closed-form of Fisher information matrix (FIM) is derived, and

the CRB is analyzed from the perspective of joint TOA and AOA estimations. A least-squares estimator (LSE) for joint TOA and AOA with multipath-aided acquisition is generalized from a self-steering beam-former to mitigate the beam diffusion due to the path-overlapping effects in dense cluttered environments. A low-complex implementation for this LSE is proposed.

In Chapter 4, an extended alternating projection (AP) strategy is used to improve the system robustness to coherent multiple plane waves and multipath rays. Detection before estimation is introduced to improve the AP processing efficiency.

In Chapter 5, channel pattern recognition is designed for the purpose of NLOS error exclusion from the positioning system. Log likelihood ratio test is formulated to make decisions among three channel states. A complete design from channel estimation, channel training to channel classification is presented.

Chapter 6 concludes our work and gives advices to the further study.

Chapter 2

Literature Review

2.1 Introduction

In a navigation system, a mobile or a target can be aware of its relative position with respect to the absolute positions of anchors by building channel links between the transmitter and the receiver. UWB RFID system is a promising physical layers (PHY) solution for WSN and WPAN in dense cluttered environments due to its efficiency to model the channel characteristics. The general framework of UWB RFID navigation systems is introduced as shown in Fig. 2.1 [23,24]. In framework I, each anchor that receives the channel response of the UWB signal transmitted at the target can detect the channel state and estimate the TOA, AOA or RSS information if the LOS path is detected in the channel. Then the target can be positioned and tracked by the cooperation among anchors. In framework II, the anchor serves as the beacon that transmits a coded UWB signal, such as time-hopping UWB (TH-UWB) or direct sequence UWB (DS-UWB). The target receives and decodes the signal from each beacon, and respectively estimates the TOA, AOA or RSS information with reference to each beacon for self-navigation. The block diagram of active tag

2.1 Introduction

and reader for UWB RFID systems is presented in Fig. 2.2 [25]. The active tag consists of a microcontroller that generates the tag identity code and clock signal, a transmitter chip and a UWB antenna. At the reader side, the signal passes through the UWB antenna, out-of-band filtering, low noise amplifier, coherent detection, baseband amplifier, and analog-to-digital converter, and then the sampled digitalized data is sent to a computer for signal processing. This transceiver circuitry for UWB RFID systems is low-cost. The power consumption is very low due to low duty cycle of the UWB transmitter. Since the unlicensed use of UWB radios is allowed but subject to the peak emission limits 0dBm/50MHz according to FCC, UWB having negligible interference with other wireless devices can coexist. Therefore, the unlicensed usage and the low-cost, low-power implementations make UWB a good candidate for short and medium range applications.

Figure 2.1: General framework of UWB RFID navigation systems.

In general, TOA, AOA and RSS from channel estimations are fundamental and common techniques used for various navigation systems. TOA- or RSS- based trilat-

Figure 2.2: Block diagram of RFID tag and reader.

eration, time-difference-of-arrival (TDOA)-based hyperbola, AOA- based triangulation, the hybrid or least-squares positioning implementation can be further employed by diverse localization technologies, as shown in Fig. 2.3 [12]. If multiple or continuous channel observations over a period of time are available, the position can be tracked using Kalman filters, particle filters and grid-based estimators [26,27].

Figure 2.3: Positioning via RSS/TOA, TDOA and AOA.

Positioning in dense cluttered environments is challenging due to dense reflect-

ing, scattering and obstacles, which makes many narrowband approaches ineffective. Unlike narrowband radio signals, UWB has a wide spectrum that results in the through-wall capability and a fine temporal resolution [28]. Therefore, UWB positioning in indoor environments attracts numerous interests. In this chapter, a thorough literature review of channel estimation methods is carried out first, and then the UWB channel characteristics are summarized.

2.2 Channel Estimation Methods

As discussed earlier, a mobile in a wireless network can be positioned based on TOA, AOA and RSS estimations of channel measurements. Benefiting from UWB fine temporal resolution due to large bandwidth, most multipath clusters can be resolved. As a result, the ranging accuracy based on time estimation (TOA or TDOA) can be kept at sub-meter. AOA estimation employs a UWB antenna array at the receiver. Direction finding based on AOA benefiting from relative immunity to multipath fading using UWB has better accuracy than that using narrowband, but the principle for array processing would be different. RSS estimation using UWB is similar to that using other wireless technology, such as WLAN. And it is low complex but suffering from the shadowing and multipath fading. Hence, RSS-based ranging accuracy is low and not improved using ultra-wide bandwidth.

2.2.1 TOA Estimation

Before we go through TOA-based ranging algorithms, it is necessary to overview the fundamental limit and a number of error sources. In the absence of multipath propagation, such as free-space propagation, TOA estimation can be easily done using the cross-correlation of the received signal $r(t)$ with a local template $s(t)$, provided that the local template is synchronized with the transmitter. The TOA is indicated by the peak of the following correlation absolute values,

$$\hat{t}_1 = \arg \max_{\tau} \left| \int r(t) s(t - \tau) dt \right|. \quad (2.1)$$

The standard deviation of the corresponding range estimate is upper bounded by

$$\sqrt{\text{E}[(\hat{d} - \text{E}(d))^2]} \geq \frac{c}{\sqrt{2 \cdot \text{SNR} \cdot \overline{F^2}}}, \quad (2.2)$$

where the effective bandwidth of transmitted signal is defined as,

$$\overline{F^2} = \frac{4\pi^2 \int_{-\infty}^{+\infty} f^2 |S(f)|^2 df}{\int_{-\infty}^{+\infty} |S(f)|^2 df}. \quad (2.3)$$

In (2.2), the fundamental limit of ranging error is dependent on the signal-to-noise ratio and the effective signal bandwidth [16]. UWB with an impulse-like signal shape has a large effective bandwidth in comparison with narrowband signal, and correspondingly the ranging performance using UWB is significantly improved. However, in realistic navigation system, clock jitter and clock drift may happen to affect

time synchronization between transmitter and receiver, and then induce TOA inaccuracy. Inter-symbol interference (ISI) may significantly degrade the positioning performance, and it can be mitigated by choosing the symbol duration much longer than the channel power delay spread.

Nyquist rate usually refers to two times the upper frequency of -10dB bandwidth [29]. Low-cost sub-Nyquist rate sampling that reduces the signal resolution will be an additional error source. The signal shape is usually distorted due to nonlinear amplification or filtering effects of the antennas and circuitry making it different from the transmitted signal shape. Ranging with dirty templates may yield some TOA ambiguity. In addition, the errors from hardware implementations, multipath propagation and obstructed LOS are main channel factors arousing TOA errors [12]. The obstruction between the transmitter and receiver will attenuate the direct path strength more than other multi-paths. As shown in Fig. 2.4, in the case of light attenuation, the direct path is observed but weaker than the strongest multipath components (MPC). Then the TOA cannot be indicated by the correlation peak. In the case of heavy attenuation, the attenuated LOS path may disappear in the received signals. This makes the detection of LOS path quite challenging, and a positive bias error is usually present in the TOA estimation. NLOS with DDP and NLOS with UDP respectively refer to the first and second cases. Multipath propagation introduces the channel power delay spread in the order of a hundred nanoseconds. As shown in Fig. 2.4, consecutive multi-paths with a sufficient arrival delay can be clearly resolved at the receiver while the absence of a sufficient delay refers to the

path overlapping problem or the multipath fading [5, 12]. The first arriving path overlapping with the MPC cluster may induce a TOA bias error. Multipath fading with NLOS problem frequently happens in the dense cluttered scenario. Mitigations of NLOS errors and multipath fading are extensively developed and employed in practical navigation systems [30]. From the above discussions, it is understood that the ranging error based on TOA estimation is degraded far from the fundamental error in (2.2).

Figure 2.4: Multipath propagation of UWB radio.

Direct Sampling

For the purpose of TOA estimation, the received signal is directly sampled with Nyquist rate by ADC. For UWB signals, this implies the sampling rate on the order of a few Giga-hertz, which is quite expensive for UWB receiver. In order to facilitate low-cost and low-power design, low sampling rate that maintain a desirable ranging performance is preferred. A low sampling scheme based on UWB signal envelope [25] is presented in Fig. 2.5.

As shown in Fig. 2.5, a band-pass filter with the UWB signal bandwidth ($B_{-10\text{dB}} = f_H - f_L$) is used to filter out the out-of-band noise. A low-pass filter with bandwidth of $B_{-10\text{dB}}/2$ following a square-law device is used to extract the envelope of UWB signals. A UWB signal with its envelope is shown in the top subplot of Fig. 2.6. The UWB spectrum indicated by solid line, the square-law device output indicated by dash dot line and the LPF output indicated by dash line are presented in the bottom subplot of Fig. 2.6. As shown in Fig. 2.6, ADC can work at sampling rate of $B_{-10\text{dB}}$, which may considerably decrease the cost and complexity using Nyquist rate $2f_H$ for received UWB signals. The ADC output can be processed by the following TOA estimators, such as energy detection. As mentioned previously, the TOA accuracy is decreased when using low-cost sub-Nyquist sampling rate.

Figure 2.5: Low sampling scheme based on UWB signal envelope.

Figure 2.6: Input and output of low-sampling scheme.

Energy Detection (ED)

Energy detection for TOA estimation has gained interest due to the low-complex implementation at sub-Nyquist sampling rate. A diagram of energy detection [31–33] is given in Fig. 2.7. As shown in Fig. 2.7, received signals energy based on an adjustable integral interval is compared to a threshold, and the first threshold-crossing sample is detected as the first arriving path. The basic principle of energy detector is that the energy distribution in the presence of both signal and noise can be distinguished from that for noise-only using an empirical threshold. The threshold selection has a major influence on the detection accuracy. Based on large amounts of

channel characterizations, an empirical threshold can be decided by minimizing the TOA estimation errors or by fixing the early detection probabilities. The drawback of energy detector is mostly due to the noisy channel and the NLOS channel. As suggested in Fig. 2.8, the noisy channel may cause the early detection of TOA, while the heavy attenuation of direct path in NLOS scenario may cause the miss detection of TOA. These wrong detections will induce TOA bias errors.

Figure 2.7: Energy detector for TOA estimation.

Matched Filter (MF)

If the received signal shape is known at the receiver, a matched filter can be employed to estimate the TOA. A diagram of matched filter is shown in Fig. 2.9. The matched filter output is,

$$z(t) = \int_{-\infty}^{\infty} h(T-t)r(t)d\tau + \int_{-\infty}^{\infty} h(T-t)n(t)dt = \sum_{l=1}^L a_l R_s(t-\tau_l) + n_s(t) \quad (2.4)$$

where L denotes the multipath number while a_l is the multipath gain. $R_s(t)$ is the autocorrelation function of signal $s(t)$, and $n_s(t)$ is the colored Gaussian noise. A threshold is used to compare with the absolute values of matched filter outputs, and the first threshold-crossing instant is detected to be TOA. Matched filter works at

Figure 2.8: TOA estimation using energy detector.

Nyquist rate sampling of the input signal $r(t)$ to get an accurate autocorrelation, and hence making the ADC for MF more complex than that for ED. In the absence of multipath, where $L=1$, the matched filter can approximate the CRLB as the increasing SNR or the increasing sampling rate. In the presence of dense multipath, the performance of MF may degrade as a result of overlapping between $R(t - \tau_i)$ and $R(t - \tau_{i+1})$. Another drawback of MF is that, when the received pulse shape is not precisely known at the receiver, the energy capture capability using MF is not as good as that using ED or ranging with dirty templates. Threshold-based ranging techniques are commonly used for low-complexity UWB ranging. In addition to

Figure 2.9: Matched filter for TOA estimation.

the first threshold-crossing detection, a few alternatives, such as the jump back and search forward (JBSF), the serial backward search for single cluster (SBS-SC) and the serial backward search for multiple cluster (SBS-MC), are designed to detect TOA in NLOS scenarios [12, 32]. The threshold is used as a priori knowledge for TOA estimation, which can usually be obtained by evaluating the early detection probabilities or from training.

Maximum Likelihood (ML) Estimation

The maximum likelihood solution is formulated in (2.5).

$$\{\hat{\tau}_1, \hat{a}_1, \dots, \hat{\tau}_L, \hat{a}_L\} = \arg \min |r(t) - \sum_{l=1}^L a_l s(t - \tau_l)|^2 \quad (2.5)$$

In the absence of multipath, this ML solution is equivalent to the MF with well-known signal shape, which may achieve the best accuracy close to CRLB. In this case, the ML estimations are (2.1) and (2.6).

$$\hat{a} = \frac{\int r(t) s(t - \hat{\tau}) dt}{R_s(0)} \quad (2.6)$$

2.2 Channel Estimation Methods

Where $R_s(0)$ is the maximum value of auto-correlation function of $s(t)$. Consider a multipath scenario modeled as,

$$\mathbf{x} = \Omega(\tau)\mathbf{a}^T + \mathbf{n} \quad (2.7)$$

where $\mathbf{x}$ and $\mathbf{n}$ are N -by-1 vectors respectively denoting the discrete samples of received signal and noise, and $\mathbf{a}$ and τ are respectively L -by-1 matrix of multipath amplitudes and the multipath delay.

$$\Omega = \begin{bmatrix} \mathbf{s}^{(\tau_1)} & \mathbf{s}^{(\tau_2)} & \dots & \mathbf{s}^{(\tau_L)} \end{bmatrix}_{N \times L} \quad (2.8)$$

In this case, a generalized ML (GML) estimation can be found as [34],

$$\hat{\tau} = \arg \max \left\{ [\Omega^T(\tau)\mathbf{x}]^T \mathbf{R}_\Omega^{-1}(\tau) [\Omega^T(\tau)\mathbf{x}] \right\} \quad (2.9)$$

$$\hat{\mathbf{a}} = \mathbf{R}_\Omega^{-1}(\tau)\Omega^T(\tau)\mathbf{x} \quad (2.10)$$

where

$$\mathbf{R}_\Omega(\tau) = \Omega^T(\tau)\Omega(\tau) \quad (2.11)$$

$$\mathbf{s}^{(\tau_l)} = \begin{bmatrix} \mathbf{0}_{\tau_l} & \mathbf{s} & \mathbf{0}_{N-\tau_l-N_s} \end{bmatrix}^T \quad (2.12)$$

As we can see from (2.9), the TOA estimation τ_1 is dependent on other unknown channel parameters $\tau_2, \dots, \tau_L$. ML requires a long convergence time and high complexity to search over a group of τ values. But for a resolvable channel, each pair

of $\{a_i, \tau_i\}$ can be separated from other unknown parameters and estimated independently due to where the time delay from i to j is longer than the pulse duration of $s(t)$. Due to the independence among multipath for a resolvable channel, a simplified GML [35] can use a recursive processing to search and subtract each path successively until a given threshold is met.

Ranging with dirty templates

Since the optimal template in (2.1) and (2.4) is not available in practice, the received signal can be delayed a symbol duration T_s and used as a dirty template for cross-correlation with the next received symbol of received signals. A diagram of ranging with a dirty template is proposed in [36, 37] If the received multipath signal $s_m(t)$ with training symbols $b(i)$ is written as,

$$r(t) = \sum_{i=0}^{\infty} b(i) s_m(t - iT_s - \tau_1), \quad (2.13)$$

the cross-correlation between two consecutive symbols is derived as,

$$\begin{aligned} z(\tau) &= \int_0^{T_s} r(t + 2kT_s + \tau) r(t + (2k - 1)T_s + \tau) dt \\ &= b(2k - 1) \left[b(2k - 2) \int_{T_s - \tau'_1}^{T_s} s_m^2(t) dt + b(2k) \int_0^{T_s - \tau'_1} s_m^2(t) dt \right] \end{aligned} \quad (2.14)$$

$$\tau'_1 = (\tau_1 - \tau) \bmod T_s. \quad (2.15)$$

The implementation of (2.14) is presented in Fig. 2.10 and an example is illustrated in Fig. 2.11. The TOA estimation is searched by maximizing the squared value of $z(\tau)$.

TOA acquisition with dirty template is low-complex and easily-implemented since it is free of multipath parameter estimation. However, this approach performance may suffer from the noisy channel with strong MPC.

Figure 2.10: Cross correlator with dirty template.

Figure 2.11: Cross correlation between two consecutive symbols.

2.2.2 AOA Estimation

Consider a plane wave propagating in the unknown direction of $\{\theta, \varphi\}$, the received signals at an N -element antenna array are processed in some ways to find the incident direction. As shown in Fig. 2.12, the arriving plane wave in the direction of $\{\theta, \varphi\}$ is the input signal of the antenna array system consisting of spatially-allocated sensors. The space-time feature of the input signals can be formulated in time delays or in phase shifts [3],

$$f_n(\tau, \theta, \varphi) = f(\tau - \tau_n(\theta, \varphi)) \quad (2.16)$$

$$\mathbf{F}(\omega) = \mathbf{v}(\theta, \varphi)F(\omega), \quad (2.17)$$

where $F(\omega)$ is the Fourier transform of $f(\tau)$, and

$$\mathbf{v}(\theta, \varphi) = [\exp(-j\omega\tau_1(\theta, \varphi)) \quad \exp(-j\omega\tau_2(\theta, \varphi)) \quad \dots \quad \exp(-j\omega\tau_N(\theta, \varphi))]^T. \quad (2.18)$$

$\mathbf{v}(\theta, \varphi)$ incorporates all spatial characteristics of the array and is referred to the array manifold. Each sensor within the antenna array can be considered as a linear, time-invariant filter with response $[h_1(t), h_2(t), \dots, h_n(t)]^T$, and then the antenna array system output $y(t)$ can be written as,

$$y(t) = \sum_{n=1}^N \int_{-\infty}^{\infty} h_n(t - \tau) f_n(\tau, \theta, \varphi) d\tau. \quad (2.19)$$

Correspondingly, the array output in the frequency domain is,

$$Y(\omega) = \mathbf{H}^T(\omega) \mathbf{v}(\theta, \varphi) F(\omega), \quad (2.20)$$

where $\mathbf{H}(\omega)$ is the Fourier transform of $[h_1(t), h_2(t), \dots, h_n(t)]^T$. The array responses in (2.19) and (2.20) describe the gain of the array to an input plane wave versus the AOA of the plane wave $\{\theta, \varphi\}$, and the term $\mathbf{H}^T(\omega) \mathbf{v}(\theta, \varphi)$ is referred to the array beam pattern. To assess the array system performance, there are a few aspects of either the array response to complex propagation channel or of the array inherent properties, such as Rayleigh resolution limit, the array directivity, and the sensitivity to external perturbations [3].

Figure 2.12: Direction finding with an antenna array.

In the following, our discussions focus on the one-dimensional direction finding using a planar array consisting of all antenna elements in one plane. It can be easily extended to the estimations of both azimuth angle and elevation angle.

Beam Former

We delay the input signal for each array element so that the signals are aligned in time and sum them. This processor is referred to the conventional beam-former or Barlett beam-former [38]. The array response for Barlett beam-former is,

$$h_n(\tau) = \frac{1}{N} \delta(\tau + \tau_n) \quad (2.21)$$

$$\mathbf{H}^T(\omega) = \frac{1}{N} \mathbf{v}^H(\theta). \quad (2.22)$$

Substituting (2.22) to (2.20) yields the array output to be $F(\omega)$. Narrowband beam-former usually uses phase shifters while ultra-wide band beamformer uses a tapped delay line. Noise $\mathbf{N}(\omega)$ with spectral matrix of $\mathbf{S}_N = \mathbf{N}(\omega)\mathbf{N}^H(\omega)$ is considered as an input perturbation to each array element.

$$\mathbf{X}(\omega) = \mathbf{F}(\omega) + \mathbf{N}(\omega) = \mathbf{v}(\theta)F(\omega) + \mathbf{N}(\omega). \quad (2.23)$$

To minimize the noise effects, the minimum variance distortion-less response (MVDR) beam-former or Capon beam-former [39] is commonly used. The resulting array response is,

$$\mathbf{H}(\omega) = \frac{\mathbf{S}_N^{-1} \mathbf{v}(\theta)}{\mathbf{v}^H(\theta) \mathbf{S}_N^{-1} \mathbf{v}(\theta)}. \quad (2.24)$$

The advantage of using MVDR beam-former over conventional beam-former is that the beam width for two closely-spaced sources is sharpened. However, all beam forming approaches suffer from the correlated multipath components.

CLEAN Algorithm

UWB signals have a high temporal resolution for channel responses, which make the beam width using conventional beam-former quite sharp. CLEAN algorithm [40] is effective to resolve arriving plane waves from multiple incident directions. In Fig. 2.13, a 5-element uniform linear array with inter-element spacing of 30cm is employed to find the direction of a UWB source with a pulse duration of 2ns in multipath environments. As shown in the figure, four correlated multipath signals with TOA and AOA are indicated by dominant magnitudes in CLEAN contour. The drawback using CLEAN algorithm is that path overlapping with near-field perturbations may degrade its directivity.

Subspace Approach

Subspace approaches are well-known to greatly improve the directivity of resolving multiple uncorrelated sources with close spatial separations. The mathematical principle of subspace approaches is that the covariance matrix of received signals can be decomposed into its eigen-structure. Consider the presence of D uncorrelated signals corrupted by spatial white noise at an N -element array receiver, and then the projection between each signal subspace and the noise subspace is zero ($\|\mathbf{v}^H(\theta_i)\mathbf{U}_N\|^2 = 0$, $i=1,2,\dots,D$) because they are pair-wise uncorrelated.

because they are pair-wise orthogonal and $v(\theta_i)$ is defined as (2.18), where $\mathbf{U}_N$ is the noise subspace consisting of $(N - D)$ eigenvectors corresponding to the $(N - D)$ lowest eigen-values for the covariance matrix of $\mathbf{E}\{\mathbf{X}(\omega)\mathbf{X}^H(\omega)\}$. Take spectral

Figure 2.13: CLEAN Beam-former contour.

MUSIC algorithm [41, 42] for example, the AOA can be estimated as

$$\hat{\theta}_i = \arg \min_{\theta} \{ \mathbf{v}^H(\theta) \mathbf{U}_N \mathbf{U}_N^H \mathbf{v}(\theta) \} \quad (2.25)$$

The AOA of each signal is searched to minimize the norm of projecting $\mathbf{v}(\theta)$ onto the noise subspace. MUSIC algorithm achieves much higher resolution than conventional beam-former and Capon beam-former. However, it is susceptible to colored (correlated) noise and multipath fading. To alleviate the presence of correlated perturbations, ESPRIT algorithm [43, 44] is helpful when $\|\mathbf{v}^H(\theta_i) \mathbf{U}_N\|^2 \neq 0$. It exploits the shift structure by partitioning sub-array, and the sub-array signal subspaces can

be processed to estimate the AOAs. Partitioning of sub-arrays [3] is shown in Fig. 2.14. The shift invariance property of the array gives the relation between the two sub-array manifolds as,

$$\mathbf{V}_2 = \mathbf{V}_1 \cdot \text{diag}[e^{j\frac{2\omega d \cos \theta_1}{c}}, \dots, e^{j\frac{2\omega d \cos \theta_D}{c}}] \quad (2.26)$$

Least-square ESPRIT is taken for example. Based on (2.26), the relation Ψ between the sub-array signal subspaces $\mathbf{U}_{s1}$ and $\mathbf{U}_{s2}$ respectively obtained from sub-arrays 1 and 2, can be derived as a least-squares solution of $\mathbf{U}_{s2} = \mathbf{U}_{s1}\Psi$, and the AOAs can be estimated by finding the eigen-values of Ψ . The advantage using sub-arrays is that, forward-backward spatial smoothing can be conveniently implemented to mitigate the correlated interferences [45–47]. The performance of ESPRIT is improved, and especially is more robust to multipath fading and colored noise than MUSIC. The drawback using sub-arrays is that the effective antenna aperture is reduced.

Figure 2.14: An example of sub-arrays selection.

2.2.3 RSS Estimation

The basic principle for RSS-based ranging is the path loss model,

$$\bar{P}(d) = P_0 - 10n\log_{10}\left(\frac{d}{d_0}\right). \quad (2.27)$$

where P_0 is the received power at the reference range denoted by d_0 , and n is known as the pass loss exponent. In (2.27), the ranging denoted by d can be estimated using the power measurement of received signals based on a pre-known path loss channel model. A UWB signal experiences shadowing, path loss and small-scale fading (power delay spread) in propagation. To mitigate the effects of small-scale fading, the received power is measured as [12],

$$P(d) = \frac{1}{T} \int_0^T |r(t)|^2 dt \quad (2.28)$$

where T is a sufficient long integral interval to include all MPC. Then the received power in dB can be modeled as a normally-distributed random variable $10\log_{10}P(d) \sim N(\bar{P}(d), \sigma_{sh}^2)$, where σ_{sh} is due to the shadowing effects. RSS-based ranging error linearly increases with the actual range. RSS-based ranging is not as accurate as TOA-based ranging using UWB signals. Besides, RSS cannot provide accurate ranging in NLOS scenarios.

2.3 UWB Channel Characterization

Compared to the flat fading for narrowband systems, the frequency-selective fading within the large bandwidth of UWB systems is significant. Many channel models are proposed as emerging UWB standards in the past few years. Our discussion focuses on UWB with low data rates for localization purposes in WPAN that is referred to as IEEE 802.15.4a channel model [22]. Generally, UWB signals experience frequency-dependent path loss, large-scale fading, power delay spread and small-scale fading during the propagation. Statistical modeling of these characteristics of UWB channel is reviewed as follows.

2.3.1 Frequency-Dependent Path Loss

The received power density at distance d and frequency f can be expressed following [22]

$$P_r(d, f) = \left(\frac{f}{f_c}\right)^{-2(\kappa+1)} \left(\frac{d}{d_0}\right)^{-n} \text{PL}_0 \cdot \eta_{\text{RX - ant}}(f) \eta_{\text{TX - ant}}(f) \cdot P_{\text{TX - ant}}(f) \quad (2.29)$$

where n is the path loss exponent, κ is frequency decaying factor, and f_c is the central frequency of UWB signal. $P_{\text{TX - ant}}(f)$ is the power density besides the transmitter antenna. And $\eta_{\text{RX - ant}}$ and $\eta_{\text{TX - ant}}$ respectively indicate the antenna efficiency of the receiver and the transmitter antennas.

The path loss PL_0 at the reference distance of d_0 measured by an ideally efficient

isotropic antenna in free space is given as follows citeRappaport,

$$PL_0 = K_0 \left(\frac{c}{4\pi f_c d_0} \right)^2 \quad (2.30)$$

where K_0 is a constant. In practical system, PL_0 , n and κ are site-specific, and the path loss at a given distance can be calculated based on empirical values of PL_0 , n and κ .

Large-scale fading referred to as shadowing is defined as the variation of path loss due to the slow changes in surrounding environment. The shadowing effect on PL in dB can be modeled as a normally-distributed random variable with zero mean.

2.3.2 Power Delay Profile

In a UWB channel, multipath components arrive in multiple clusters with different amplitudes and delays. The channel impulse response is given in general as,

$$h(t) = \sum_{k=0}^K \sum_{l=0}^{L_k} a_{k,l} e^{j\phi_{k,l}} \delta(t - T_k - \tau_{k,l}) \quad (2.31)$$

where $a_{k,l}$ and $\phi_{k,l}$ respectively indicate the amplitude and phase of the l^{th} path in the k^{th} cluster.

The number of clusters K is modeled as a Poisson-distributed random variable. The cluster arrival times T_k and the ray arrival times $\tau_{k,l}$ are modeled respectively by a Poisson process and a mixture of two Poisson processes. As shown in Fig. 2.15, the power delay profile defined as $P(\tau) = |h(t)|^2$ is normalized and is exponential

within each cluster, and the mean energy of the clusters follows an exponential decay. The variation of the multipath amplitude $|a_{k,l}|$ referred to as the small-scale fading is modeled to be Nakagami-distributed. Temporal dispersion of the power delay profile is usually evaluated by mean excess delay, root-mean-square delay spread and rise time.

Figure 2.15: Power delay profile of UWB signals.

2.3.3 NLOS Problems

Compared to that in LOS scenario, the UWB channel in NLOS scenario characterizes large PL, long power delay spread and flat power profile. Statistical models of channel

parameters in LOS and NLOS scenarios can be differentiated using an empirical threshold for a site-specific environment. Performance improvement can benefit from the channel patterns recognition. On one hand, range estimation can use algorithms corresponding to different channel patterns. On the other hand, NLOS errors can be identified and mitigated.

2.4 AOA Resolution

The studies about the angular resolution for the ULA and UAA are given as follows [48]. Define the function below as a sum of absolute time shifts among the array sensors,

$$f(\theta) \triangleq \sum_e |\Delta\tau^e(\theta, r_0)|. \quad (2.32)$$

Applying the Taylor series expansion,

$$f(\hat{\theta}) = f(\theta_0) + \sum_{n=1}^{\infty} \frac{f^{(n)}(\theta_0)}{n!} (\hat{\theta} - \theta_0)^n \quad (2.33)$$

Let Δt is the time resolution, the inherent angular $\Delta\theta$ resolution depends on,

$$\Delta t \triangleq f(\hat{\theta}) - f(\theta_0) = \sum_{n=1}^{\infty} \frac{f^{(n)}(\theta_0)}{n!} (\Delta\theta)^n. \quad (2.34)$$

In the case of ULA,

$$f(\theta) \triangleq \sum_e |\Delta\tau^e(\theta, r_0)| = \frac{N \cdot r_0}{c} |\cos(\theta)| \quad (2.35)$$

$$\frac{c \cdot \Delta t}{N \cdot r_0} = \sum_{n=1}^{\infty} \frac{|\cos(\theta_0)|^{(n)}}{n!} (\Delta\theta)^n. \quad (2.36)$$

In the case of UCA,

$$f(\theta) \triangleq \sum_e |\Delta\tau^e(\theta, r_0)| = \frac{r_0}{c} \sum_e \left| \cos \left(\theta + (e-1) \frac{2\pi}{N} \right) \right|, \quad (2.37)$$

$$\frac{c \cdot \Delta t}{r_0} = \sum_{n=1}^{\infty} \frac{(\Delta\theta)^n}{n!} \sum_e \left| \cos \left(\theta_0 + (e-1) \frac{2\pi}{N} \right) \right|^{(n)}. \quad (2.38)$$

Chapter 3

Indoor Positioning in Presence of Dense Multipath with Path Overlapping

3.1 Introduction

Indoor environments have complicated signal propagation characteristics with clustering of multipath arrivals, obstructed LOS, LOS traversal delay through materials and the distortion of transmitted signal. UWB impulse radio as a good PHY candidate for the purpose of indoor positioning attracts numerous interests in ranging [32, 35, 49, 50] and direction finding [40, 51–57]. However, the localization performance with UWB signals suffers if the LOS is obstructed [30, 58], or the direct path is not clearly resolved because of the clustering of multipath arrivals within the direct path signal duration [23] in dense cluttered environments. The latter channel condition is reported in [23, 48, 59] as the path overlapping effects on TOA and AOA ambiguities of the direct path. To improve performance in these channel conditions,

cooperative positioning of targets (agents) are helpful as shown in [24, 60–62] when high density deployments are available, in which the channel link can be recognized and then used for positioning through maximum-a-posteriori (MAP) estimation. But for an estimator, high resolution of MPCs in TOA or AOA is useful to mitigate the errors induced by these channel conditions. A study of improved TOA and AOA estimators with UWB signals is reviewed as follows. In [63], super-resolution TOA technique is proposed to estimate the TOAs and amplitudes of the multipath channel using MUSIC. In [64], disjoint TOA estimation via matched filter before joint amplitude estimation is proposed. Phase correlators are studied in [65, 66]. A pattern to identify closely-spaced direct path and ground reflection is given in [67]. TDOA based AOA estimators work with measurements of the baseband pulses and thus have a lower hardware complexity, but the performance is constrained by TOA error [48, 51, 52]. Beam-forming of time correlations is studied in [53] but in the absence of multipath. Two closely-spaced correlated UWB sources in multipath-free environments are recognized by one-dimensional (1-D) expectation maximization (EM) algorithm in [55]. High angular resolution using 2-D unitary ESPRIT is demonstrated in [57] by exploiting requires spatial smoothing.

Motivated by the need for joint TOA and AOA estimator that can adapt to non-overlapping and overlapping multi-paths at low cost, this chapter first studies the performance bound of such a joint estimator. The proposed joint TOA and AOA estimator structure is generalized from the self-steering beam-forming system in [53]. The algorithm uses a conditional maximum likelihood (CML) estimator yielding the

least squared-error by the initial candidates from the steering beam followed by multipath-aided acquisition. Compared to the spectrum error function in [68], our modifications adapt to the UWB array received signals and the uncertain number of overlapping multi-paths. Our work is innovative in that it features the implementation for joint estimation of TOA and AOA with improved efficiency by selecting the in-band power spectrum and searching the clustering of multipath arrivals. Performance comparisons are made with the CRB and the method of 1-D search [52] in IEEE 802.15.4a CM3 channel model [22] and in realistic indoor UWB environments.

3.2 Theoretical Bound Derivation

Consider a self-navigation problem as follows: The active tag with UWB signal which serve as beacons with known absolute coordinates are mounted in the environment. A mobile receiver with an antenna array can locate itself with respect to the beacon by jointly estimating the TOA and AOA of the direct path. The UWB-IR ranging signal transmitted from the beacon can be given as,

$$s(t) = \sum_{i=-\infty}^{\infty} u(t - iT_f), \quad (3.1)$$

where $u(t)$ is the UWB signal pulse shape with an ultra-short duration, and T_f is the pulse repetitive period. In LOS dense multipath propagation environments, far-field radiation is satisfied by the direct path and most multipath due to the small inter-element spacing of antenna array. The exceptions are rays from near-field scatters.

3.2 Theoretical Bound Derivation

Considering L plane waves impinging on an N -element antenna array with $L_e - L$ near-field perturbations, the time signal received at the e^{th} antenna element can be expressed as,

$$x^e(t) = \sum_{l=1}^L a_l s(t - \tau_l^o + \Delta\tau^e(\theta_l)) + \sum_{l=L+1}^{L_e} a_l^e s(t - \tau_l^e) + n^e(t) \quad (3.2)$$

where θ_l and a_l are respectively the AOA and amplitude of the l^{th} plane wave, a_l^e and τ_l^e denote the near-field path amplitude and time delay that are inconsistent among the array elements, and $n^e(t)$ is assumed as the spatial white noise with a double-sided power spectral density $N_0/2$. For the plane wave propagation, the TOA at the e^{th} antenna element is constrained by the antenna array geometry as shown in Fig. 3.1.

The following equations respectively give the uniform circular array (UCA) and the uniform linear array (ULA) geometry effects on the relative delay $\Delta\tau^e$ at the e^{th} antenna element with respect to the TOA at the array geometric center τ_l^o ,

$$\Delta\tau_{\text{UCA}}^e(\theta_l) = \frac{r_0}{c} \cos \left((e-1) \frac{2\pi}{N} + \theta_l \right) \quad (3.3)$$

$$\Delta\tau_{\text{ULA}}^e(\theta_l) = \left(\frac{N+1}{2} - e \right) \cdot \frac{r_0 \cos \theta_l}{c} \quad (3.4)$$

where r_0 denotes the distance between ULA sensors, and equals the UCA radius, and c is the speed of light. It should be noted that the multipath signal model here is different from that used in [48, 54]. The interfering waves from reflections or scattering by objects at different directions θ_l in dense cluttered environments are

3.2 Theoretical Bound Derivation

considered and given by a vector of parameters describing the array received signals as,

$$\underline{\eta} = \begin{bmatrix} \begin{bmatrix} \tau_1^o \\ \theta_1 \\ a_1 \end{bmatrix}^T & \dots & \begin{bmatrix} \tau_L^o \\ \theta_L \\ a_L \end{bmatrix}^T & \underline{\gamma}^1 & \dots & \underline{\gamma}^N \end{bmatrix} \quad (3.5)$$

where

$$\underline{\gamma}^e = \begin{bmatrix} \begin{bmatrix} \tau_{L+1}^e \\ a_{L+1}^e \end{bmatrix}^T & \dots & \begin{bmatrix} \tau_{L_e}^e \\ a_{L_e}^e \end{bmatrix}^T \end{bmatrix} \quad e \in \{1, \dots, N\} \quad (3.6)$$

$\underline{\gamma}^e$ denotes the near-field perturbation at the e^{th} antenna element.

Additive white Gaussian noise (AWGN) with double-sided power spectral density $N_0/2$ is assumed in section 3.2. The *pdf* of the noise discrete sample n_i can be expressed as follows,

$$p_{n_i} = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{n_i^2}{2\sigma^2}\right), \quad (3.7)$$

where the noise power is σ^2 . Then the following equation can be derived due to the independence of AWGN.

$$p_{\{n_1, \dots, n_i, \dots, n_{N_s}\}} = \prod_{i=1}^{N_s} p_{n_i} = (2\pi\sigma^2)^{-\frac{N_s}{2}} \exp\left(-\sum_{i=1}^{N_s} \frac{n_i^2}{2\sigma^2}\right) \quad (3.8)$$

The log-likelihood function can be obtained as,

$$\ln p_{\{n_1, \dots, n_i, \dots, n_{N_s}\}} = -\sum_{i=1}^{N_s} \frac{n_i^2}{2\sigma^2} = -\sum_{i=1}^{N_s} \frac{n_i^2 \cdot dt}{2\sigma^2 \cdot dt} = -\frac{\int_{-\infty}^{\infty} n^2(t) dt}{N_0}. \quad (3.9)$$

3.2 Theoretical Bound Derivation

According to (3.2), the above equation can be rewritten as,

$$\ln p_{\{n_1, \dots, n_i, \dots, n_{N_s}\}} = -\frac{1}{N_0} \int_{-\infty}^{\infty} (x^e(t) - \sum_{l=1}^L a_l s(t - \tau_l^o + \Delta\tau^e(\theta_l)) - \sum_{l=L+1}^{L_e} a_l^e s(t - \tau_l^e))^2 dt. \quad (3.10)$$

Skip the unnecessary terms in above equation, the log-likelihood function of received signal conditioned on the channel parametric estimation can be expressed in a brief form as equation (3.8) [23]. In the case of spatial white noise, the *pdf* of the array received signals $\mathbf{x}$ conditioned on the vector $\underline{\eta}$ can be written as [69],

$$\ln p(\mathbf{x}|\underline{\eta}) = \sum_{e=1}^N \ln p(\mathbf{x}^e|\underline{\eta}) \quad (3.11)$$

where

$$\begin{aligned} \ln p(\mathbf{x}^e|\underline{\eta}) = & \frac{2}{N_0} \int x^e(t) \sum_{l=1}^L a_l s(t - \tau_l^o + \Delta\tau^e(\theta_l)) dt + \frac{2}{N_0} \int x^e(t) \sum_{l=L+1}^{L_e} a_l^e s(t - \tau_l^e) dt \\ & - \frac{1}{N_0} \int \left[\sum_{l=1}^L a_l s(t - \tau_l^o + \Delta\tau^e(\theta_l)) + \sum_{l=L+1}^{L_e} a_l^e s(t - \tau_l^e) \right]^2 dt \end{aligned} \quad (3.12)$$

$\mathbf{x}^e$ is the discrete signal $x^e(t)$ sampled at or above Nyquist rate. For a UWB-IR signal, Nyquist rate is referred to as two times the upper frequency of the -10dB emission point¹. The FIM is defined in [69] as,

$$J(\mathbf{x}|\underline{\eta}; \eta_i, \eta_j) \triangleq -E \left\{ \frac{\partial^2 \ln p(\mathbf{x}|\underline{\eta})}{\partial \eta_i \partial \eta_j} \right\} \quad (3.13)$$

¹This is also called as the upper frequency of -10dB bandwidth of the UWB signal.

3.2 Theoretical Bound Derivation

As derived by the above equation, the FIM of interest has a form as follows,

$$\mathbf{J}(\mathbf{x}|\underline{\eta}) = \begin{bmatrix} \mathbf{A} & \mathbf{C}_1 & \dots & \mathbf{C}_N \\ \mathbf{C}_1^T & \mathbf{B}_1 & \mathbf{0} & \mathbf{0} \\ \vdots & \mathbf{0} & \ddots & \mathbf{0} \\ \mathbf{C}_N^T & \mathbf{0} & \mathbf{0} & \mathbf{B}_N \end{bmatrix} \quad (3.14)$$

where $\mathbf{A}$ is a square matrix of order $3L$, and $\mathbf{B}_e$ is a square matrix of order $2(L_e-L)$ with $e \in \{1, \dots, N\}$, and $\mathbf{C}_e$ is a $3L$ -by- $2(L_e-L)$ matrix with $e \in \{1, \dots, N\}$. Since $\mathbf{J}(\mathbf{x}|\underline{\eta})$ is a matrix of high orders, the insight into the precision can be given by a equivalent FIM (EFIM) of low orders [23, 48].

The CRB for the direct path estimation τ_1^o , θ_1 and a_1 are the first three diagonal elements of the inverse of FIM. The block matrix can be inverted as follows [70]

$$\begin{bmatrix} \mathbf{A} & \mathbf{B} \\ \mathbf{C} & \mathbf{D} \end{bmatrix}^{-1} = \begin{bmatrix} (\mathbf{A} - \mathbf{B}\mathbf{D}^{-1}\mathbf{C})^{-1} & -(\mathbf{A} - \mathbf{B}\mathbf{D}^{-1}\mathbf{C})^{-1}\mathbf{B}\mathbf{D}^{-1} \\ -\mathbf{D}^{-1}\mathbf{C}(\mathbf{A} - \mathbf{B}\mathbf{D}^{-1}\mathbf{C})^{-1} & \mathbf{D}^{-1} + \mathbf{D}^{-1}\mathbf{C}(\mathbf{A} - \mathbf{B}\mathbf{D}^{-1}\mathbf{C})^{-1}\mathbf{B}\mathbf{D}^{-1} \end{bmatrix}, \quad (3.15)$$

Accordingly, the EFIM can be derived as,

$$\mathbf{A} - \begin{bmatrix} \mathbf{C}_1 & \dots & \mathbf{C}_N \end{bmatrix} \begin{bmatrix} \mathbf{B}_1 & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \ddots & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{B}_N \end{bmatrix}^{-1} \begin{bmatrix} \mathbf{C}_1^T \\ \vdots \\ \mathbf{C}_N^T \end{bmatrix}. \quad (3.16)$$

The EFIM is a square matrix of order $3L$. The CRB for the direct path estimation τ_1^o , θ_1 and a_1 are the first three diagonal elements of the inverse of EFIM, as shown

3.2 Theoretical Bound Derivation

below.

$$\text{CRB}(\tau_1^o, \theta_1, a_1) = \left[\left(\mathbf{A} - \sum_{e=1}^N \mathbf{C}_e \mathbf{B}_e^{-1} \mathbf{C}_e^T \right)^{-1} \right]_{3 \times 3} \quad (3.17)$$

Substitute the array geometries (3.3) or (3.4) into (3.12), the generalized forms of

$\mathbf{A}$, $\mathbf{B}_e$ and $\mathbf{C}_e$ are found as,

$$\mathbf{A} = \begin{bmatrix} \mathbf{A}^{(1,1)} & \dots & \mathbf{A}^{(1,L)} \\ \vdots & \ddots & \ddots \\ [\mathbf{A}^{(1,L)}]^T & \ddots & \mathbf{A}^{(L,L)} \end{bmatrix} \quad (3.18)$$

$$\mathbf{A}^{(i,j)} = \frac{2}{N_0} \begin{bmatrix} a_i a_j \sum_{e=1}^N \ddot{R}_s(\tau_j^e - \tau_i^e) & -a_i a_j \sum_{e=1}^N \ddot{R}_s(\tau_j^e - \tau_i^e) \Lambda_i^e & a_i \sum_{e=1}^N \dot{R}_s(\tau_j^e - \tau_i^e) \\ -a_i a_j \sum_{e=1}^N \ddot{R}_s(\tau_j^e - \tau_i^e) \Lambda_i^e & a_i a_j \sum_{e=1}^N \ddot{R}_s(\tau_j^e - \tau_i^e) \Lambda_i^e \Lambda_j^e & -a_i \sum_{e=1}^N \dot{R}_s(\tau_j^e - \tau_i^e) \Lambda_i^e \\ -a_j \sum_{e=1}^N \dot{R}_s(\tau_j^e - \tau_i^e) & a_j \sum_{e=1}^N \dot{R}_s(\tau_j^e - \tau_i^e) \Lambda_j^e & \sum_{e=1}^N R_s(\tau_j^e - \tau_i^e) \end{bmatrix}$$

$$\mathbf{B}_e = \begin{bmatrix} \mathbf{B}_e^{(L+1,L+1)} & \dots & \mathbf{B}_e^{(L+1,L_e)} \\ \vdots & \ddots & \ddots \\ \mathbf{B}_e^{(L_e,L+1)} & \ddots & \mathbf{B}_e^{(L_e,L_e)} \end{bmatrix} \quad (3.19)$$

$$\mathbf{B}_e^{(i,j)} = \frac{2}{N_0} \begin{bmatrix} a_i^e a_j^e \ddot{R}_s(\tau_j^e - \tau_i^e) & a_i^e \dot{R}_s(\tau_j^e - \tau_i^e) \\ -a_j^e \dot{R}_s(\tau_j^e - \tau_i^e) & R_s(\tau_j^e - \tau_i^e) \end{bmatrix}$$

$$\mathbf{C}_e = \begin{bmatrix} \mathbf{C}_e^{(1,L+1)} & \dots & \mathbf{C}_e^{(1,L_e)} \\ \vdots & \ddots & \ddots \\ \mathbf{C}_e^{(L,L+1)} & \ddots & \mathbf{C}_e^{(L,L_e)} \end{bmatrix} \quad (3.20)$$

$$\mathbf{C}_e^{(i,j)} = \frac{2}{N_0} \begin{bmatrix} a_i a_j^e \ddot{R}_s(\tau_j^e - \tau_i^e) & a_i \dot{R}_s(\tau_j^e - \tau_i^e) \\ -a_i a_j^e \Lambda_i^e \ddot{R}_s(\tau_j^e - \tau_i^e) & -a_i \Lambda_i^e \dot{R}_s(\tau_j^e - \tau_i^e) \\ -a_j^e \dot{R}_s(\tau_j^e - \tau_i^e) & R_s(\tau_j^e - \tau_i^e) \end{bmatrix}$$

where $\tau_i^e = \tau_i^o - \Delta\tau^e(\theta_i)$ for the i^{th} plane wave $i \in \{1, \dots, L\}$, and $\Lambda_i^e = \frac{d\Delta\tau^e(\theta_i)}{d\theta_i}$, where $\Delta\tau^e(\theta_i)$ is determined by the array geometry as given in (3.3) or (3.4). Auto-correlation and cross-correlation functions of the source signal $s(t)$ and time derivative of the signal denoted by $\dot{s}(t)$ are derived as,

$$R_s(\tau) \triangleq \int s(t)s(t-\tau)dt = \int_{-\infty}^{+\infty} |S(f)|^2 e^{j2\pi f\tau} df \quad (3.21)$$

$$\dot{R}_s(\tau) \triangleq \int s(t)\dot{s}(t-\tau)dt = -2\pi j \int_{-\infty}^{+\infty} f |S(f)|^2 e^{j2\pi f\tau} df \quad (3.22)$$

$$\ddot{R}_s(\tau) \triangleq \int \dot{s}(t)\dot{s}(t-\tau)dt = 4\pi^2 \int_{-\infty}^{+\infty} f^2 |S(f)|^2 e^{j2\pi f\tau} df \quad (3.23)$$

where $S(f)$ is the Fourier transform of $s(t)$. Equations (3.21), (3.22) and (3.23) are known as the inherent characteristics of a UWB-IR signal $s(t)$. Besides the impact from the transmitter signal characteristics, the channel effects on the CRB in (3.17) can be categorized into (i) the LOS path is well-separated in time from the multi-paths, or (ii) the LOS path is partially overlapped by the multi-paths.

3.2.1 Well-separated LOS Path

The LOS path is so-called clearly resolved or well-separated when the delay difference between the direct path and the second path (multipath) is larger than the pulse

3.2 Theoretical Bound Derivation

Figure 3.1: Antenna array: ULA and UAA.

duration. In this case, $\mathbf{A}^{(1,j)} = 0$ and $\mathbf{C}_e^{(1,j)} = 0$, where $j \neq 1$ and $e \in \{1, \dots, N\}$.

Substituting these values into (3.17) yields

$$\text{CRB}(\tau_1^o, \theta_1, a_1) = [\mathbf{A}^{(1,1)}]^{-1} \quad (3.24)$$

The matrix $\mathbf{A}^{(1,1)}$ is diagonal because $\dot{R}_s(0)=0$ and $\sum_{e=1}^N \Lambda_1^e=0$. Thus, the CRB for τ_1^o and θ_1 can be expressed as:

$$\text{CRB}(\tau_1^o) = \frac{1}{[\mathbf{A}^{(1,1)}]_{1,1}} = \frac{N_0}{2a_1^2 N \ddot{R}_s(0)} = \frac{1}{2N \overline{F^2} \cdot \text{SNR}} \quad (3.25)$$

$$\text{CRB}(\theta_1) = \frac{1}{[\mathbf{A}^{(1,1)}]_{2,2}} = \frac{1}{2\overline{F^2} \cdot \text{SNR} \sum_{e=1}^N (\Lambda_1^e)^2} \quad (3.26)$$

where

$$\text{SNR} \triangleq \frac{a_1^2 R_s(0)}{N_0} \quad (3.27)$$

$$\overline{F^2} \triangleq \frac{\ddot{R}_s(0)}{R_s(0)} = \frac{4\pi^2 \int_{-\infty}^{+\infty} f^2 |S(f)|^2 df}{\int_{-\infty}^{+\infty} |S(f)|^2 df}. \quad (3.28)$$

The above equation is referred to as the effective bandwidth of source signal (2.3) in Chapter 2, and is closely related to the power spectrum of source signal. The physical meaning can be interpreted as follows [12]: The ultra-short high-energy pulse (signal shape) can induce a high value of the effective bandwidth, which increases the temporal resolution of signal and further improve the TOA-based range estimation as suggested by the CRB.

The following conclusions are drawn for the case of resolved LOS path: (i) CRB of direct path TOA estimation error in (3.25) is inversely proportional to the antenna elements number of array N , SNR, signal effective bandwidth $\overline{F^2}$ and is not related to the array geometry. (ii) CRB of direct path AOA estimation error in (3.26) is inversely proportional to the SNR, signal effective bandwidth, and a factor which is related to the array geometry and number of elements. These results agree with those derived in [48].

3.2.2 Overlapped LOS Path

In dense cluttered LOS environments, the reflective objects close to the transmitter induce clusters of interfering plane waves as denoted by the L terms in (3.2), and the reflective objects close to the array receiver cause near-field perturbations as denoted by the $L_e - L$ terms in (3.2). When a cluster of plane waves falls into the direct path signal duration, the joint plane waves give $\mathbf{A}^{(1,j)} \neq 0$, where $j \neq 1$, while near-field

3.2 Theoretical Bound Derivation

perturbations whose paths overlap with the direct path signal duration result in $\mathbf{C}_e^{(1,j)} \neq 0$, where $j \neq 1$ and $e \in \{1, \dots, N\}$. To gain insights into these effects let us now consider two cases:

i) Only one reflective object close to the transmitter is present resulting in direct path overlap. In this case $L=L_e=2$ and $\mathbf{C}_e^{(1,j)} = 0$. Substituting these values into (3.17) gives CRB of the direct path as the diagonal elements of

$$[\mathbf{A}^{(1,1)} - \mathbf{A}^{(1,2)}[\mathbf{A}^{(2,2)}]^{-1}[\mathbf{A}^{(1,2)}]^T]^{-1}.$$

ii) Only one reflective object close to the receiver is present resulting in direct path overlap. In this case, $L=1$, $L_e=2$ and $\mathbf{A}^{(1,j)} = 0$. Substituting these values into (3.17) gives CRB of the direct path as the diagonal elements of

$$[\mathbf{A}^{(1,1)} - \sum_e \mathbf{C}_e^{(1,2)}[\mathbf{B}_e^{(2,2)}]^{-1}[\mathbf{C}_e^{(1,2)}]^T]^{-1}.$$

The above results suggest that the error bounds of the direct path estimation τ_1^o , θ_1 and a_1 are degraded by nonzero $\mathbf{A}^{(1,j)}$ or $\mathbf{C}_e^{(1,j)}$, where j denotes any interfering plane wave or near-field perturbation. A few remarks about the path overlapping effects on the CRB can be drawn:

i) Non-overlapping plane waves giving $\mathbf{A}^{(1,j)} = 0$ and non-overlapping near-field perturbations giving $\mathbf{C}_e^{(1,j)} = 0$ have no impact on CRB for the direct path estimation of τ_1^o , θ_1 and a_1 .

ii) It turns out that the amplitude of the l^{th} plane wave a_l and near-field perturbation a_l^e are canceled out in the computation of (3.17) or the EFIM matrix of order 3. Therefore, the CRB for the direct path estimation of τ_1^o , θ_1 and a_1 is

3.2 Theoretical Bound Derivation

independent of multipath amplitude a_l^e ($l \neq 1$). The detailed explanation can be found in Appendix B.

- iii*) The CRB of τ_1^o estimation error is not strictly inversely proportional to the number of array elements N . This is because the factors inducing the CRB degradation, $\mathbf{A}^{(1,j)}$ is not proportional to N , and $\mathbf{C}_e$ for every antenna element is different from each other. The physical meaning is that, interfering plane waves propagation and/or near-field perturbations from different directions will decrease the TOA estimation efficiency of the antenna array.
- iv*) The CRB of θ_1 estimation error is dependent on the different directions θ_j of the first cluster plane waves that arrives within the direct path signal duration. This is investigated further in Section 3.4 through simulations.
- v*) Channel effects in the form of matrices $\mathbf{A}$, $\mathbf{B}_e$ and $\mathbf{C}_e$ can be obtained from the IEEE 802.15.4a channel model [22]. The number of interfering plane waves and near-field perturbations is characterized by the channel power delay profile, while the spaces in time between the direct path and interferences are characterized by path arrival rate. Heavy path overlapping tends to occur as the path arrival rate increases and the channel power decay is slow. This is investigated further in Section 3.4 through simulations.

The above results extend the multipath channel model used in [23] to directional plane wave model with near-field perturbations. New insights are thus obtained into the impact from the array elements number and incident directions of inter-

fering plane waves. The theoretical analysis also gives some hint on performance improvement by exploiting multipath-aided acquisition in the first cluster.

3.3 Joint TOA and AOA Estimation of the Direct Path

A delay-and-sum beam-former with directional finding for UWB-IR signals is given in [53] together with its performance in the absence of multipath. The self-steering array beam-former is capable of achieving high angular resolution in the absence of multipath. Motivated by the good performances of this beam former, we adopt the delay-and-sum beam-former structure and investigate its performance in the presence of multi-paths that overlap with the direct path. To simplify hardware complexity, we replace the sliding correlator in [53] with a band-pass filter (BPF) matched to the signal bandwidth around UWB-IR center frequency followed by a square-law detector and a low-pass filter (LPF).

Following the signal model in (3.2) of L multi-paths which are far-field plane waves and $L_e - L$ multi-paths which are near-field perturbations, the delay-and-sum beam former output can be derived as,

$$y(t, \theta_i) \triangleq \sum_{e=1}^N x^e(t - \Delta\tau^e(\theta_i)) = Na_i s(t - \tau_i^o) + \sum_{l \neq i} \sum_{e=1}^N a_l^e s(t - \tau_l^e - \Delta\tau^e(\theta_i)) + \sum_{e=1}^N n^e(t)$$

$$i \in \{1, \dots, L\} \quad l \in \{1, \dots, (i-1), (i+1), \dots, L_e\} \quad (3.29)$$

Figure 3.2: Received signals at a 4-element UAA.

In the above equation, the antenna array is steered towards the AOA θ_i of the i^{th} plane wave and the received signals from the i^{th} far-field path form into a beam. Since the direct path plane wave is usually dominant in LOS environments, the maximum responses at TOA τ_1^o and AOA θ_1 result in the main beam of intensity proportional to the array elements number N . As shown in the top subplot of Fig. 3.3, $\theta_1=150^\circ$ and $\tau_1=3.05\text{ns}$. However, if an interfering plane wave from $\theta_2=120^\circ$ and $\tau_2=3.95\text{ns}$ falls into the direct path signal duration, the beam is diffused, raising ambiguities in TOA and AOA of the direct path, as shown in the bottom subplot of Fig. 3.3. Moreover, the beam peak of the direct path is biased in steering direction

Figure 3.3: Beam-former output in normalized magnitude.

and time by the interfering plane wave in the first cluster. If the approach of beam energy maximization in [52] is used in this case, the beam diffusion leads to the direct path estimation with TOA and AOA error of 0.1ns and 7° respectively. Therefore, fine tuning of the estimation by multipath-aided acquisition after initial estimation by beam-forming is proposed to avoid the bias in TOA and AOA induced by the clustering of multipath arrivals.

The beam-forming signal $y(t, \theta_i)$ can be more efficiently processed in frequency

domain as follows,

$$Y_n \triangleq \text{FFT}\{y(t, \theta_i)\} \quad n \in \{1, \dots, N_f\}$$

$$\mathbf{Y} = [Y_1 \quad \dots \quad Y_{N_f}]^T \quad (3.30)$$

where $\mathbf{Y}$ denotes the discrete Fourier transform of $y(t, \theta_i)$ with N_f samples, and θ_i is one of the initial estimation candidates. The source signal spectrum is also obtained by the fast Fourier transform (FFT),

$$S_n \triangleq \text{FFT}\{s(t)\} \quad n \in \{1, \dots, N_f\}. \quad (3.31)$$

Multipath channel propagation (includes both the far-field plane waves which are not in the beam-formed direction and the near-field perturbations), represented by the second term in (3.29), induces fading effects. These fading effects can be represented by amplitude gain d_n and phase change ϕ_n on the n^{th} frequency component, where $n \in \{1, \dots, N_f\}$. That is,

$$d_n e^{j\phi_n} \triangleq \sum_{l=1}^{L_e} a_l^e \exp(-j\omega_n \tau_l^e), \quad \omega_n = 2\pi \left(\frac{(n-1)f_s}{N_f} - \frac{f_s}{2} \right) \quad (3.32)$$

where f_s represents the sampling rate. The observation error based on the channel

fading modeling is formulated as,

$$\left\| \mathbf{Y} - \sum_{e=1}^N \begin{bmatrix} S_1 e^{-j\omega_1 \Delta \tau^e(\theta_i)} & 0 & 0 \\ 0 & \ddots & 0 \\ 0 & 0 & S_{N_f} e^{-j\omega_{N_f} \Delta \tau^e(\theta_i)} \end{bmatrix} \cdot \begin{bmatrix} d_1 e^{j\phi_1} \\ \vdots \\ d_{N_f} e^{j\phi_{N_f}} \end{bmatrix} \right\|^2. \quad (3.33)$$

In the above formula, the channel fading effect can be decomposed as

$$[d_1 e^{j\phi_1} \quad \dots \quad d_{N_f} e^{j\phi_{N_f}}]^T = \mathbf{A}^e \mathbf{a}^e, \quad (3.34)$$

where the phase $\mathbf{A}^e$ and amplitude matrix $\mathbf{a}^e$ are respectively written as,

$$\mathbf{A}^e \triangleq \begin{bmatrix} \exp(-j\omega_1 \tau_1^e) \dots \exp(-j\omega_1 \tau_{L_e}^e) \\ \vdots \\ \exp(-j\omega_{N_f} \tau_1^e) \dots \exp(-j\omega_{N_f} \tau_{L_e}^e) \end{bmatrix} \quad (3.35)$$

$$\mathbf{a}^e \triangleq \begin{bmatrix} a_1^e & \dots & a_{L_e}^e \end{bmatrix}^T \quad (3.36)$$

Applying the FFT linear property to Y_n , we get $Y_n = \sum_{e=1}^N X_n^e \exp(-j\omega_n \Delta \tau^e(\theta_i))$,

where $\mathbf{X}^e$ is the discrete Fourier transform of an observation of received signal $x^e(t)$.

Substituting this into (3.33), the phase term $\exp(-j\omega_n \Delta \tau^e(\theta_i))$ is canceled out by

its conjugate when computing the Euclidean norm $\|\cdot\|$. Therefore, the squared error

formula in (3.33) denoted by E can be rewritten as,

$$E = \sum_{e=1}^N \left\| \left(\mathbf{I} - \mathbf{S} \mathbf{A}^e \left((\mathbf{S} \mathbf{A}^e)^H \mathbf{S} \mathbf{A}^e \right)^{-1} (\mathbf{S} \mathbf{A}^e)^H \right) \mathbf{X}^e \right\|^2 \quad (3.37)$$

where $\mathbf{S}$ is a diagonal matrix of source spectral samples S_n . Given the initial estimations in TOA and AOA which are close to the main beam, the squared error E can be minimized by multipath-aided acquisition as follows,

$$\{\hat{\tau}_1, \hat{\theta}_1, [\tau_2^1, \dots, \tau_2^N], [\tau_3^1, \dots, \tau_3^N], \dots\} = \arg \min_{\{\cdot\} \subset \text{beam}} (E) \quad (3.38)$$

For narrowband signals, (3.38) can be optimized through alternating projection (AP), expectation maximization (EM) [67] or coordinate descent (CD) [68] algorithms. For UWB-IR signals, we devise a strategy to search (3.38) with reduced computational complexity as follows,

- i*) UWB-IR signals indoor propagation is characterized by well-spaced clusters of multipath arrivals. Observed data $\mathbf{X}^e$ can be shortened by truncating the received signal $x^e(t)$ in equation (3.2) to separate the first cluster from well-spaced multi-paths. Fig. 3.2 illustrates the first dominant cluster, signal-off period and next resolved multipath cluster for $x^2(t)$. In this separation process, a threshold at 7.8dB above the standard deviation of the noise amplitude is used to determine signal clusters exceeding that level.
- ii*) The direct path plane wave TOA and AOA can be initially estimated by beam forming magnitude crossing a given threshold. As shown in Fig. 3.2, the enve-

lopes $p^e(t)$ is extracted for every windowed signal $x^e(t)$ received at a 4-element UAA. In the case shown in Fig. 3.2, the transmitted signal has -10dB bandwidth of 1.4GHz, and the channel impulse responses are induced by three plane waves in TOA's and AOA's respectively: $\tau_1=3.05\text{ns}$ and $\theta_1=150^\circ$, $\tau_2=3.95\text{ns}$ and $\theta_2=120^\circ$, $\tau_3=7.25\text{ns}$ and $\theta_3=45^\circ$. The envelopes of the windowed signals $p^e(t)$ is used to build a beam in steering direction and time with normalized magnitude as shown in the bottom subplot of Fig. 3.3. As suggested in [32], an acceptable false alarm rate P_{ed} of the direct path TOA detection can be achieved by adjusting the threshold-to-noise ratio (TNR). A TNR of 15dB is required to ensure the probability of false alarm to be less than 10^{-3} . In our case, this corresponds to a normalized threshold of 0.8 taking into consideration the received worst case SNR=10dB and $N=4$.

- iii*) UWB signal has energy spectrum confined within the bandwidth B_w around the center frequency f_c . Truncation of spectral samples to $f_n \in [f_c - B_w/2, f_c + B_w/2]$ of the windowed received signals and transmitter template is used to reduce the number of data samples.
- iv*) The search strategy of (3.38) can be implemented by serial search or fixed-step serial search [68, 71]. Note in a flat fading channel, the search step is the spacing between local peaks of the auto-correlation function of source signal [72]. However in a multipath fading channel, the time search step cannot be obtained from the a-priori path-arrival-rate [22] or from the spacing between local peaks of the auto-correlation function [68]. Therefore, conventional serial search is

employed in our case. It uses an iterative process: in the current k^{th} iteration, minimize the squared error (3.38) over τ_l^e while fixing $\tau_1^e, \dots, \tau_{l-1}^e, \tau_{l+1}^e, \dots, \tau_{L_e}^e$ at the last iteration $(k-1)^{th}$ estimations, until the difference among successive iterations is below a certain threshold. In the initial round $k=0$, τ_1 and θ_1 are obtained from the threshold-crossing beam forming, and the rest $\tau_2^e, \dots, \tau_{L_e}^e$ can be sequentially estimated by sensor-CLEAN [40] or matched filter [35].

A few remarks about the efficiency of the above LSE computation are of interest.

i) The beam is diffused due to the weak direct LOS signal and heavy path overlapping. If the beam around the beam peak has no misalignment in steering direction and time, the computational cost converges to that of 1-D search in [52].

ii) Computational complexity of L -dimensional serial search is evaluated as

$$\sum_{e=1}^N O(T_w^{L_e-1}), \text{ while AP has the complexity of } \sum_{e=1}^N O((L_e - 1)T_w \cdot N_c), \text{ where } T_w$$

is the pulse width and N_c is the iteration number to get to convergence. If the

fixed-step serial search is employed in the above strategies, the computational

$$\text{complexity of } L\text{-dimensional search reduces to } \sum_{e=1}^N O((T_w/\Delta)^{L_e-1}), \text{ while that}$$

$$\text{of AP is } \sum_{e=1}^N O(N_c(L_e - 1)T_w/\Delta), \text{ where } \Delta \text{ is the search step in time. As we}$$

can see, rapid convergence benefiting from the accurate initial estimations with

a certain L_e makes AP and CD more efficient than L -dimensional search.

iii) A-priori channel knowledge of the minimum time space Δ between multipath arrivals and the number of dominant multipath L_e in the first cluster helps to

reduce the complexity.

3.4 Simulation Results

The performance of the proposed joint TOA and AOA estimator for a UWB-IR based RFID localization system is studied through simulations using the IEEE 802.15.4a CM3 channel model and model parameters [22]. The pulse shape of the UWB-IR signal is measured from a UWB RFID-tag with center frequency f_c of 3.4GHz and -10dB bandwidth B_w of 1.4GHz. The pulse duration is 2ns, the pulse repetitive interval (PRI) is $1\mu s$, and a receiver sampling interval of 50ps is used. The channel power delay spread is always shorter than the PRF. The AOA of the direct path plane wave θ_1 is taken as a uniformly distributed random variable in the range of $[0, 2\pi)$. The TOA of the direct path at each array element τ_1^e is determined by an assumed value for τ_1^o and $\Delta\tau_{\text{UAA}}^e(\theta_1)$ calculated using (3.3). The l^{th} path TOA at each array element τ_l^e is assumed to follow a Poisson process with rate λ . For the study of path-arrival-rate λ effects on the performance, we make an adjustment from the mixture of two Poisson processes to a Poisson process. The expected amplitude of the l^{th} path is characterized by an exponential decay of the mean cluster amplitude with rate Γ , and another exponential decay of the intra-cluster mean ray amplitude with rate γ . The multi-paths power decay and small-scale fading parameters of IEEE 802.15.4a CM3 model are given in [22]. Time domain signals received at a 4-element uniform angular array with $r_0=25\text{cm}$ are simulated. The range of the transmitter is assumed to be much larger than the array radius and hence the direct path signal

3.4 Simulation Results

received at each receiver antenna element is assumed to have the same SNR. The channel multi-paths at each receiver antenna element follow either the plane wave propagation or near-field perturbations. The noise power spectral density at array antenna elements is assumed to be the same. In performance evaluation, root-mean-square-error (RMSE) of the direct path TOA and AOA estimation is taken over 400 simulations of the array measurements.

Figure 3.4: SNR effects on AOA estimations.

Fig. 3.4 and Fig. 3.5 present the direct path SNR effects on the AOA and TOA estimations performance respectively with near-field perturbations denoted by a certain path-arrival-rate λ . When $\lambda = 0.32$ 1/ns, the mean number of dominant

Figure 3.5: SNR effects on TOA estimations.

paths $L_e = 2$ and this is the case of the direct path and a multipath overlapping within the direct path signal duration. The performance result of our method denoted by L-D is compared with the 1-D search method used in [52], and the CRB. As shown in Fig. 3.4, the CRB and AOA estimations improve as the SNR increases. When the sampling rate f_s is limited to 20GHz, this improvement appears to reach a floor with AOA error of 1.5° when the SNR is over 30dB. A higher sampling rate of 80GHz can decrease the gap between the CRB and AOA estimations especially in high SNR regions as shown in the figure. The error floor with a gap to the theoretical CRB is firstly due to the limit of the time sampling interval. Two sampling

3.4 Simulation Results

frequency of 20GHz and 80GHz are employed in simulations. As shown in Fig. 3.4 and Fig. 3.5, the error floor is reduced by decreasing the time sampling interval. The limit of the simulation times is the second source of the error floor. In other words, if the small enough time interval can be used, or the simulation times is large enough, the RMSE is approximate to the theoretical CRB. The error floor with a gap to the theoretical CRB can be also found in the studies of other ranging algorithms [32, 52]. As also discussed in [12], the theoretical bounds may be very difficult to achieve with practical estimators because the CRB derived theoretically assume perfect knowledge of the probability distribution. Such information may not be available in practice. Compared with the 1-D method, our L -D method has better AOA estimation performance at SNR higher than 20dB. This performance improvement is more substantial at the higher sampling rate of 80GHz. In Fig. 3.5, the CRB and TOA estimations are presented which show performance improving with increasing SNR. When the fs is 20GHz, 1-D estimations tend to reach a floor with TOA error of 0.01ns, while L -D estimation errors are bounded at 0.005ns. The performance gap between the CRB and TOA estimations in high SNR regions is reduced by a higher sampling rate of 80GHz. Compared with the 1-D method, our L -D method has better TOA estimation performance at SNR higher than 25dB. This performance improvement is more substantial at the higher sampling rate of 80GHz.

Table 3.1: The multipath number in the first cluster versus path arrival rate.

λ [1/ns]	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
T_{cd} [ns]	0.3	0.7	1.2	1.8	2.5	2.9	3.7	3.9	4.6	5.2
L_e	1.2	1.5	1.8	2.3	2.9	3.4	4.2	4.6	5.3	6.1

3.4 Simulation Results

Figure 3.6: AOA errors versus path arrival rates.

Next, Far-field plane wave overlapping together with near-field perturbations on AOA and TOA estimations are examined. The relationship between the number of dominant paths L_e in the first cluster with path-arrival-rate λ is presented in Table. 3.1. The first cluster duration of T_{cd} is evaluated as the time delay spread of continuous multipath components with respect to the direct path TOA. The result shown in the table is the average over 400 simulations. As illustrated in the table, L_e and T_{cd} increase with path-arrival-rate λ . The computational cost increases significantly for L_e beyond 5 and thus we limit our investigations for λ values up to 1. Fig. 3.6 and Fig. 3.7 show the path-arrival-rate effects on the AOA and TOA estimations performance when the SNR is fixed at 25dB in the presence of two overlapping

Figure 3.7: TOA errors versus path arrival rates.

plane waves. These interfering plane waves are at $\Delta\tau=1\text{ns}$, $\Delta\theta = \pi/6$ and $\Delta\tau=1\text{ns}$, $\Delta\theta = \pi/3$ with respect to the direct path plane wave TOA and AOA. The following markers are used in the figures: L -D search is marked with ' $\diamond$ ' and 1-D search is marked with ' x ' whereas CRB is with no marker. The direct path plane wave is denoted by $\Delta\tau=0$, and $\Delta\theta=0$. As shown in Fig. 3.6, the CRB and AOA estimation errors increase as λ increases. The advantages of using L -D over 1-D can be verified by accuracy improvements of 6.1° , 17.5° and 15.7° respectively in the cases of $\Delta\tau=0$, $\Delta\theta=0$, $\Delta\tau=1\text{ns}$, $\Delta\theta = \pi/6$ and $\Delta\tau=1\text{ns}$, $\Delta\theta = \pi/3$. As shown in Fig. 3.7, increasing λ also increases errors in TOA estimations and the CRB. The performance improvements using L -D over 1-D are 0.8cm, 2.9cm and 3.4cm respectively in cases

3.5 Simulation Results

of $\Delta\tau=0$, $\Delta\theta=0$, $\Delta\tau=1\text{ns}$, $\Delta\theta = \pi/6$ and $\Delta\tau=1\text{ns}$, $\Delta\theta = \pi/3$. The performance gap between the CRB and estimations in both Fig. 3.6 and Fig. 3.7 suggests the CRB of AOA and TOA errors is not a tight bound in dense multipath environments.

The performance improvement using L -D over 1-D is based on the simulation results in the IEEE 802.15.4a CM3 channel scenario of increasing path-arrival rate and a fixed SNR. Firstly, IEEE 802.15.4a model is a channel standard of UWB with low data rates for localization purposes in WPAN, where the CM3 indicates the indoor office LOS environment. Secondly, it is well-known for multipath arrivals to follow a Poisson process with a rate. As the path-arrival rate increases, the multipath arrival intervals decrease. Thirdly, the path-arrival-rate effects on the algorithm performance in the presence of two overlapping plane waves are examined in Fig. 3.6 and Fig. 3.7, where $\Delta\tau$ and $\Delta\theta$ respectively denote the time-difference and angle-difference of arrival between this two plane waves. As shown in Fig. 3.6, the advantages of using L -D over 1-D can be verified by the accuracy improvements of 6.1° , 17.5° and 15.7° respectively in the cases of $(\Delta\tau = 0, \Delta\theta = 0)$, $(\Delta\tau = 1\text{ns}, \Delta\theta = \pi/6)$ and $(\Delta\tau = 1\text{ns}, \Delta\theta = \pi/3)$. As shown in Fig. 3.7, the performance improvements using L -D over 1-D are 0.8 cm, 2.9 cm and 3.4 cm respectively in the cases of $(\Delta\tau = 0, \Delta\theta = 0)$, $(\Delta\tau = 1\text{ns}, \Delta\theta = \pi/6)$ and $(\Delta\tau = 1\text{ns}, \Delta\theta = \pi/3)$. So the average improvement in AOA and TOA is 13.1° and 2.4cm respectively.

3.5 Measurement Results

An active UWB RFID tag is used to transmit the pulse signal every $1\mu\text{s}$. The power spectrum of signal is in compliance with the FCC EIRP mask, where the central frequency is 4.1GHz and the 10dB bandwidth is 1.8GHz. The pulse width is 1.5ns. The transmitter peak power output is 23dBm. The transmitter circuits consist of a microcontroller unit board (MCU) and a UWB pulse generator board. The transmitter chip design is explained in details in [25]. Omni-directional antenna with 0dBi gain is used at the tag. A planar 4-sensor uniform circular array with 25cm radius is assembled as shown in Fig. 3.8. At each sensor, a bi-conical antenna with 0dBi gain is used to drive the input of the receiver circuit board incorporating a Wireless Local Area Network (WLAN) notch filter and a three-stage variable gain low-noise amplifier (LNA). The output waveforms are measured by a four-channel 4GHz LeCroy oscilloscope with 50ohms input impedance. The four-channel received signals are synchronized by the triggered signal from the active tag. The sampling frequency is 20GHz. Pulse distortion due to the nonlinear filtering and the amplifier saturation exists. The received pulse shape has the duration of 2ns as shown in [67]. Although the exact same design of antenna, sensor circuits and the cables is deployed in the measurement setup, pre-calibration is used to calibrate out the delay difference among sensors. The measurement environment is in an indoor open hall of 30 x 25 m². The measured azimuth angles are 0°, 45° and 90°. The measured range is from 1m to 21m, where the direct path is with SNR from 44.7dB to 13.1dB. At each measured location, the number of samples taken is 4 x 100.

3.5 Measurement Results

The measured signals at the receiver array are normalized and truncated to an observation window as shown in the Fig 3.2. The expected SNR of the direct path is obtained by fitting the path loss model to the peak amplitude measured in a range from 1m to 21m, as shown in [67].

The channel impulse response $h(t)$ at each measured location is estimated. Therefore, the theoretical CRB for TOA and AOA error is obtained. The performance is also acquired based on the simulated signals, where the convolution between the signal template and $h(t)$ is used to simulate received signals. As shown in Fig. 3.9 and Fig. 3.10, there is almost no performance difference between measured signals and simulated signals. The channel characteristics in term of the mean excess delay τ_m and channel delay spread τ_{rms} for the measured environment are listed as follows.

Table 3.2: Channel profile estimated in the measurement environment.

Range(m)	1-8	9	10	11	12	13	14	15	16	17	18	19	20	21
τ_m (ns)	0	0.16	0	0.60	0.02	0.52	0.15	0.05	0.28	0.87	0.54	0.08	0.59	0.29
τ_{rms} (ns)	0	0.20	0	1.09	0.04	1.01	0.27	0.09	0.59	1.55	0.95	0.13	1.02	0.49

As shown in Fig. 3.9 and Fig. 3.10, the CRB, AOA and TOA estimation errors increase with increasing Tag-Receiver separations. The L -D search decreases the AOA error from 10.6° to 7.2° , and reduces the TOA error from 2.1cm to 1.9cm. As we can see from Fig. 3.9 and Fig. 3.10, the corresponding simulation results denoted by L -D simulated have little difference from the measurement results. Performance gap between the CRB and estimations in both AOA and TOA exists in real environments. The error in area² of practical interest is less than 0.1m^2 within range of 11m, and

²The sector area formula gives $dS = r dr d\theta$, where r is the actual range, dr is given by two times

3.5 Measurement Results

Figure 3.8: Measurement instruments setup.

rises to 0.2m^2 at range of up to 16m , and is bounded at 0.5m^2 within 20m .

of the RMSE of TOA multiplied by the speed of light, and $d\theta$ is two times of the RMSE of AOA.

3.5 Measurement Results

Figure 3.9: AOA error versus range in real measurement.

3.5 Measurement Results

Figure 3.10: TOA error versus range in real measurement.

3.6 Conclusion

Joint TOA and AOA estimation of the direct path is challenging in dense cluttered environments. Our approach considering the main beam diffusion in a self-steering beam former appears to yield good results. Initial estimations of the main beam are improved by separating well-spaced multi-paths and avoiding the side-lobes disturbances. An efficient algorithm is implemented to identify the beam diffusion characteristics through iterative joint TOA and AOA estimation. For IEEE 802.15.4a CM3 channel model at 25dB, our estimator is shown to have joint TOA and AOA accuracy improvements of 2.4cm and 13.1° respectively. Performance in a real environment shows the error in area is restricted under 0.5m^2 in a measured range of 20m.

Chapter 4

Robust Ultra-wideband Direction Finding in Dense Cluttered Environments

4.1 Introduction

Cooperative wireless network [62] is an emerging solution for reliable localization and navigation in cluttered environments, in which ultra-wideband impulse radio (UWB-IR) is considered as a promising PHY layer alternative [22] among peer nodes. In a cooperative scenario, network nodes orientation with respect to each other are valuable information, which can be estimated by distances measured from neighboring nodes, or obtained using angle-of-arrival (AOA) estimation techniques. In dense cluttered environments with many walls, furniture and machines, the signal propagation is complicated. There are multiple propagation paths from the transmitting node to the receiving node due to reflecting surfaces and scattering objects in the environment resulting in clusters of multipath arrivals in different spatial direction-

s. In addition, the propagation paths may penetrate through walls and materials resulting in distorted signal shape. The reflecting surfaces at different orientations in the far-field of the receiver result in multiple plane waves which can be spatially separated if an antenna array is employed at the receiver. However, reflecting and scattering objects in the near-field create correlated multi-paths which are superimposed on these plane waves. Furthermore, the direct (line-of-sight) path may be obstructed, resulting in the strength of the direct path plane wave being comparable to the multipath and interfering plane waves. These phenomena in dense cluttered environments bring challenges to the AOA estimation.

Source direction finding or AOA estimation is a major topic in radar-related applications, and attracts numerous interests in narrow-band and broad-band array processing [3]. The basic principle for this estimation is to detect the phase difference among spatial-calibrated antenna elements of the array for an arriving plane wave while the multipath interferences are averaged out. State-of-the-art array processing is briefly reviewed leading to our research motivation. Conventional beam-forming method known as Bartlett beam-former [38] is used in radars to maximize the received power in a particular (beam-formed) direction. However, the spatial resolution of this method is limited by the beam width [3]. The spatial resolution can be improved by a sharpened beam width using the minimum variance distortionless response (MVDR) known as Capon beam-former [39]. The spatial resolution is significantly improved using subspace methods, e.g. MUSIC (Multiple Signal Classification) algorithm [41,42]. However, correlated multipath disturbs the eigen-value

decomposition used in subspace methods [57,63,73], and the robustness to the colored noise and multipath propagation is dramatically reduced [6,72,74]. Another famous subspace method known as ESPRIT (estimation of signal parameter via rotational invariance techniques) [43,44] exploits the shift structure by partitioning sub-arrays. The advantage using sub-arrays is that, forward-backward spatial smoothing can be conveniently implemented to mitigate the correlated interferences [45–47]. However, spatial smoothing works for independent multipath but fails for interfering plane waves. Parametric AOA estimation, which exploits the underlying statistical model, is usually accompanied by a multi-dimensional (M -D) optimization. The most well-known parametric method is the maximum likelihood (ML) technique [3], which can be approximated in the least-squares sense by subspace fitting [75] or weighted subspace fitting (WSF) [76]. A few commonly-used M -D techniques include Quasi-Newton, alternating projection (AP) and expectation maximization (EM) [3]. Polynomial parameterization of WSF, ML, ESPRIT and MUSIC has resulted in efficient variants Root-WSF [77], IQML (iterative quadratic maximum likelihood) [78], unitary ESPRIT [79] and Root-MUSIC [80]. The computational efficiency is further improved with UWB-IR signals because the ultra-wide bandwidth provides some degree of immunity to multi-paths [40]. In [54], the multipath impinging on an UWB array from a single direction is considered and solved using 1-D signal subspace. Two closely-spaced UWB correlated sources in multipath-free environments are recognized by 1-D EM algorithm in [55]. High resolution in indoor environments is demonstrated using 2-D unitary ESPRIT with UWB signals in [57]. Joint estima-

tion of AOA and time-of-arrival (TOA) with a UWB antenna array is investigated in [52].

Motivated from the need for efficient and reliable direction finding in dense cluttered environments, we studied the effects on direct path AOA and TOA accuracies due to overlapping correlated multi-paths using UWB-IR signal with varied SNR and the path arrival rate, and proposed a joint TOA and AOA estimator to adapt to non-overlapping and overlapping multi-paths in [81]. The investigations however did not distinguish between overlapping multi-paths that are far-field plane waves and near-field multipath. It also did not address the issue of an uncertain number of arriving far-field planewave signals in the computation. This chapter proposes a robust direction finding solution with UWB-IR signals in dense cluttered environments. The robustness of the algorithm is evaluated by changing SNR, the far-field reflector spacing, and the number of interfering plane waves with near-field perturbations. The results are compared with 1-D MUSIC algorithm [56,82], M -D least-squares [81] and the Cramér-Rao bound. The novelty of this work is summarized as follows: (i) The computational time is saved using the detection of plane waves prior to AOA estimation. (ii) Subspace fitting with alternating projection (AP) method is first applied to the UWB direction finding, and this strategy is extended to multiple coherent plane waves. High angular resolution is obtained benefiting from processing with given number of plane waves and the ultra-wide bandwidth.

Figure 4.1: Propagation model in dense cluttered environments.

4.2 System Model

Propagation model for UWB-IR signals in dense cluttered environments is shown in Fig. 4.1. The line-of-sight path may be obstructed, and the signal from this direct path is attenuated and delayed due to the obstruction. Specular reflector in the environment creates a strong ray whereas scattering object creates many rays with varied phase and hence much weaker. Consider an N -element antenna array receiving UWB signals from a distant transmitting antenna. The transmitted, reflected and scattered signals in the far-field of the receiver array result in plane waves impinging on the antenna array with amplitude and AOA that are consistent among array elements, while the reflected and scattered signals in the near-field of receiver array result in multi-paths with significant differences in amplitude and AOA among array elements. Note that, most multi-paths including the direct path follow the plane-wave radiation due to the small spacing among array elements in comparison with the open environments and the distant source. Consider the case of a single UWB-IR source: At the receiver, the direct path plane wave is attenuated by the blockages, and

is superimposed with strong coherent plane waves from far field reflectors, correlated near-field multipath and noise. For the purpose of direction finding, this direct path is assumed to be detectable. Due to the ultra-wide bandwidth of UWB signals, the number of coherent planewaves interfering with the direct path planewave is limited [22]. Assuming D plane waves are included in the first cluster, and the minimum angle-difference-of-arrival (ADOA) among planewaves can be differentiated by a high enough sampling rate. It should be noted that scattering objects in the far-field of the receiver array may cause multiple planewaves with un-differentiable ADOA, and this scenario is not considered in our studies. However in practice, these scattered signal amplitudes are small in comparison with the reflected signals in the far field in most cases. Furthermore, near-field multipath and noise in the first cluster add challenges to the estimation of the direct path planewave. With these considerations, the received UWB signals in the first cluster at the e^{th} array element denoted by $x^e(t)$ is written as,

$$x^e(t) = \sum_{i=1}^D r_i(t + \Delta\tau^e(\theta_i)) + w^e(t) \quad (4.1)$$

where $r_i(t)$ denotes the i^{th} coherent plane wave with AOA θ_i , and $\Delta\tau^e(\theta_i)$ gives time-difference-of-arrival (TDOA) of the i^{th} plane wave between the e^{th} array element and the reference array element. $w^e(t)$ is treated as colored noise at each sensor, which includes uncorrelated noise and correlated near-field multipath. Each plane wave can

be further modeled as an attenuated and delayed source signal $s(t)$.

$$r_i(t) = a_i s(t - \tau_i) \quad (4.2)$$

where a_i and τ_i are respectively the amplitude and time delay of the i^{th} plane wave.

In the frequency domain ω , the D plane waves impinging on the N -element antenna array with colored noise can be modeled as,

$$\mathbf{X}(\omega) = \mathcal{F}\{[x^1(t) \ \dots \ x^N(t)]^T\} = \mathbf{V}(\Theta)\mathbf{R}(\omega) + \mathbf{W}(\omega) \quad (4.3)$$

where $\mathcal{F}$ denotes the Fourier transform, and ω is the angular frequency. $\mathbf{R}(\omega) \triangleq [R_1(\omega) \ \dots \ R_D(\omega)]^T$ is defined as a column vector of the plane wave spectrum, where $R_i(\omega)$ is the spectrum of the i^{th} plane wave $r_i(t)$. $\mathbf{V}(\Theta) \triangleq [\mathbf{v}(\theta_1) \ \dots \ \mathbf{v}(\theta_D)]$ incorporates the spatial characteristics of the array in response to the D plane waves, where $\mathbf{v}(\theta_i) \triangleq [e^{j\omega\Delta\tau^1(\theta_i)} \ \dots \ e^{j\omega\Delta\tau^N(\theta_i)}]^T$ is referred as the array manifold for the i^{th} plane wave, and an AOA collection defined as $\Theta \triangleq [\theta_1 \ \dots \ \theta_D]$. Assume additive white Gaussian noise (AWGN) of double-sided power spectral density $N_0/2$ at each receiver sensor, then the spectrum of colored noise $\mathbf{W}(\omega) = \mathcal{F}\{[w^1(t) \ \dots \ w^N(t)]^T\}$ can be evaluated as,

$$\mathbb{E}\{\mathbf{W}(\omega)\mathbf{W}^H(\omega)\} = \tilde{\mathbf{\Lambda}} + \frac{N_0}{2} \cdot \mathbf{I} \quad (4.4)$$

where $\mathbb{E}\{\cdot\}$ denotes the expected value, and $\mathbf{W}^H(\omega)$ is the conjugate transpose of $\mathbf{W}(\omega)$. $\tilde{\mathbf{\Lambda}}$ is the spectral matrix of composite near-field multipath. $\mathbf{I}$ is an identity

matrix of size N . Then, the likelihood function of discrete $\mathbf{X}(\omega)$ can be derived as,

$$L_{\mathbf{X}}(\Theta) = -K \ln \det(\tilde{\mathbf{\Lambda}} + \frac{N_0}{2} \cdot \mathbf{I}) - \sum_{k=1}^K [\mathbf{X}(\omega_k) - \mathbf{V}_k(\Theta) \mathbf{R}(\omega_k)]^H (\tilde{\mathbf{\Lambda}} + \frac{N_0}{2} \cdot \mathbf{I})^{-1} [\mathbf{X}(\omega_k) - \mathbf{V}_k(\Theta) \mathbf{R}(\omega_k)] \quad (4.5)$$

where

$$\omega_k = 2\pi \left(\frac{(k-1)f_s}{K} - \frac{f_s}{2} \right) \quad (4.6)$$

$$k \in \{1, \dots, K\}$$

f_s represents the sampling rate. K is the sample number of discrete Fourier transform, and $\det(\cdot)$ gives the matrix determinant. Due to the lack of knowledge of $\tilde{\mathbf{\Lambda}}$, the ML estimation is approximated by the least-squares estimation for convenience.

$$\hat{\Theta}_{\text{LS}} = \arg \min_{\Theta} \left\{ \sum_{k=1}^K \|\mathbf{X}(\omega_k) - \mathbf{V}_k(\Theta) \mathbf{R}(\omega_k)\|^2 \right\} \quad (4.7)$$

where $\|\cdot\|$ denotes the Euclidean norm. The linear solution of $\mathbf{X}(\omega) = \mathbf{V}(\Theta) \mathbf{R}(\omega)$ gives $\mathbf{R}(\omega) = \mathbf{V}^\dagger(\Theta) \mathbf{X}(\omega)$, where $\mathbf{V}^\dagger = [\mathbf{V}^H \mathbf{V}]^{-1} \mathbf{V}^H$ is defined as the Moore-Penrose pseudo inverse of $\mathbf{V}$. Substitute $\mathbf{R}(\omega)$, and the derivation is given as follows,

$$\begin{aligned} & \|\mathbf{X}(\omega) - \mathbf{V}(\Theta) \mathbf{R}(\omega)\|^2 \\ &= \|(\mathbf{I} - \mathbf{V}(\Theta) \mathbf{V}^\dagger(\Theta)) \mathbf{X}(\omega)\|^2 = \|\mathbf{P}_{\mathbf{V}(\Theta)}^\perp \mathbf{X}(\omega)\|^2 \\ &= \text{tr} [\mathbf{P}_{\mathbf{V}(\Theta)}^\perp \mathbf{X}(\omega) \mathbf{X}^H(\omega) \mathbf{P}_{\mathbf{V}(\Theta)}^\perp] \end{aligned} \quad (4.8)$$

where $\text{tr}[\cdot]$ gives the matrix trace. And $\mathbf{P}_{\mathbf{V}(\Theta)}^\perp$ is termed the orthogonal complement of the projection matrix $\mathbf{P}_{\mathbf{V}(\Theta)}$.

$$\mathbf{P}_{\mathbf{V}(\Theta)} = \mathbf{V}(\Theta)\mathbf{V}^\dagger(\Theta) \quad (4.9)$$

$$\mathbf{P}_{\mathbf{V}(\Theta)}^\perp = \mathbf{I} - \mathbf{P}_{\mathbf{V}(\Theta)} \quad (4.10)$$

The sample of received spectral matrix is defined as $\mathbf{C}_{\mathbf{X}(k)} \triangleq \mathbf{X}(\omega_k)\mathbf{X}^H(\omega_k)$. The properties of matrix trace and projection are applied in (4.8) to derive (4.11).

$$\hat{\Theta}_{\text{SF}} = \arg \min_{\Theta} \left\{ \sum_{k=1}^K \text{tr} [\mathbf{P}_{\mathbf{V}(\Theta)}^\perp \mathbf{C}_{\mathbf{X}(k)}] \right\} \quad (4.11)$$

And it is mathematically equivalent to the following,

$$\hat{\Theta}_{\text{SF}} = \arg \max_{\Theta} \left\{ \sum_{k=1}^K \text{tr} [\mathbf{P}_{\mathbf{V}(\Theta)} \mathbf{C}_{\mathbf{X}(k)}] \right\} \quad (4.12)$$

The formula (4.12) and (4.11) are referred to as subspace fitting (SF) estimation [3], and they are respectively interpreted as the projection of received signals onto the D -dimensional subspace $\mathbf{U}_S$ spanned by the columns of $\mathbf{V}(\Theta)$ and the projection of received signals onto the subspace orthogonal to $\mathbf{U}_S$, where the projection matrices are respectively defined as $\mathbf{P}_{\mathbf{V}(\Theta)}$ and $\mathbf{P}_{\mathbf{V}(\Theta)}^\perp$. Explicitly, the D -dimensional subspace $\mathbf{U}_S$ indicates the collection of eigenvectors corresponding to the first D eigenvalues $\lambda_1, \lambda_2, \dots, \lambda_D$ for the eigen-decomposition of the expected received spectral matrix

$\mathbf{S}_{\mathbf{X}(\omega)}$, which is termed the plane-wave subspace.

$$\mathbf{S}_{\mathbf{X}(\omega)} = \frac{1}{K} \sum_{k=1}^K \mathbf{X}(\omega_k) \mathbf{X}(\omega_k)^H = \mathbf{U}_S \text{diag}\{\lambda_1, \lambda_2, \dots, \lambda_D\} \mathbf{U}_S^H + \mathbf{U}_N \text{diag}\{\lambda_{D+1}, \dots, \lambda_N\} \mathbf{U}_N^H \quad (4.13)$$

The subspace $\mathbf{U}_N$ orthogonal to $\mathbf{U}_S$ is termed the noise subspace. The physical meaning of (4.11) is to minimize the colored noise effects on the received signals, which can be interpreted as minimizing the projection of received signals onto the noise subspace. And it is equivalent to maximize the projection of received signals onto the plane-wave subspace, and the physical meaning of (4.12) is to maximize the plane waves effects on the receive signals.

The number of coherent plane waves included in the first cluster of received UWB signals determines the independent columns of $\mathbf{V}(\Theta)$ and the dimensions of signal $\mathbf{U}_S$ and noise subspace $\mathbf{U}_N$. Hence, this uncertain number causes much complexity in implementation of the surface fitting of (4.11) or (4.12), and is hereby suggested to be detected before the AOA estimation.

4.3 UWB Plane Waves Detection

The uncertain number of uncorrelated plane waves can be detected by the rank test [73] of the spectral matrix $\mathbf{S}_{\mathbf{R}}$, where the spectral matrix of uncorrelated plane waves is defined as $\mathbf{S}_{\mathbf{R}} \triangleq \mathbb{E} \{ \mathbf{R}(\omega) \mathbf{R}^H(\omega) \}$. However, in the scenario of plane waves from correlated multipath, this rank detector cannot work. UWB signals have high temporal resolution of channel responses, which make the beam width using con-

4.3 UWB Plane Waves Detection

ventional beam former [38] to be quite sharp. Sensor CLEAN [40] algorithm as a conventional beam forming technique is effective to recover an UWB propagation channel, which can be used to find the number of coherent plane waves in our scenario. The process is summarized as below:

i) A signal beam is initialized as,

$$B^{(0)}(t, \theta) = \sum_{e=1}^N x^e(t - \Delta\tau^e(\theta)) \quad (4.14)$$

where $c \cdot t$ gives the distance, and θ is steering direction. The first plane wave is resolved as,

$$\hat{b}_1(t, \theta) = \sum_{e=1}^N s \left(t - \hat{\tau}_1 + \Delta\tau^e(\hat{\theta}_1) - \Delta\tau^e(\theta) \right) \quad (4.15)$$

where

$$\{\hat{\tau}_1, \hat{\theta}_1\} = \arg \max_{\{\tau, \theta\}} (B^{(0)}) \quad (4.16)$$

ii) The i^{th} signal beam is generated as,

$$B^{(i)}(t, \theta) = B^{(i-1)}(t, \theta) - \hat{a}_i \cdot \hat{b}_i(t, \theta) \quad (4.17)$$

where

$$\hat{a}_i = \frac{\max \{B^{(i-1)}(t, \theta)\}}{\max \{\hat{b}_i(t, \theta)\}} \quad (4.18)$$

And the $(i + 1)^{th}$ plane wave is resolved as,

$$\hat{b}_{i+1}(t, \theta) = \sum_{e=1}^N s \left(t - \hat{\tau}_{i+1} + \Delta\tau^e(\hat{\theta}_{i+1}) - \Delta\tau^e(\theta) \right) \quad (4.19)$$

where

$$\{\hat{\tau}_{i+1}, \hat{\theta}_{i+1}\} = \arg \max_{\{\tau, \theta\}} (B^{(i)}) \quad (4.20)$$

This iterative process stops when $\hat{a}_{i+1}$ decreases below a given threshold. And the number of plane waves detected is i .

Figure 4.2: Iterative processes of sensor CLEAN. The signal beams $B^{(0)}$, $B^{(1)}$, $B^{(2)}$ and $B^{(3)}$ are respectively shown in the top left, top right, bottom left and bottom right subplots.

In practice, the amplitude threshold is set at $1.5N\sigma_w$, where $N\sigma_w$ is the AWGN amplitude in the beam. Benefiting from ultra-wide bandwidth, the first cluster of received UWB signals can be isolated from those temporally-resolved multipath clusters. The number of plane waves in the first cluster is detected first, and then this information is incorporated into the AOA estimation described in next section. The iterative process of sensor CLEAN algorithm is illustrated in Fig. 4.3, where an envelope filter before beam forming is employed to improve the beam clarity. As indicated in Fig. 4.3, the plane wave $\hat{b}_i$ is successively detected and filtered out from the current signal beam $B^{(i-1)}$. In a case of interfering plane waves superimposed with near-field multipath, where the mean excess delay and the root-mean-squares (RMS) delay spread are 3.3ns and 3.0ns respectively, four plane waves are detected before meeting the condition, $\hat{a}_5 < 1.5N\sigma_w$. Generally, the plane wave power due to beam forming effect is $10\log_{10}N$ stronger than the individual multipath power. More results and discussions on the performance of this detector in the presence of strong near-field multipath or noise are presented in the section 4.5.

4.4 AOA Estimation

Since 1-D solutions [52, 54–56, 82] in dense cluttered environments are sensitive to correlated multipath, multi-dimensional (M -D) solution [81] can be used. However, M -D solution will suffer if the search converges to local minima due to bad initial estimations. Moreover, the uncertain dimension in M -D solution [81] increases the optimization complexity. Alternating projection (AP) [83] is a well-known optimiza-

tion strategy for direction finding of narrowband sources. But for UWB signals, surface fitting with AP can be directly used as both an initial estimator and an optimizer, where the dimension of plane-wave subspace detected before in Section 4.3 is used for initialization. The resolution of spectral peaks is significantly improved due to the ultra-wide bandwidth, which is verified in Section 4.5. In the presence of correlated multipath, (11) and (12) lose accuracy because the square matrix of $\mathbf{V}^H(\Theta)\mathbf{V}(\Theta)$ is nearly singular, that can be solved by AP strategy. The principle for alternating projection is iteratively updating the plane-wave subspace based on the former estimations. The AP formulation is extended to multiple coherent plane waves for UWB direction finding using the procedure below.

- i*) In the initial round, the AOA of the first (direct path) plane wave $\hat{\theta}_1^{(0)}$ is estimated using surface fitting as (12),

$$\hat{\theta}_1^{(0)} = \arg \max_{\theta_1} \left\{ \sum_{k=1}^K \text{tr} [\mathbf{P}_{\mathbf{v}(\theta_1)} \mathbf{C} \mathbf{x}_{(k)}] \right\} \quad (4.21)$$

where $\mathbf{P}_{\mathbf{v}(\theta_1)}$ is calculated using (9).

- ii*) In the initial round, the AOA of the second plane wave $\hat{\theta}_2^{(0)}$ is on trial while keeping the former estimation $\hat{\theta}_1^{(0)}$. So (12) can be presented by,

$$\hat{\theta}_2^{(0)} = \arg \max_{\theta_2} \left\{ \sum_{k=1}^K \text{tr} [\mathbf{P}_{\mathbf{v}(\hat{\theta}_1^{(0)}, \theta_2)} \mathbf{C} \mathbf{x}_{(k)}] \right\} \quad (4.22)$$

where $\mathbf{P}_{\mathbf{v}(\hat{\theta}_1^{(0)}, \theta_2)}$ is the projection matrix onto the 2-dimensional plane-wave subspace spanned by the vectors $\mathbf{v}(\hat{\theta}_1^{(0)})$ and $\mathbf{v}(\theta_2)$. The square matrix of

$\mathbf{V}^H(\hat{\theta}_1^{(0)}, \theta_2) \mathbf{V}(\hat{\theta}_1^{(0)}, \theta_2)$ is nearly singular because the second plane wave is correlated with the direct path plane wave. Hence, the evaluation of (9) is inaccurate since this nearly-singular matrix is almost not invertible. To evaluate the projection matrix $\mathbf{P}_{\mathbf{V}(\hat{\theta}_1^{(0)}, \theta_2)}$, a basis of space $\mathbf{V}(\hat{\theta}_1^{(0)}, \theta_2)$ can be acquired by the Gram-Schmidt process [70].

$$\mathbf{P}_{\mathbf{V}(\hat{\theta}_1^{(0)}, \theta_2)} = \mathbf{U}(\mathbf{U}^H \mathbf{U})^{-1} \mathbf{U}^H \quad (4.23)$$

where the basis $\mathbf{U}$ contains a set of linearly-independent vectors $\mathbf{U} = \begin{bmatrix} \mathbf{u}_1 & \mathbf{u}_2 \end{bmatrix}$, and

$$\mathbf{u}_1 = \mathbf{v}(\hat{\theta}_1^{(0)}) \quad (4.24)$$

$$\mathbf{u}_2 = \mathbf{P}_{\mathbf{v}(\hat{\theta}_1^{(0)})}^\perp \mathbf{v}(\theta_2) \quad (4.25)$$

Based on the former estimation, $\mathbf{P}_{\mathbf{v}(\hat{\theta}_1^{(0)})}^\perp$ is calculated using (10). Substitute (24) and (25) into (23), we get,

$$\mathbf{P}_{\mathbf{V}(\hat{\theta}_1^{(0)}, \theta_2)} = \mathbf{P}_{\mathbf{u}_1} + \mathbf{P}_{\mathbf{u}_2} \quad (4.26)$$

Substitute (26) into (22), and $\mathbf{P}_{\mathbf{u}_1}$ can be dropped due to $\mathbf{u}_1$ independent of θ_2 . Therefore, (22) is equivalent to (27).

$$\hat{\theta}_2^{(0)} = \arg \max_{\theta_2} \left\{ \sum_{k=1}^K \text{tr} [\mathbf{P}_{\mathbf{u}_2} \mathbf{C}_{\mathbf{X}(k)}] \right\} \quad (4.27)$$

where $\mathbf{u}_2$ is from (25), and $\mathbf{P}_{\mathbf{u}_2}$ is calculated using (9).

iii) Apply (26) in multiple coherent plane waves scenario, and the plane-wave subspace is updated based on the former estimations $\{\hat{\theta}_1^{(0)}, \dots, \hat{\theta}_{i-1}^{(0)}\}$ as follows,

$$\begin{aligned} & \mathbf{P}_{\mathbf{V}(\hat{\theta}_1^{(0)}, \dots, \hat{\theta}_{i-1}^{(0)}, \theta_i)} \\ &= \mathbf{P}_{\mathbf{V}(\hat{\theta}_1^{(0)}, \dots, \hat{\theta}_{i-1}^{(0)})} + \mathbf{P}_{[\mathbf{P}_{\mathbf{V}(\hat{\theta}_1^{(0)}, \dots, \hat{\theta}_{i-1}^{(0)})}^\perp] \mathbf{v}(\theta_i)} \end{aligned} \quad (4.28)$$

Given the current plane-wave subspace for i plane waves above, (12) is maximized over the parameter θ_i while keeping $\{\hat{\theta}_1^{(0)}, \dots, \hat{\theta}_{i-1}^{(0)}\}$ at the former estimations. Similarly, $\mathbf{P}_{\mathbf{V}(\hat{\theta}_1^{(0)}, \dots, \hat{\theta}_{i-1}^{(0)})}$ is irrelevant to θ_i that can be dropped. To evaluate the last term in (28), an orthonormal basis of space $\mathbf{V}(\hat{\theta}_1^{(0)}, \dots, \hat{\theta}_{i-1}^{(0)}, \theta_i)$ can be acquired by the Gram-Schmidt process [70].

$$\mathbf{P}_{[\mathbf{P}_{\mathbf{V}(\hat{\theta}_1^{(0)}, \dots, \hat{\theta}_{i-1}^{(0)})}^\perp] \mathbf{v}(\theta_i)} = \mathbf{e}_i \mathbf{e}_i^H \quad (4.29)$$

where

$$\mathbf{e}_i = \frac{\mathbf{u}_i}{\|\mathbf{u}_i\|} \quad (4.30)$$

$$\mathbf{u}_i = [\mathbf{P}_{\mathbf{V}(\hat{\theta}_1^{(0)}, \dots, \hat{\theta}_{i-1}^{(0)})}^\perp] \mathbf{v}(\theta_i) \quad (4.31)$$

Based on the former estimations, $\mathbf{P}_{\mathbf{V}(\hat{\theta}_1^{(0)}, \dots, \hat{\theta}_{i-1}^{(0)})}^\perp$ is calculated using (10), and $\mathbf{P}_{\mathbf{V}(\hat{\theta}_1^{(0)}, \dots, \hat{\theta}_{i-1}^{(0)})}$ is computed iteratively using (28). Substitute (29), and (12) is simplified to be,

$$\hat{\theta}_i^{(0)} = \arg \max_{\theta_i} \left\{ \sum_{k=1}^K \mathbf{e}_i^H \mathbf{C}_{\mathbf{x}(k)} \mathbf{e}_i \right\} \quad (4.32)$$

iv) In the k^{th} ($k \geq 1$) round, (12) is maximized over the parameter $\theta_i^{(k)}$ while keeping

4.4 AOA Estimation

$\{\hat{\theta}_1^{(k)}, \dots, \hat{\theta}_{i-1}^{(k)}, \hat{\theta}_{i+1}^{(k-1)}, \dots, \hat{\theta}_D^{(k-1)}\}$ at the former estimations, where $\{\hat{\theta}_1^{(k)}, \dots, \hat{\theta}_{i-1}^{(k)}\}$ are the first $(i-1)$ estimations optimized in the current k^{th} round and $\{\hat{\theta}_{i+1}^{(k-1)}, \dots, \hat{\theta}_D^{(k-1)}\}$ are estimations in the last round. D that is set in the initial round is given by the number of plane waves detected. Apply (32) to search $\theta_i^{(k)}$, in which the orthonormal basis is given by,

$$\mathbf{e}_i = \frac{[\mathbf{P}_{\mathbf{v}(\hat{\theta}_1^{(k)}, \dots, \hat{\theta}_{i-1}^{(k)}, \hat{\theta}_{i+1}^{(k-1)}, \dots, \hat{\theta}_D^{(k-1)})}^\perp] \mathbf{v}(\theta_i^{(k)})}{\left\| [\mathbf{P}_{\mathbf{v}(\hat{\theta}_1^{(k)}, \dots, \hat{\theta}_{i-1}^{(k)}, \hat{\theta}_{i+1}^{(k-1)}, \dots, \hat{\theta}_D^{(k-1)})}^\perp] \mathbf{v}(\theta_i^{(k)}) \right\|} \quad (4.33)$$

Based on the former estimations, $\mathbf{P}_{\mathbf{v}(\hat{\theta}_1^{(k)}, \dots, \hat{\theta}_{i-1}^{(k)}, \hat{\theta}_{i+1}^{(k-1)}, \dots, \hat{\theta}_D^{(k-1)})}^\perp$ is calculated using (10), and $\mathbf{P}_{\mathbf{v}(\hat{\theta}_1^{(k)}, \dots, \hat{\theta}_{i-1}^{(k)}, \hat{\theta}_{i+1}^{(k-1)}, \dots, \hat{\theta}_D^{(k-1)})}$ is computed iteratively using (28). The iteration terminates when the AOA estimations $\hat{\Theta}^{(k)}$ of the k^{th} round converge to the estimated values $\hat{\Theta}^{(k-1)}$ of the $(k-1)^{th}$ round.

High resolution of AOA estimation can help to simplify TOA estimation. The i^{th} plane wave AOA estimation $\hat{\theta}_i$ leads to the following estimation,

$$\hat{R}_i(\omega) = \mathbf{v}^\dagger(\hat{\theta}_i) \mathbf{X}(\omega) \quad (4.34)$$

Then the i^{th} plane wave TOA can be successively estimated to maximize the output of a matched filter denoted by $z(\tau)$,

$$z(\tau) = \left| \int_{-\infty}^{\infty} \hat{r}_i(t) s(t - \tau) dt \right| \quad (4.35)$$

where

$$\hat{r}_i(t) = \mathcal{F}^{-1}\{\hat{R}_i(\omega)\} \quad (4.36)$$

$\mathcal{F}^{-1}\{\cdot\}$ denotes the inverse Fourier transform. Note that, because of the estimation of disjoint plane wave in time domain, the effects of interfering plane waves and overlapping multipath can be mitigated significantly.

Figure 4.3: (a) The AOA spectrum for SNR=13dB (solid line) and SNR=14dB (dashed line). (b) Received signal and the matched filter output for SNR=30dB.

Fig. 4.3 shows a case where the direct path plane wave from 37° is overlapped in time with interfering plane wave from 26° . The time-domain first cluster received signals with SNR of 30dB received at the reference array element is shown in Fig 4.3(b).

The mean excess delay and the RMS delay spread are 0.71ns and 0.77ns respectively. The received signal strength is subsequently decreased and its corresponding AOA peaks $\hat{\Theta}$ estimated by the surface fitting with AP method are shown in Fig. 4.3(a) for SNR of 14dB and 13dB. As shown in the case of 14dB, the AOA spectrum has correct estimations at 37° and 26° but in the case of 13dB, wrong estimation at 55° is generated. The matched filter output in (35) is shown in Fig. 4.3(b), where the peak indicates the TOA estimation.

As shown in Fig. 4.3, the AOA spectrum is estimated in the case of the direct path plane wave from 37° overlapped in time with interfering plane wave from 26°. The first cluster received signals with the SNR of 30dB received at the reference array element is shown in time domain in Fig. 4.3(b). The mean excess delay and the RMS delay spread are 0.71ns and 0.77ns respectively. If the SNR decreases to 14dB or 13dB, the corresponding AOA spectral peaks are shown in Fig. 4.3(a). In the case of 14dB, although the AOA spectrum has accurate estimations, the spike at 27° is slight. In the case of 13dB, the spike at 27° is replaced by a fake at 55°. The main cause of this error is the low SNR level. This error is randomly triggered. The waveforms of AWGN are random and uncorrelated with each other. The 1-dB increment cannot correct the fake AOA spike for sure. However, the ADOA performance in RMSE can benefit from the SNR improvement of 1dB, as shown in the Fig. 4.4. The gap between the error floor and the CRB can be reduced by increasing the sampling frequency. Both the time resolution of multipath and the phase differences among the array elements increase as the increasing sampling frequency. On the one hand,

the array performance benefits from the high resolution of large phase change. On the other hand, the ranging and direction finding algorithms suffer from poor resolution of dense multipath. The spectral matrix $\tilde{\mathbf{A}}$ of composite near-field multipath (treated as colored noise) is modeled as unavailable and is not used in our method. The fading level of the dense multipath is evaluated by both the channel delay spread in Table 4.1 and the energy captured ratio in Fig. 4.2 following [22, 34].

4.5 Simulation Scenarios

To evaluate the robustness of a direction finding system in dense cluttered environments, Monte Carlo simulations of channel impulse responses (CIR) with varied SNR, far-field reflector spacing, number of interfering plane waves and amount of near-field perturbations are simulated and convoluted with a UWB-IR signal source. The UWB-IR source signal $s(t)$ is measured from a UWB RFID-tag with center frequency of 3.4GHz and -10dB bandwidth of 1.4GHz. The pulse shape is shown in [81], and the pulse duration denoted by T_w is 2ns. A 5-element uniform linear antenna (ULA) array with the inter-element spacing of 30cm is employed as the receiver. As shown in [81], the AOA of the plane wave is taken with respect to the array antennas axis, while the TOA of the plane wave is taken at a reference antenna that is selected to be the array element first receiving signal when the plane wave is impinging at 0° . For the plane-wave radiation, the TOA at each antenna element is constrained by the ULA array geometry and the AOA, while the amplitudes are assumed to be the same among antenna elements. Coherent plane waves are produced by the reflectors

closely-spaced with transmitting antenna (Tx) in the far-field of the receiver array (Rx). The spatial separation between Tx and reflector induces an angle-difference-of-arrival (ADOA) between the direct path and specular reflection plane waves. And the corresponding temporal spacing $\Delta\tau_{\min}$ gives the time-difference-of-arrival (TDOA) between the direct path and specular reflecting plane waves. Same as in [81], the SNR is defined as $a_1^2 R_s(0)/N_0$, where $R_s(0)$ is the auto-correlation function of source signal. Since the multi-paths are delayed signals with respect to the direct path, the strength of specular reflecting plane wave is uniformly distributed in the range of 0 to 1 of the direct path plane wave strength. IEEE 802.15.4a CM1 channel model [22] is used to generate multi-paths that are independent among antenna elements and are superimposed on the plane waves. The signal strength ratio of the composite multi-paths over the direct path denoted by α is used to evaluate the near-field perturbations.

In the presence of both interfering plane waves and near-field multipath, the AOA is not affected if the direct path plane wave is well isolated in time from the interfering plane wave, i.e. $\Delta\tau_{\min} > T_w$ and the channel delay spread is small in the first cluster. Contrarily, the AOA is much affected if this spacing is smaller than the pulse duration ($\Delta\tau_{\min} < T_w$) or the channel delay spread is heavy in the first cluster. Dense spatial spacing $\Delta\tau_{\min}$ usually causes close angular spacing. And this angular spacing is set to be at least differentiated by a sampling rate as $v \triangleq |\Delta\tau^e(\theta_2) - \Delta\tau^e(\theta_1)| \geq 1/f_s$.

In Table I, the mean excess delay τ_m and the RMS delay spread τ_{rms} are evaluated for the first cluster of received signals from the Monte Carlo simulation of the

Table 4.1: Channel Delay Spread Corresponding to $\Delta\tau_{min}$ and α .

α		0.1	0.3	0.5	0.7
v [1/ f_s]	$\Delta\tau_{min}$ [T_w]	τ_m/τ_{rms} [ns]	τ_m/τ_{rms} [ns]	τ_m/τ_{rms} [ns]	τ_m/τ_{rms} [ns]
1	0.1	0.09/0.15	0.11/0.21	0.15/0.26	0.19/0.30
3	0.3	0.26/0.41	0.27/0.43	0.30/0.46	0.33/0.49
5	0.5	0.44/0.69	0.50/0.73	0.60/0.77	0.70/0.78
7	0.7	0.62/0.98	0.76/1.08	0.96/1.11	1.13/1.09
9	0.9	0.80/1.26	0.93/1.31	1.09/1.30	1.24/1.24

CIR, corresponding to the temporal and angular spacing and the near-field multipath strength ratio. As we can see, the τ_m (mean excess delay) and τ_{rms} (delay spread) increase slightly with increasing α as expected with the increasing near-field perturbations level. As the temporal spacing increases, there is also a corresponding increase in multipath excess delay and spread, τ_m and τ_{rms} . As the channel delay spread increases with the increasing α or increasing spacing, the near-field multipath captured energy ratio increases as shown in Fig. 4.4.

Additive white Gaussian noise (AWGN) with power spectral density $N_0/2$ is assumed. The sampling rate is 20GHz. The simulated received signals are processed by the plane wave number detector followed by surface fitting with AP estimator. The performance susceptibilities to the SNR, the far-field reflector spacing, the number of interfering plane waves and the near-field perturbations are respectively examined using the Cramér-Rao bound (CRB), MUSIC algorithm [56,82], M-dimensional least-squares [81] and our proposed method.

Figure 4.4: Near-field multipath captured energy.

4.5.1 Effects of SNR

The SNR effects are first investigated in a scenario where there is one reflected plane wave closely spaced with the direct plane wave with temporal spacing of $\Delta\tau_{\min}=0.1T_w$. In this scenario, no near-field perturbations ($\alpha=0$) is considered as a baseline for comparison among the different algorithms. The theoretical lower bounds of ADOA and AOA errors are referred to as the Cramér-Rao bound (CRB) given in Appendix, where the ADOA is the difference between AOA estimations $\hat{\theta}_2$ and $\hat{\theta}_1$ while the AOA of direct path plane wave is $\hat{\theta}_1$. As shown in Fig. 4.5, the AP performance improves with increasing SNR, and reaches a floor at 0.80° when SNR

is over 25dB. The gap between this floor and CRB can be reduced by increasing the sampling rate f_s . The disadvantage of MUSIC in the coherent plane waves scenario is shown in the figure. The angular resolution of MUSIC can be improved by increasing f_s especially when SNR is over 30dB. As we can see, MUSIC has difficulty in resolving two coherent plane waves due to the problem of directly estimating the plane wave subspace $\mathbf{U}_S$ in the presence of correlated multipath whereas the use of AP strategy is able to resolve this.

Figure 4.5: Standard deviation of ADOA $\Delta\theta$ versus SNR in a two closely spaced plane waves scenario free of near-field perturbations.

A comparison between AP and 2-D least-squares algorithm in resolving AOA in the presence of a closely spaced plane wave is shown in Fig. 4.6. AP as well as

2-D least-squares can reach a floor of 0.76° when SNR is over 23dB. And this floor decreases to 0.19° if the sampling rate is increased to 80GHz. As depicted in Fig. 4.6, 2-D least-squares perform better than AP method when SNR is less than 23B. However, the complexity of 2-D least-squares is $\sum_{e=1}^5 O(T_w^2)$ which is much higher than $4O(T_w)$ the complexity of AP with two round convergence.

Figure 4.6: Standard deviation of AOA θ_1 versus SNR in a two closely spaced plane waves scenario free of near-field perturbations.

4.5.2 Effects of Near-field Perturbations

This is a scenario where there are densely populated reflecting and scattering objects in the near field of the receiver. The near-field perturbation level is investigated by

varying the strength ratio α in the presence of a second plane wave with spacing scenario of $\Delta\tau_{\min}=0.1T_w$, where SNR=25dB. The CRB of ADOA and AOA [81] are provided for reference. As shown in Fig. 4.7, increasing multipath strength α degrades both ADOA and AOA performances, as suggested in the CRB and verified by the methods we used. The performances of AP and 2-D least squares are better than MUSIC with 2-D least-squares having the best performance. It is also observed that the increase in AOA error is linear with increase in near-field multipath strength beyond around $\alpha=0.2$. The degradation in AOA error is directly proportional to the increase in captured near-field multipath energy, as shown in Fig. 4.4, which shows captured multipath energy increase directly in proportion with α .

4.5.3 Effects of Far-field Reflector Spatial Spacing

The effect of temporal spacing between the direct path and reflected path plane waves is investigated by varying the spacing for between 0.1 to 1 T_w for SNR=25dB and $\alpha=0.3$. The CRB of ADOA and AOA extracted from [81] are plotted in Fig. 4.8. The error bounds show approximate floors of 0.03° and 0.06° for AOA and ADOA respectively for temporal spacing greater than $0.3T_w$. The results in Fig. 4.8 show that the performances using all three methods improve as the temporal spacing increases to $0.4T_w$, and then deteriorate as the spacing increases further. The increase in temporal spacing in the two plane waves at first helps to isolate the direct path plane wave and hence result in improved AOA and ADOA estimation. However, this increase in temporal spacing also increases the amount of captured near-field

Figure 4.7: Standard deviation of ADOA and AOA versus near-field perturbation level in a dense cluttered scenario with SNR=25dB.

multipath energy as indicated by the increase in channel delay spread as shown in Table 1. As shown in Fig. 4.4, the corresponding near-field multipath captured energy increases from around 0.05% to 0.08% for $\alpha=0.3$, when $\Delta\tau_{\min}$ increase from 0.1 to 0.9 T_w . ADOA and AOA estimation degrade linearly with the increase in channel delay spread for $\Delta\tau_{\min}$ greater than around $0.5T_w$ and 2-D least-squares has the best performance.

Figure 4.8: Standard deviation of ADOA and AOA versus temporal spacing between plane waves in a scenario of SNR=25dB and $\alpha=0.3$.

4.5.4 Effects of Number of Interfering Plane Waves

In this scenario, we investigate the ability of the algorithm to resolve multiple closely spaced plane waves from reflectors around the transmitter in the presence of cluttered objects in the near field of the receiver. The robustness of surface fitting with AP strategy to a number of interfering plane waves with near-field perturbations is tested when SNR=30dB. First three plane waves, from the direct path in the direction of 90° and the reflected paths in the directions of 96° and 84° respectively, are superimposed with near-field multipath, where the τ_m and τ_{rms} are 2.4ns and 2.6ns respectively, and the near-field multipath captured energy occupies around 14%. As shown in the

top subplot of Fig. 4.9, the three plane waves with AOA peaks are clearly resolved with and without near-field perturbations. In the bottom subplot of Fig. 4.9, four plane waves with the direct path in the direction of 90° and the reflected paths in the directions of 96° , 84° and 102° respectively are superimposed with near-field multipath, where the τ_m and τ_{rms} are 3.3ns and 3.0ns respectively. The near-field multipath captured energy occupies around 11%. As shown in the bottom subplot, only three peaks are detected for both runs missing one of the reflectors for each run. As the number of plane waves D impinging on the N -element antenna array increases close to N , the plane-wave subspace is D -dimensional, whereas the $(N - D)$ -dimensional noise subspace is sparse and poorly-structured which is not enough for AP to achieve a complete estimation.

4.5.5 Effects on Detection Performance

Channel effects on correct probability P_d and false alarm P_f of the number of plane waves detected by sensor CLEAN are investigated in Fig. 4.10. The envelope filter consists of a matched band-pass filter with center frequency of 3.4GHz and pass band of 1.4GHz followed by a square-law device and a low-pass filter with bandwidth of 0.7GHz. An interfering plane wave without the near-field perturbations $\alpha=0$ is first considered. As shown in the top subplot in Fig. 4.10, the detection probability P_d increases and the false alarm P_f decreases as the temporal spacing $\Delta\tau_{\min}$ increases. When the spacing is less than $0.2T_w$, the false alarm P_f increases and the missed detection P_m decreases as SNR increases, and the correct detection P_d ($P_d = 1 - P_m - P_f$)

Figure 4.9: AOA resolution of multiple coherent plane waves.

decreases with the increasing SNR. The number of plane waves tends to be overestimated with the increasing SNR in the case of spacing less than $0.2T_w$. A SNR=23dB scenario with an interfering plane wave superimposed with different multipath profile is next considered and the results are shown in the bottom subplot of Fig. 4.10. The false alarm P_f increases and the correct detection P_d decreases as the near-field multipath strength α increases. When the spacing is less than $0.2T_w$, the false alarm P_f increases and the missed detection P_m decreases as α increases, and the correct detection P_d ($P_d = 1 - P_m - P_f$) increases with the increasing α . The number of plane waves tends to be overestimated with the increasing near-field perturbations α in the

Figure 4.10: Channel effects on detection probability and false alarm.

case of spacing less than $0.2T_w$. As the temporal spacing increases over $0.3T_w$, the correct detection P_d and the false alarm P_f reach ceilings that are dependent on the near-field perturbation level α .

4.6 Concluding Remarks

A robust UWB direction finding solution in dense cluttered environments is proposed in this paper. The efficiency is improved by introducing the detection of a number of plane waves prior to AOA estimation. The robustness to interfering plane waves and the near-field perturbation is solved by a surface fitting with alternating projec-

4.6 Concluding Remarks

tion strategy, and is demonstrated in various densely cluttered indoor environments. Monte Carlo experiments have shown the AOA error and the angular resolution improve as the SNR or the sampling rate increases, and deteriorate with the increasing channel delay spread, the decreasing spatial spacing between coherent plane waves and the increasing number of plane waves in the cluster.

Chapter 5

NLOS Identification Using Empirical Threshold Selection for UWB Indoor Positioning

5.1 Introduction

Obstructed line-of-sight (LOS) propagation is a major error source for wireless localization systems in harsh environments [12]. In the non-line-of-sight (NLOS) scenarios, the direct path is attenuated and delayed by the obstructions during the propagation. The direct path is much weaker than the dominant multipath or even disappear, which results in biased time-of-arrival (TOA), weakened received signal strength (RSS) and wrong angle-of-arrival (AOA), and thus imposes localization error. In order to mitigate the NLOS impact on cooperative localization system, the principle to deal with NLOS measurements is widely understood as [58]: Range bias can be corrected if a-priori information of NLOS statistics is available. Otherwise, the NLOS measurements are discarded and excluded from localization. NLOS miti-

gation is explicitly based on the premise of accurate detection that the channel can be distinguished between LOS and NLOS conditions. The basic idea for NLOS identification is detecting the consistency of estimations (TOA, RSS and AOA) statistics or/and channel characteristics with the aid of single or multiple anchors. Multipath characteristics are first introduced in [84], which can be used for independent NLOS identification where a single anchor is available [85, 86]. In some applications where multiple anchors are available [87–91], such as cellular network, NLOS channel can be identified by cooperation of mobiles and base stations. High density deployment of anchors is helpful to alleviate the NLOS error [92, 93] if NLOS detection is unaffordable.

Ultra-wide bandwidth makes UWB-IR indoor positioning much competent especially in harsh environments [50]. The complex propagation channel can be finely modeled and characterized using UWB signals [94, 95]. In addition, the ultra-wide bandwidth has lower frequency components with high penetration capabilities which may not be blocked by the blockages whereas the higher frequency components with low penetration capabilities may be blocked. However, the channel characteristics that are site-specific are hardly completely known [22, 84, 96] in cluttered indoor environments. The likelihood ratio test (LRT) suffers from the information loss of channel statistics, easily making wrong decisions [4, 91, 97]. The potential using UWB signals for NLOS detection is reviewed as follows: An overview of NLOS identification and mitigation techniques using UWB-IR is given in [8, 98]. Channel statistics can be extracted from real measurements or IEEE 802.15.4a model

in [30, 62, 99–103]. Received signal energy detection [104] is not complex but is sensitive to the dense multipath. Power attenuation of the subsequent maximum paths is used in [105]. Metrics based on the first detected path and the strongest path are introduced in [106, 107]. The peakedness of received multipath signals indicated by the kurtosis is evaluated in [108]. RSS- or TOA- based range is statistically modeled in [100, 109]. The channel delay spread, the total power and the first detected path work together in [101] while the channel is characterized by the excess delay, the delay spread and the kurtosis in [102]. Multiple channel metrics used for NLOS detection can give better performance in [101, 102] and are helpful to identify multi-level NLOS conditions in [62, 103]. Non-parametric approaches in [90, 110, 111] give another solutions to the channel statistical characterization. Training is used in [111] to determine the bound to classify LOS and NLOS before the bound validation while regression is used to correct the NLOS range error in [110]. Cooperative localization system based on NLOS identification and mitigation is demonstrated in [62, 111, 112].

However, the channel transfer function or the channel impulse response, and its direct use in NLOS identification are unaffordable in many applications. And the channel feature extraction and the performance validation are neglected in most works. Our study compared to the literature is innovative and complete in two aspects:

- i*) The UWB array processing for AOA/TOA collection is novel.
- ii*) Decision-making for the threshold validation in the joint LRT is new.

Detection performance is shown that the correct probability in LOS conditions

achieves 93.1% while those in NLOS conditions are respectively 71.9% for UDP and 70.1% for DDP.

5.2 Channel Estimation

A robust strategy capable to achieve the consistent performance is expected to characterize the site-specific channel. Firstly, the TOA and AOA of the first detected path are estimated. As the multipath is abundant indoors, the multipath effects on the first detected path should be taken care carefully and differentiated from the NLOS effects. Assume the first arriving signal at an N -element antenna array is from the direct path, and its TOA and AOA are denoted by τ_1 and θ_1 . The received UWB signals can be expressed as,

$$x^e(t) = \sum_{i=1}^D r_i(t + \Delta\tau^e(\theta_i)) + w^e(t) \quad (5.1)$$

$x^e(t)$ is received at the e^{th} element of the receiver antenna array that includes the multipath signal $r_i(t)$ and the noise $w^e(t)$. Assume D multi-paths are present that induce the signals temporally spaced at the array elements. And $\Delta\tau^e(\theta_i)$ denotes the delay offset between the e^{th} element and the first element for the signal from the direction of θ_i (planewave). θ_i gives the AOA of the i^{th} path that is consistent within the array. The direct path signal is given by,

$$r_1(t) = a_1 s(t - \tau_1) \quad (5.2)$$

where the amplitude is a_1 , and the transmitted pulse shape is indicated by $s(t)$. Correspondingly, the received signals can be formulated in the frequency domain as,

$$\mathbf{X}(\omega) = \mathcal{F} \left\{ \begin{bmatrix} x^1(t) \\ \vdots \\ x^N(t) \end{bmatrix} \right\} = \mathbf{V}(\Theta) \mathbf{R}(\omega) + \mathbf{W}(\omega) \quad (5.3)$$

where $\mathcal{F}\{.\}$ is the Fourier transform, and ω represents the angular frequency. The D multi-paths signals vector is built as,

$$\mathbf{R}(\omega) = [R_1(\omega) \cdots R_D(\omega)]^T \quad (5.4)$$

The noise vector including noise independent among the N antenna elements is built as,

$$\mathbf{W}(\omega) = [W^1(\omega) \cdots W^N(\omega)]^T \quad (5.5)$$

The array manifold matrix including D vectors is presented as,

$$\mathbf{V}(\Theta) = [\mathbf{v}(\theta_1) \cdots \mathbf{v}(\theta_D)] \quad (5.6)$$

The vector contains the phase shift at each antenna element dependent on ω ,

$$\mathbf{v}(\theta_i) = [e^{j\omega\Delta\tau^1(\theta_i)} \cdots e^{j\omega\Delta\tau^N(\theta_i)}]^T \quad (5.7)$$

The maximum likelihood (ML) solution of $\mathbf{R}(\omega)$ can be further derived as a function of AOA,

$$\mathbf{R}(\omega) = \mathbf{V}^\dagger(\Theta)\mathbf{X}(\omega) \quad (5.8)$$

where the Moore-Penrose pseudo inverse [70] is given by,

$$\mathbf{V}^\dagger(\Theta) = (\mathbf{V}^H(\Theta)\mathbf{V}(\Theta))^{-1}\mathbf{V}^H(\Theta) \quad (5.9)$$

Then the ML estimation of AOA Θ can be written in the form of subspace fitting [3],

$$\hat{\Theta} = \arg \min_{\Theta} \left\{ \sum_{\omega} \text{tr}[\mathbf{P}_{\mathbf{V}(\Theta)}^\perp \mathbf{C}_{\mathbf{X}}] \right\} \quad (5.10)$$

$$\mathbf{C}_{\mathbf{X}} \triangleq \mathbf{X}(\omega)\mathbf{X}^H(\omega) \quad (5.11)$$

where the square matrix trace is denoted by $\text{tr}[\cdot]$. The spectral matrix is defined as above. The orthogonal complement of matrix $\mathbf{P}_{\mathbf{V}(\Theta)}$ can be obtained as,

$$\mathbf{P}_{\mathbf{V}(\Theta)}^\perp = \mathbf{I} - \mathbf{P}_{\mathbf{V}(\Theta)} \quad (5.12)$$

where $\mathbf{I}$ is an identity matrix of size N . $\mathbf{P}_{\mathbf{V}(\Theta)}$ is referred to as a projection matrix onto the D -dimensional signal subspace, which is defined as,

$$\mathbf{P}_{\mathbf{V}(\Theta)} \triangleq \mathbf{V}(\Theta)\mathbf{V}^\dagger(\Theta) \quad (5.13)$$

5.2 Channel Estimation

In the case that the column vectors are correlated, the Gram-Schmidt process [70] is used to find the basis of $\mathbf{V}(\Theta)$. Then the projection matrix is evaluated as,

$$\mathbf{P}_{\mathbf{V}(\theta_1, \dots, \theta_i)} = \mathbf{P}_{\mathbf{V}(\theta_1, \dots, \theta_{i-1})} + \mathbf{P}_{\mathbf{u}_i} \quad (5.14)$$

where $1 < i \leq D$, and the basis denoted by $\mathbf{u}_i$ is obtained as,

$$\mathbf{u}_i = [\mathbf{P}_{\mathbf{V}(\theta_1, \dots, \theta_{i-1})}^\perp] \mathbf{v}(\theta_i) \quad (5.15)$$

Since the AOA from the direct path is only of interest, the multipath effects can be mitigated using the following procedures.

- i*) Apply a window function to the first cluster of received signals and have the windowed signals $x^e(t)$ in time domain. The discrete-time Fourier transform (DFT) of windowed signals yields,

$$\omega = 2\pi \left(\frac{(k-1)f_s}{K} - \frac{f_s}{2} \right) \quad k \in \{1, \dots, K\} \quad (5.16)$$

K is the DFT samples. The sampling rate is denoted by f_s that should satisfy,

$$f_s \geq 2f_h \quad (5.17)$$

f_h is the upper frequency of the UWB bandwidth.

- ii*) Initial θ_1 is estimated using (5.10), where $\mathbf{V}(\Theta) = \mathbf{v}(\theta_1)$.

- iii*) Keep the previous estimations and θ_i ($i \geq 2$) is initially estimated using (5.10), where $\mathbf{V}(\Theta)$ includes i correlated column vectors.
- iv*) If the θ_i initial estimation equals one of the previous estimations $\{\theta_1, \dots, \theta_{i-1}\}$, keep $\{\theta_1, \dots, \theta_{i-1}\}$ ($D=i-1$) estimations only and go to step (*v*). Otherwise, i is increased by 1 and return step (*iii*).
- v*) Keep the previous estimations and θ_i^k ($i \geq 1$) is optimized in turn in the k^{th} ($k > 1$) round, where $\mathbf{V}(\Theta)$ includes D correlated column vectors. In the current moment, $\{\theta_1^k, \dots, \theta_{i-1}^k\}$ are the first ($i-1$) estimations optimized in the k^{th} round, and $\{\theta_{i+1}^{k-1}, \dots, \theta_D^{k-1}\}$ from the $(k-1)^{th}$ round are queuing for being optimized in the next moments.
- vi*) The process terminates if the estimations $\{\theta_1^k, \dots, \theta_D^k\}$ of the k^{th} round converge to the previous estimations $\{\theta_1^{k-1}, \dots, \theta_D^{k-1}\}$ of the $(k-1)^{th}$ round. Otherwise, repeat step (*v*).

The TOA of the direct path can benefit from the estimated value of θ_1 and is estimated as bellows,

$$\hat{\tau}_1 = \arg \max_{\tau} \left\{ \int_{-\infty}^{\infty} \hat{r}_1(t) s(t - \tau) dt \right\} \quad (5.18)$$

where the direct path is detected as,

$$\hat{r}_1(t) = \mathcal{F}^{-1} \{ \hat{R}_1(\omega) \} = \mathcal{F}^{-1} \{ \mathbf{v}^\dagger(\hat{\theta}_1) \mathbf{X}(\omega) \} \quad (5.19)$$

Based on the TOA and AOA estimations of the first detected path, three parameters are extracted as follows to characterize the channel.

- Rise Time

The rise time is used to evaluate the time delay from the first detected path to the strongest multipath.

$$T_{\text{rise}} = \tau_{\text{max}} - \hat{\tau}_1 \quad (5.20)$$

where τ_{max} indicates the moment of the maximum signal amplitude received at the first antenna element.

- Excess Attenuation of the First Detected Path

The path-loss model in the LOS scenario is known as,

$$P_r \propto D^{-n} \quad (5.21)$$

where P_r is the received power expectation, n is the path loss exponent and D is the distance between transmitter and receiver. Assume clock synchronization between transmitter and receiver is achieved, then the direct path amplitude in the LOS propagation is expected to be,

$$a_1(\hat{\tau}_1) = a_1(D_0) \left(\frac{D_0}{c\hat{\tau}_1} \right)^{\frac{n}{2}} \quad (5.22)$$

where D_0 denotes the reference distance, such as 1 meter. Both the path loss exponent n and the received power expectation for reference $a_1(D_0)$ need to be

pre-calibrated. The excess attenuation of the first detected path is defined as,

$$\Delta a_1 = a_1(\hat{\tau}_1) - \hat{a} \quad (5.23)$$

where the estimated a measures the signal amplitude of the first detected path $r_1(t)$.

- Kurtosis Analysis

The kurtosis for the received signal envelope is defined as,

$$\kappa(\widetilde{x}^e) \triangleq \frac{1}{K\sigma^4} \sum_{i=1}^K (\widetilde{x}_i^e - \mu)^4 \quad (5.24)$$

where the envelope is usually obtained by passing $x^e(t)$ to a square-law device followed by a low-pass filter. The mean and the standard deviation of the discrete-time envelope signal are respectively denoted by μ and σ .

The dense multipath scenarios are simulated as shown in the top subplot of Fig. 5.1, Fig. 5.2 and Fig. 5.3. The direct path from the direction of 37° arrives at 10.6 ns, and the dominant multipath from the direction of 60° comes at 12.8 ns. TOAs of the second and the third multipath respectively from 26° and 90° are 11.4 ns and 15.5 ns.

- LOS

The ML estimations of AOA under the assumption of $D=2$ are indicated in the bottom subplot of Fig. 5.1. As indicated by the first detected path $r_1(t)$ in the top subplot, TOA is estimated as 10.6 ns. The rise time equals the

half UWB pulse duration. The excess attenuation Δa_1 is characterized as the random distribution with non-bias because the measured signal amplitude follows path-loss model in LOS environment, and is expected to achieve the theoretical mean. The kurtosis value of 12.5 is high since the signal is relatively sharp due to the presence of the strongest direct path.

Figure 5.1: The first detected path in LOS scenario.

- NLOS with DDP

The direct path is detected as $r_1(t)$ and extracted as shown in the top subplot of Fig. 5.2. As indicated by $r_1(t)$ the attenuated direct path amplitude is smaller than the peak of the received signal envelope but still can be observed

in NLOS with DDP scenario. As shown in the bottom subplot of Fig. 5.2, the direct path from the direction of 37° can be barely detected from the multipath interferences. TOA of the first detected path is estimated as 10.6 ns. The rise time is longer than the half UWB pulse duration. The kurtosis value of 6.4 is relative low since the signal shape is flat due to the attenuation of direct path. The excess attenuation Δa_1 follows,

$$\Delta a_1 = a_{\text{LOS}} - a_{\text{DDP}} \approx a_{\text{LOS}}(1 - \alpha) \quad 0 \leq \alpha \leq 1 \quad (5.25)$$

where α denotes the attenuation coefficient due to the NLOS blockage, and a_{LOS} is the expected amplitude of non-obstructed direct path under assumption of LOS channel model and a_{DDP} is the signal amplitude of obstructed direct path detected as $r_1(t)$. In this simulated scenario, this coefficient α is about 0.3.

- NLOS with UDP

As shown in the bottom subplot of Fig. 5.3, the direct path from the direction of 37° is not detected in NLOS with UDP scenario. Another two paths are detected under assumption of $D=2$. As indicated by the first detected path $r_1(t)$ in the top subplot of Fig. 5.3, the estimated TOA of the first detected path is 11.4 ns that is later than the true TOA of the direct path 10.6 ns. The rise time is longer than half UWB pulse duration. The kurtosis value takes a relative low value of 8.5 since the signal shape is flat due to the absence of

5.2 Channel Estimation

Figure 5.2: The first detected path in NLOS with DDP scenario.

dominant direct path. The excess attenuation Δa_1 follows,

$$\Delta a_1 = a_1(\hat{\tau}_1) - a_{\text{UDP}} \approx a_1(\hat{\tau}_1)(1 - \Gamma) \quad 0 \leq \Gamma \leq 1 \quad (5.26)$$

Since the first detected path $r_1(t)$ is from the direction of 26° , the expectation of its amplitude in LOS environment $a_1(\tau_1)$ is much higher than real amplitude a_{UDP} of the extracted signal $r_1(t)$ because the scattering coefficient Γ and the attenuation coefficient α usually do not equal 1.

Figure 5.3: The first detected path in NLOS with UDP scenario.

5.3 Channel Detection

The hypothesis test known as Neyman-Pearson lemma [4] is formulated as,

$$\Lambda = \frac{p(\gamma|\mathcal{H}_i)}{p(\gamma|\mathcal{H}_j)} \underset{\mathcal{H}_j}{\overset{\mathcal{H}_i}{\geq}} \eta_\gamma \quad (5.27)$$

where the probability density function (*pdf*) of a channel parameter under a certain hypothesis of channel condition denoted by $\mathcal{H}_i$ is assumed to be the log-normal distribution,

$$p(\gamma|\mathcal{H}_i) = \frac{1}{\gamma\sqrt{2\pi}\sigma_i} \exp \left[-\frac{(\ln \gamma - \mu_i)^2}{2\sigma_i^2} \right] \quad (5.28)$$

5.3 Channel Detection

Then the log-likelihood ratio (LLR) test is expressed as,

$$\ln \Lambda(\gamma) = \left(\frac{\ln \gamma - \mu_j}{\sigma_j} \right)^2 - \left(\frac{\ln \gamma - \mu_i}{\sigma_i} \right)^2 \underset{\mathcal{H}_j}{\overset{\mathcal{H}_i}{\gtrless}} \eta'_\gamma \quad (5.29)$$

Assume the rise time, the excess attenuation and the kurtosis are independently distributed for convenience. The joint likelihood test can be derived as,

$$\ln \Lambda(T_{\text{rise}}) + \ln \Lambda(\Delta a_1) + \ln \Lambda(\kappa) \underset{\mathcal{H}_j}{\overset{\mathcal{H}_i}{\gtrless}} \hat{\eta} \quad (5.30)$$

The threshold η can be estimated to minimize the detection error probability P_e by training,

$$P_e \triangleq \sum_{i \neq j} P\{\mathcal{D} = \mathcal{H}_i | \mathcal{H}_j\} \quad (5.31)$$

In other words, training data is collected to characterize the channel model and validate the empirical threshold.

Monte Carlo simulation is deployed as follows,

Table 5.1: Simulation Parameters.

Parameter	Value
Path-loss exponent	2.0
SNR [dB]	$\text{SNR}_{\text{dB}} \sim U(18 \sim 40)$
Reflection coefficient	$\Gamma \sim U(10^{\frac{15-\text{SNR}}{20}} \sim 0.8)$
DDP coefficient	$\alpha_{\text{DDP}} \sim U(10^{\frac{12-\text{SNR}}{20}} \sim 10^{\frac{-3}{20}} \cdot \Gamma)$
UDP coefficient	$\alpha_{\text{UDP}} \sim U(0 \sim 10^{\frac{12-\text{SNR}}{20}})$
MPCs coefficient	$a_{\text{MPC}} \sim U(0 \sim 10^{\frac{12-\text{SNR}}{20}})$

The transmitted UWB impulse radio signal is with central frequency of 4GHz and -10dB bandwidth of 1.3GHz which is measured from an active RFID tag [25]. The

sampling rate of 20GHz is used at the receiver analog-digital-converter (ADC). Considering a 5-element uniform-linear-planar-array with the antenna inter-spacing of 30cm, the received signals are simulated as follows: IEEE 802.15.4a channel model is used to generate the multipath profile for each receiver antenna. The direct path and another multipath are respectively from the AOA θ_1 and θ_2 , and the corresponding arrival time τ_1 and τ_2 are generated also by IEEE 802.15.4a. The AOAs are uniformly distributed in the range of $[0, \pi]$ but with different values. Then the TOA at each antenna element is determined by the AOA θ_i and the plane-wave arrival time τ_i . The plane waves are superimposed onto the multipath profile generated before. The path-loss exponent in the free space is assumed, and the direct path amplitude gain ranges from 40dB to 18dB. Then the channel impulse responses are delayed correspondingly with respect to the TOA of the direct path that is derived from the amplitude gain and the path-loss exponent. In the LOS scenario, the second plane-wave is attenuated by the reflection coefficient Γ . In the DDP scenario, the direct path is further attenuated by an attenuation coefficient α_{DDP} . In the UDP scenario, the attenuation coefficient for the direct path is denoted by α_{UDP} . The amplitude gain for multipath components (MPCs) is denoted by α_{MPC} . All the coefficients are modeled as uniform-distributed random variables with the distribution parameters listed in Table 5.1.

The first path is estimated with its TOA and AOA in different simulated scenarios. Based on the estimation results, the rise time, the excess attenuation and the kurtosis are evaluated respectively for different channel scenarios: LOS, NLOS with

DDP and NLOS with UDP. In the training phase, the key distribution parameters used to model the channel characteristics in (5.28) and the empirical threshold for detection based on single metric (5.29) or joint metrics (5.30) are evaluated for the later detection phase. The corresponding errors for TOA and AOA estimations for

Figure 5.4: CDFs of TOA and AOA errors.

the first detected path are shown in the cumulative distribution function (CDF) in Fig. 5.4. As shown in the figure, the first path resolutions in TOA and AOA decrease as the channel conditions deteriorate. This feature is further interpreted by three channel parameters. As shown in Fig. 5.5, Fig. 5.6 and Fig. 5.7, each parameter can be approximately modeled as a log-normal random variable. The distribution

5.3 Channel Detection

parameters dependent on the channel condition are estimated in Table 5.2.

Table 5.2: Log-normal Distribution Parameter for Channel Recognition.

	t_{rise} [ns]		$ \Delta a_1 $		κ	
$\mathcal{H}_i$	μ_i	σ_i	μ_i	σ_i	μ_i	σ_i
$\mathcal{H}_{\text{LOS}}$	-0.0067	0.065	-1.1	1.4	2.4	0.54
$\mathcal{H}_{\text{DDP}}$	0.69	0.84	1.7	1.5	2.3	0.47
$\mathcal{H}_{\text{UDP}}$	0.097	0.34	1.2	1.6	2.6	0.48

Figure 5.5: CDF of rise time t_{rise} for $\mathcal{H}_i$.

The threshold can be decided by minimizing the error detection probability P_e based on the training data. The threshold decisions together with the LLR histogram of training data (respectively simulated in the LOS, DDP, UDP and UDP scenarios from the top to the bottom subplot) are illustrated in Fig. 5.8. As shown in the

Figure 5.6: CDF of the first detected path excess attenuation $|\Delta a_1|$ for $\mathcal{H}_i$.

figure, the channel condition can be detected by comparing the LLR value with the threshold indicated by the red solid line.

Figure 5.7: CDF of kurtosis κ for $\mathcal{H}_i$.

5.3 Channel Detection

Figure 5.8: Threshold decision based on LLR test.

5.4 Detection Performance

Some combinations of three channel metrics are used to detect the channel states as presented in Table 5.3. The performance is based on 10000 detection results. As given in the table, the LRT using joint *pdf* of the rise time, the excess attenuation of first detected path and the kurtosis can acquire the highest detection probability P_D , where

$$P_D = \sum_i P\{\mathcal{D} = \mathcal{H}_i | \mathcal{H}_i\} \quad (5.32)$$

in which the detection probability in LOS, UDP and DDP scenarios are respectively 93.1%, 71.9% and 70.1%. For comparison, the use of rise time only in [107] gives 73.1% the average detection probability, and its joint use with the excess attenuation or the kurtosis increases the average detection probability to 77.1% and 74.2% respectively. The use of kurtosis only in [108] gives 48.5% the average detection probability, and its joint use with the rise time or the excess attenuation increases the performance to 74.2% and 62.1% respectively.

5.5 Concluding Remarks

Table 5.3: Detection probability $P\{\mathcal{D} = \mathcal{H}_i | \mathcal{H}_j\}$ using $\{t_{\text{rise}}\}$ (1st row), $\{|\Delta a_1|\}$ (2nd row), $\{\kappa\}$ (3rd row), $\{t_{\text{rise}}, |\Delta a_1|\}$ (4th row), $\{t_{\text{rise}}, \kappa\}$ (5th row), $\{|\Delta a_1|, \kappa\}$ (6th row) and $\{t_{\text{rise}}, |\Delta a_1|, \kappa\}$ (7th row).

$\mathcal{H} \backslash \mathcal{D}$	$\mathcal{H}_{\text{LOS}}$	$\mathcal{H}_{\text{DDP}}$	$\mathcal{H}_{\text{UDP}}$
$\mathcal{H}_{\text{LOS}}$	94.89%	1.33%	3.78%
	81.44%	17.95%	0.61%
	3.99%	59.17%	36.84%
	94.07%	1.69%	4.24%
	95.32%	1.25%	3.43%
	80.76%	13.93%	5.31%
	93.10%	2.11%	4.79%
$\mathcal{H}_{\text{UDP}}$	27.71%	10.92%	61.37%
	26.40%	47.92%	25.68%
	0.16%	28.46%	71.38%
	15.20%	9.56%	75.24%
	27.86%	9.98%	62.16%
	24.38%	34.45%	41.17%
	14.07%	14.05%	71.88%
$\mathcal{H}_{\text{DDP}}$	10.57%	63.18%	26.25%
	14.09%	63.20%	22.71%
	2.60%	70.24%	27.16%
	5.84%	62.12%	32.04%
	9.84%	65.24%	24.92%
	11.88%	64.48%	23.64%
	5.12%	70.09%	24.79%

5.5 Concluding Remarks

NLOS identification based on the channel parameter estimation techniques is studied in this chapter. The complete investigation includes the performance evaluation of ranging and direction finding algorithms, the channel characteristics selection, the data training for the *pdf* approximation and the threshold determination, and the detection performance. Three channel patterns consisting of LOS, NLOS with UDP and NLOS with DDP are recognized using channel characteristics: the rise time, the excess attenuation of first-detected path and the kurtosis of received signal

5.5 Concluding Remarks

shape. The performances based on 10000 detections show that the correct detection probability in LOS scenario achieves 93.1%, while those in NLOS scenarios are 71.9% for UDP and 70.1% for DDP.

Chapter 6

Conclusions and Recommendations

6.1 Conclusions

The work presented in this thesis focuses on the analysis and design of direction finding and ranging algorithms using ultra-wideband (UWB) signals in dense cluttered environments.

A comprehensive review on the ranging and direction finding techniques and relevant UWB channel model was given in Chapter 2. Based on this review, the theoretical model about UWB channel effects on the ranging and direction finding performance was derived in Chapter 3. For the purpose of approximating the theoretical performance with low complexity, a joint TOA and AOA estimator was designed to mitigate the beam diffusion due to the path-overlapping effects in dense cluttered environments. Accuracy improvements are shown for IEEE 802.15.4a CM3 channel model and for a measured range of up to 21m.

The performance accuracy versus SNR and path arrival rate was given in Chapter 3, and the robustness to dense far-field coherent sources spacing, near-field perturbations and an uncertain number of plane waves were further studied in Chapter 4.

An extended alternating projection (AP) strategy is designed to improve the system robustness to coherent multiple plane waves and multipath rays. Detection before estimation is introduced to save computational time used by the joint TOA and AOA estimator.

The AP strategy has good capability to resolve multiple coherent plane waves as elaborated in Chapter 4, and was therefore used to extract channel characteristics for NLOS channel identification in Chapter 5. Log-likelihood ratio test is formulated to recognize three channel patterns. A complete design from channel estimation, channel training to channel classification is presented.

In conclusion, the advantages of a UWB based direction finding system is superior than a narrow band based AOA system in the following aspects: Firstly, the CRB theoretical AOA error bound in Chapter 3 gives the suggestions as: The large effective bandwidth is much helpful to reduce the AOA error. A UWB direction finding system benefits from the large effective bandwidth. Secondly, the UWB has good immunity to multipath fading. A narrowband system has to mitigate the multipath interfering effects by spatial smoothing with antenna array. Thirdly, the ranging accuracy under centimeters is much helpful to improve the angular resolution.

6.2 Recommendations for Future Work

Many efforts have been made to design a reliable tracking and positioning UWB system in dense cluttered environments. Nevertheless, there are still some aspects on this topic to deserve further investigation.

- NLOS error mitigation needs to be discussed after NLOS identification in Chapter 5. When there are available anchors that are in DDP channel conditions, positioning can be improved by excluding those anchors that are in UDP channel conditions.
- Cooperative positioning system design is challenging but useful in practice. The relative location information among mobiles can be used to improve the positioning performance when the number of available anchors is small. However the identification among multiple tag's ID will increase the system cost.
- Real-time tracking system requires reasonable processing speed with portable device. It limits both the transceiver design and the algorithm complexity. Channel training is helpful to acquire good performance with low computational burden.

Author's Publications

Journal Papers

1. Y. Luo and C. L. Law, "Indoor positioning using UWB-IR signals in the presence of dense multipath with path overlapping," *IEEE Trans. Wireless Commun.*, vol. 11, no. 10, pp. 3734–3743, 2012.

Submitted and under Review

1. Y. Luo and C. L. Law, "Robust ultra-wideband direction finding in dense cluttered environments," minor revision suggested by *IEEE Trans. Wireless Commun.*
2. Y. Luo and C. L. Law, "NLOS identification using empirical threshold selection for UWB indoor positioning," submitted to *IEEE Trans. Wireless Commun.*

Conference Papers

1. Y. Luo and C. L. Law, "UWB indoor positioning based on uniform circular antenna array," in *11th IEEE Singapore International Conference on Communication Systems, ICCS*, 2008, pp. 138–142.
2. Y. Luo and C. L. Law, "Angle-of-arrival estimation with array in a Line-of-Sight indoor UWB-IR," in *7th International Conference on Information, Communications and Signal Processing, ICICS*, 2009, pp. 1–5.
3. Y. Luo and C. L. Law, "A Least-Squares Algorithm for Multipath Estimation Using an UWB-IR Link," in *Proc. IEEE WCNC*, 2010, pp. 1–6.
4. Y. Luo and C. L. Law, "Range Error Analysis of TDOA Based UWB-IR Indoor Positioning System," accepted by 2014 *IEEE 2nd International Symposium on Telecommunication Technologies, ISTT'14*.

Bibliography

- [1] M. I. Skolnik, *Introduction to Radar Systems*, McGraw-Hill, New York, 1980.
- [2] W. C. Knight, R. G. Pridham, and S. M. Kay, “Digital signal processing for sonar,” *Proc. IEEE*, vol. 69, no. 11, pp. 1451–1506, 1981.
- [3] H. L. Van Trees, *Optimum Array Processing: Part IV of Detection, Estimation, and Modulation Theory*, John Wiley & Sons, Inc., 2002.
- [4] S. M. Kay, *Fundamentals of Statistical Signal Processing Volume II: Detection Theory*, Prentice Hall, 2006.
- [5] T. Rappaport, *Wireless Communications: Principles and Practice*, Prentice Hall PTR Upper Saddle River, NJ, USA, 2001.
- [6] H. Krim and M. Viberg, “Two decades of array signal processing research: the parametric approach,” *IEEE Signal Process. Mag.*, vol. 13, no. 4, pp. 67–94, 1996.
- [7] C. J. Hegarty and E. Chatre, “Evolution of the global navigation satellite system (GNSS),” *Proc. IEEE*, vol. 96, no. 12, pp. 1902–1917, 2008.

Bibliography

- [8] S. A. Zekavat and R. M. Buehrer, *Handbook of Position Location: Theory, Practice and Advances*, John Wiley & Sons, Inc., 2011.
- [9] J. B.-Y. Tsui, *Fundamentals of Global Positioning System Receivers: A Software Approach*, Wiley Series in Microwave & Optical Engineering, 2004.
- [10] J. Marais, M. Berbineau, and M. Heddebaut, “Land mobile GNSS availability and multipath evaluation tool,” *IEEE Transactions on Vehicular Technology*, vol. 54, no. 5, pp. 1697–1704, 2005.
- [11] G. Seco-Granados, J.A. Fernandez-Rubio, and C. Fernandez-Prades, “ML estimator and hybrid beamformer for multipath and interference mitigation in GNSS receivers,” *IEEE Transactions on Signal Processing*, vol. 53, no. 3, pp. 1194–1208, 2005.
- [12] Z. Sahinoglu, S. Gezici, and I. Guvenc, *Ultra-Wideband Positioning Systems: Theoretical Limits, Ranging Algorithms, and Protocols*, Cambridge University Press, 2008.
- [13] A. K. Salkintzis, C. Fors, and R. Pazhyannur, “WLAN-GPRS integration for next-generation mobile data networks,” *IEEE Wireless Communications*, vol. 9, no. 5, pp. 112–124, 2002.
- [14] N. Patwari, J. N. Ash, S. Kyperountas, A.O. Hero, R.L. Moses, and N.S. Correal, “Locating the nodes: cooperative localization in wireless sensor networks,” *IEEE Signal Processing Magazine*, vol. 22, no. 4, pp. 54–69, 2005.

- [15] J. Zhang, P. V. Orlik, Z. Sahinoglu, A.F. Molisch, and P. Kinney, “UWB systems for wireless sensor networks,” *Proc. IEEE*, vol. 97, no. 2, pp. 313–331, 2009.
- [16] S. Gezici, Z. Tian, G. B. Giannakis, H. Kobayashi, A. F. Molisch, H. V. Poor, and Z. Sahinoglu, “Localization via ultra-wideband radios: a look at positioning aspects for future sensor networks,” *IEEE Signal Process. Mag.*, vol. 22, no. 4, pp. 70–84, 2005.
- [17] “Federal communications commission, first report and order 02-48,” *Federal Communications Commission*, Feb. 2002.
- [18] “Technical specification for ultra wideband (UWB) devices,” *Info-Communications Development Authority of Singapore*, 2007.
- [19] D. Dardari, R. D’Errico, C. Roblin, A. Sibille, and M.Z. Win, “Ultrawide bandwidth RFID: The next generation?,” *Proc. IEEE*, vol. 98, no. 9, pp. 1570–1582, 2010.
- [20] Y. Zhou, C. L. Law, and J. Xia, “Ultra low-power UWB-RFID system for precise location-aware applications,” in *IEEE Wireless Communications and Networking Conference Workshops (WCNCW)*, 2012, pp. 154–158.
- [21] “IEEE standard for information technology - telecommunications and information exchange between systems - local and metropolitan area networks - specific requirement part 15.4: Wireless medium access control (MAC) and physical

- layer (PHY) specifications for low-rate wireless personal area networks (WPANs),” *IEEE Std 802.15.4a-2007 (Amendment to IEEE Std 802.15.4-2006)*, pp. 1–203, 2007.
- [22] A. F. Molisch, D. Cassioli, C.-C. Chong, S. Emami, A. Fort, B. Kannan, J. Karedal, J. Kunisch, H. G. Schantz, K. Siwiak, and M. Z. Win, “A comprehensive standardized model for ultrawideband propagation channels,” *IEEE Trans. Antennas Propag.*, vol. 54, no. 11, pp. 3151–3166, 2006.
- [23] Y. Shen and M. Z. Win, “Fundamental limits of wideband localization part I: A general framework,” *IEEE Trans. Inf. Theory*, vol. 56, no. 10, pp. 4956–4980, 2010.
- [24] Y. Shen, H. Wymeersch, and M. Z. Win, “Fundamental limits of wideband localization - part II: Cooperative networks,” *IEEE Trans. Inf. Theory*, vol. 56, no. 10, pp. 4981–5000, 2010.
- [25] 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 Trans. Microw. Theory Tech.*, vol. 58, no. 12, pp. 4040–4051, 2010.
- [26] M.S. Arulampalam, S. Maskell, N. Gordon, and T. Clapp, “A tutorial on particle filters for online nonlinear/non-gaussian bayesian tracking,” *IEEE Transactions on Signal Processing*, vol. 50, no. 2, pp. 174–188, 2002.

- [27] R. E. Kalman and R. S. Bucy, “New results in linear filtering and prediction theory,” *Transactions of the ASME. Series D, Journal of Basic Engineering*, vol. 83, pp. 95–107, 1961.
- [28] M. Z. Win and R. A. Scholtz, “Impulse radio: how it works,” *IEEE Commun. Lett.*, vol. 2, no. 2, pp. 36–38, 1998.
- [29] M.-G. D. Benedetto and G. Giancola, *Understanding Ultra Wide Band Radio Fundamentals*, Prentice Hall PTR, 2004.
- [30] D. Jourdan, D. Dardari, and M. Win, “Position error bound for UWB localization in dense cluttered environments,” *IEEE Trans. Aerosp. Electron. Syst.*, vol. 44, no. 2, pp. 613–628, 2008.
- [31] L. Reggiani and G.M. Maggio, “Rapid search algorithms for code acquisition in UWB impulse radio communications,” *IEEE Journal on Selected Areas in Communications*, vol. 23, no. 5, pp. 898–908, 2005.
- [32] D. Dardari, Chia-Chin Chong, and M. Z. Win, “Threshold-based time-of-arrival estimators in UWB dense multipath channels,” *IEEE Trans. Commun.*, vol. 56, no. 8, pp. 1366–1378, 2008.
- [33] I. Guvenc, Z. Sahinoglu, and P.V. Orlik, “TOA estimation for IR-UWB systems with different transceiver types,” *IEEE Transactions on Microwave Theory and Techniques*, vol. 54, no. 4, pp. 1876–1886, 2006.

- [34] M. Z. Win and R. A. Scholtz, “Characterization of ultra-wide bandwidth wireless indoor channels: a communication-theoretic view,” *IEEE J. Sel. Areas Commun.*, vol. 20, no. 9, pp. 1613–1627, 2002.
- [35] J.-Y. Lee and R. A. Scholtz, “Ranging in a dense multipath environment using an UWB radio link,” *IEEE J. Sel. Areas Commun.*, vol. 20, no. 9, pp. 1677–1683, 2002.
- [36] L. Yang and G. B. Giannakis, “Ultra-wideband communications: an idea whose time has come,” *IEEE Signal Process. Mag.*, vol. 21, no. 6, pp. 26–54, 2004.
- [37] L. Yang and G.B. Giannakis, “Timing ultra-wideband signals with dirty templates,” *IEEE Transactions on Communications*, vol. 53, no. 11, pp. 1952–1963, 2005.
- [38] M. S. Bartlett, “Smoothing periodograms from time series with continuous spectra,” *Nature*, vol. 161, pp. 686–687, 1948.
- [39] J. Capon, “High-resolution frequency-wavenumber spectrum analysis,” *Proc. IEEE*, vol. 57, no. 8, pp. 1408–1418, 1969.
- [40] R. J. M. Cramer, R. A. Scholtz, and M. Z. Win, “Evaluation of an ultra-wide-band propagation channel,” *IEEE Trans. Antennas Propag.*, vol. 50, no. 5, pp. 561–570, 2002.

- [41] R. Schmidt and R. Franks, “Multiple source DF signal processing: An experimental system,” *IEEE Trans. Antennas Propag.*, vol. 34, no. 3, pp. 281–290, 1986.
- [42] G. Bienvenu and L. Kopp, “Optimality of high resolution array processing using the eigensystem approach,” *IEEE Trans. Acoust., Speech, Signal Process.*, vol. 31, no. 5, pp. 1235–1248, 1983.
- [43] A. Paulraj, R. Roy, and T. Kailath, “A subspace rotation approach to signal parameter estimation,” *Proc. IEEE*, vol. 74, no. 7, pp. 1044–1046, 1986.
- [44] R. Roy and T. Kailath, “ESPRIT-estimation of signal parameters via rotational invariance techniques,” *IEEE Trans. Acoust., Speech, Signal Process.*, vol. 37, no. 7, pp. 984–995, 1989.
- [45] J. E. Evans, J. R. Johnson, and D. F. Sun, *Application of Advanced Signal Processing Techniques to Angle of Arrival Estimation in ATC Navigation and Surveillance Systems*, Technical report, MIT Lincoln Laboratory, June 1982.
- [46] B. Friedlander and A.J. Weiss, “Direction finding using spatial smoothing with interpolated arrays,” *IEEE Trans. Aerosp. Electron. Syst.*, vol. 28, no. 2, pp. 574–587, 1992.
- [47] T.-J. Shan, M. Wax, and T. Kailath, “On spatial smoothing for direction-of-arrival estimation of coherent signals,” *IEEE Trans. Acoust., Speech, Signal Process.*, vol. 33, no. 4, pp. 806–811, 1985.

- [48] Yuan Shen and M. Z. Win, “On the accuracy of localization systems using wideband antenna arrays,” *IEEE Trans. Commun.*, vol. 58, no. 1, pp. 270–280, 2010.
- [49] Z. N. Low, J. H. Cheong, C. L. Law, W. T. Ng, and Y. J. Lee, “Pulse detection algorithm for line-of-sight (LOS) UWB ranging applications,” *IEEE Antennas Wireless Propag. Lett.*, vol. 4, pp. 63–67, 2005.
- [50] D. Dardari, A. Conti, U. Ferner, A. Giorgetti, and M. Z. Win, “Ranging with ultrawide bandwidth signals in multipath environments,” *Proc. IEEE*, vol. 97, no. 2, pp. 404–426, 2009.
- [51] M. Navarro and M. Najar, “TOA and DOA estimation for positioning and tracking in IR-UWB,” in *Proc. IEEE Int. Conf. Ultra-Wideband*, Singapore, Sept. 2007, pp. 574–579.
- [52] L. Taponecco, A. A. D’Amico, and U. Mengali, “Joint TOA and AOA estimation for UWB localization applications,” *IEEE Trans. Wireless Commun.*, vol. 10, no. 7, pp. 2207–2217, 2011.
- [53] M. G. M. Hussain, “Principles of space-time array processing for ultrawide-band impulse radar and radio communications,” *IEEE Trans. Veh. Technol.*, vol. 51, no. 3, pp. 393–403, 2002.
- [54] J. P. Lie, C. M. See, and B. P. Ng, “Ultra wideband direction finding using digital channelization receiver architecture,” *IEEE Commun. Lett.*, vol. 10, no. 2, pp. 85–87, 2006.

- [55] K. Haneda, Jun-ichi Takada, and T. Kobayashi, “A parametric UWB propagation channel estimation and its performance validation in an anechoic chamber,” *IEEE Trans. Microw. Theory Tech.*, vol. 54, no. 4, pp. 1802–1811, 2006.
- [56] N. Iwakiri and T. Kobayashi, “Joint TOA and AOA/AOD spectrum for ultra-wideband indoor double-directional channel estimation,” in *Proc. 2008 IEEE Veh. Tech. Conf.*, pp. 1–5.
- [57] Yongwei Zhang, A. K. Brown, W. Q. Malik, and D. J. Edwards, “High resolution 3-D angle of arrival determination for indoor UWB multipath propagation,” *IEEE Trans. Wireless Commun.*, vol. 7, no. 8, pp. 3047–3055, 2008.
- [58] Yihong Qi, H. Kobayashi, and H. Suda, “Analysis of wireless geolocation in a non-line-of-sight environment,” *IEEE Trans. Wireless Commun.*, vol. 5, no. 3, pp. 672–681, 2006.
- [59] A. Mallat, C. Oestges, and L. Vandendorpe, “CRBs for UWB multipath channel estimation: Impact of the overlapping between the MPCs on MPC gain and TOA estimation,” in *Proc. IEEE Int. Conf. Commun.*, Dresden, Germany, June 2009, pp. 1–6.
- [60] H. Wymeersch, J. Lien, and M. Z. Win, “Cooperative localization in wireless networks,” *Proc. IEEE*, vol. 97, no. 2, pp. 427–450, 2009.
- [61] M. Z. Win, A. Conti, S. Mazuelas, Yuan Shen, W. M. Gifford, D. Dardari, and M. Chiani, “Network localization and navigation via cooperation,” *IEEE Commun. Mag.*, vol. 49, no. 5, pp. 56–62, 2011.

- [62] A. Conti, M. Guerra, D. Dardari, N. Decarli, and M. Z. Win, “Network experimentation for cooperative localization,” *IEEE J. Sel. Areas Commun.*, vol. 30, no. 2, pp. 467–475, 2012.
- [63] X. Li and K. Pahlavan, “Super-resolution TOA estimation with diversity for indoor geolocation,” *IEEE Trans. Wireless Commun.*, vol. 3, no. 1, pp. 224–234, 2004.
- [64] L. Mucchi, C. Falsi, D. Dardari, and M. Z. Win, “Channel parameters estimation for UWB realistic environments,” in *Proc. IEEE Int. Conf. Ultra-Wideband*, Waltham, MA, USA, Sept. 2006, pp. 155–160.
- [65] C. M. Keller and D. P. Young, “Ultra-wideband (UWB) signal localization using a vehicle-sized array,” in *Proc. IEEE Int. Conf. Ultra-Wideband*, ETH Zurich, Switzerland, Sept. 2005, pp. 290–295.
- [66] Y. Zhou, Y. L. Guan, and C. L. Law, “Modified phase-only correlator with kurtosis-based amplified-noise suppression,” *IEEE Trans. Wireless Commun.*, vol. 9, no. 11, pp. 3341–3345, 2010.
- [67] Y. Luo and C. L. Law, “A least-squares algorithm for multipath estimation using an UWB-IR link,” in *Proc. IEEE Wireless Commun. Netw. Conf.*, Sydney, Australia, Apr. 2010, pp. 1–6.
- [68] T. G. Manickam, R. J. Vaccaro, and D. W. Tufts, “A least-squares algorithm for multipath time-delay estimation,” *IEEE Trans. Signal Process.*, vol. 42, no. 11, pp. 3229–3233, 1994.

Bibliography

- [69] Steven M. Kay, *Fundamentals of Statistical Signal Processing Volume I: Estimation Theory*, Prentice Hall, 2006.
- [70] Ward Cheney and David R. Kincaid, *Linear Algebra: Theory and Applications*, 2009.
- [71] W. Suwansantisuk and M. Z. Win, “Multipath aided rapid acquisition: Optimal search strategies,” *IEEE Trans. Inf. Theory*, vol. 53, no. 1, pp. 174–193, 2007.
- [72] X.-L. Xu and K. Buckley, “An analysis of beam-space source localization,” *IEEE Trans. Signal Process.*, vol. 41, no. 1, pp. 501–504, 1993.
- [73] C.-M. Cho and P. M. Djuric, “Detection and estimation of DOA’s of signals via bayesian predictive densities,” *IEEE Trans. Signal Process.*, vol. 42, no. 11, pp. 3051–3060, 1994.
- [74] H. Krim and J. G. Proakis, “Smoothed eigenspace-based parameter estimation,” *Automatica, Special Issue on Statistical Signal Processing and Control*, vol. 30, no. 1, pp. 27–38, 1994.
- [75] P. Stoica and K.C. Sharman, “Maximum likelihood methods for direction-of-arrival estimation,” *IEEE Trans. Acoust., Speech, Signal Process.*, vol. 38, no. 7, pp. 1132–1143, 1990.

- [76] M. Viberg, B. Ottersten, and T. Kailath, “Detection and estimation in sensor arrays using weighted subspace fitting,” *IEEE Trans. Signal Process.*, vol. 39, no. 11, pp. 2436–2449, 1991.
- [77] P. Stoica and K.C. Sharman, “Novel eigenanalysis method for direction estimation,” *Radar and Signal Processing, IEE Proceedings F*, vol. 137, no. 1, pp. 19–26, 1990.
- [78] Y. Bresler and A. Macovski, “Exact maximum likelihood parameter estimation of superimposed exponential signals in noise,” *IEEE Trans. Acoust., Speech, Signal Process.*, vol. 34, no. 5, pp. 1081–1089, 1986.
- [79] M. Haardt and J.A. Nosssek, “Unitary ESPRIT: how to obtain increased estimation accuracy with a reduced computational burden,” *IEEE Trans. Signal Process.*, vol. 43, no. 5, pp. 1232–1242, 1995.
- [80] A. Barabell, “Improving the resolution performance of eigenstructure-based direction-finding algorithms,” in *Proc. 1983 IEEE Acoust., Speech, Signal Process. Conf.*, vol. 8, pp. 336–339.
- [81] Y. Luo and C. L. Law, “Indoor positioning using UWB-IR signals in the presence of dense multipath with path overlapping,” *IEEE Trans. Wireless Commun.*, vol. 11, no. 10, pp. 3734–3743, 2012.
- [82] H. Keshavarz, “Weighted signal-subspace direction-finding of ultra-wideband sources,” in *Proc. 2005 IEEE Int. Conf. Wireless Mobile Comput. Netw. Commun.*, pp. 23–29 Vol. 1.

- [83] I. Ziskind and M. Wax, “Maximum likelihood localization of multiple sources by alternating projection,” *IEEE Trans. Acoust., Speech, Signal Process.*, vol. 36, no. 10, pp. 1553–1560, 1988.
- [84] T. S. Rappaport, “Characterization of UHF multipath radio channels in factory buildings,” *IEEE Trans. Antennas Propag.*, vol. 37, no. 8, pp. 1058–1069, 1989.
- [85] X. Diao and F. Guo, “Method distinguishing line of sight (LOS) from non-line of sight (NLOS) in CDMA mobile communication system,” U.S. Patent 7 099 640 B2, Aug. 2006.
- [86] M. Heidari, N. A. Alsindi, and K. Pahlavan, “UDP identification and error mitigation in TOA-based indoor localization systems using neural network architecture,” *IEEE Trans. Wireless Commun.*, vol. 8, no. 7, pp. 3597–3607, 2009.
- [87] C. Ma, R. Klukas, and G. Lachapelle, “A nonline-of-sight error-mitigation method for TOA measurements,” *IEEE Trans. Veh. Technol.*, vol. 56, no. 2, pp. 641–651, 2007.
- [88] M. P. Wylie and J. Holtzman, “The non-line of sight problem in mobile location estimation,” in *Proc. IEEE Int. Conf. Univer. Pers. Commun.*, 1996, vol. 2, pp. 827–831.
- [89] M. P. Wylie and J. Holtzman, “Method and system for mobile location estimation,” U.S. Patent 5 974 329, Oct. 1989.

- [90] S. Gezici, H. Kobayashi, and H. V. Poor, “Non-parametric non-line-of-sight identification,” in *Proc. IEEE Veh. Tech. Conf.*, 2003, vol. 4, pp. 2544–2548.
- [91] S. Venkatraman and Jr. Caffery, J., “A statistical approach to non-line-of-sight BS identification,” in *Proc. 5th Int. Symp. Wireless Pers. Multimedia Commun.*, 2002, vol. 1, pp. 296–300.
- [92] I. Guvenc and C.-C. Chong, “A survey on TOA based wireless localization and NLOS mitigation techniques,” *IEEE Commun. Surveys Tuts.*, vol. 11, no. 3, pp. 107–124, 2009.
- [93] P.-C. Chen, “A non-line-of-sight error mitigation algorithm in location estimation,” in *Proc. IEEE Wireless Commun. Netw. Conf.*, 1999, vol. 1, pp. 316–320.
- [94] D. Cassioli, M. Z. Win, and A. F. Molisch, “The ultra-wide bandwidth indoor channel: from statistical model to simulations,” *IEEE J. Sel. Areas Commun.*, vol. 20, no. 6, pp. 1247–1257, 2002.
- [95] A. F. Molisch, “Ultra-wide-band propagation channels,” *Proc. IEEE*, vol. 97, no. 2, pp. 353–371, 2009.
- [96] F. Tehoffo-Talom, B. Uguen, E. Plouhinec, and G. Chassay, “A site-specific tool for UWB channel modeling,” in *Proc. Int. Workshop Ultra Wideband Syst.*, 2004, pp. 61–65.

- [97] J. Borras, P. Hatrack, and N. B. Mandayam, “Decision theoretic framework for NLOS identification,” in *Proc. IEEE Veh. Tech. Conf.*, 1998, vol. 2, pp. 1583–1587.
- [98] J. Khodjaev, Y. Park, and A. S. Malik, “Survey of NLOS identification and error mitigation problems in UWB-based positioning algorithms for dense environments,” *Ann. Telecommun.*, vol. 65, pp. 301–311, 2010.
- [99] B. Alavi and K. Pahlavan, “Modeling of the TOA-based distance measurement error using UWB indoor radio measurements,” *IEEE Commun. Lett.*, vol. 10, no. 4, pp. 275–277, 2006.
- [100] N. A. Alsindi, B. Alavi, and K. Pahlavan, “Measurement and modeling of ultrawideband TOA-based ranging in indoor multipath environments,” *IEEE Trans. Veh. Technol.*, vol. 58, no. 3, pp. 1046–1058, 2009.
- [101] M. Heidari, F. O. Akgul, and K. Pahlavan, “Identification of the absence of direct path in indoor localization systems,” in *Proc. IEEE 18th Int. Symp. Pers., Indoor and Mobile Radio Commun.*, 2007, pp. 1–6.
- [102] I. Guvenc, C.-C. Chong, and F. Watanabe, “NLOS identification and mitigation for UWB localization systems,” in *Proc. IEEE Wireless Commun. Netw. Conf.*, 2007, pp. 1571–1576.
- [103] M. Guerra and A. Conti, “Experimental multilevel NLOS characterization for UWB network localization,” in *Proc. IEEE Statistical Signal Process. Workshop*, 2011, pp. 173–176.

- [104] A. Rabbachin, I. Oppermann, and B. Denis, “ML time-of-arrival estimation based on low complexity UWB energy detection,” in *Proc. IEEE Int. Conf. Ultra Wideband*, 2006, pp. 599–604.
- [105] J. Schroeder, S. Galler, K. Kyamakya, and T. Kaiser, “Three-dimensional indoor localization in non line of sight UWB channels,” in *Proc. IEEE Int. Conf. Ultra Wideband*, 2007, pp. 89–93.
- [106] J. Schroeder, S. Galler, K. Kyamakya, and K. Jobmann, “NLOS detection algorithms for ultra-wideband localization,” in *Proc. 4th Workshop Positioning, Navigation and Commun.*, 2007, pp. 159–166.
- [107] A. Maali, H. Mimoun, G. Baudoin, and A. Ouldali, “A new low complexity NLOS identification approach based on UWB energy detection,” in *Proc. IEEE Symp. Radio and Wireless*, 2009, pp. 675–678.
- [108] L. Mucchi and P. Marocchi, “A new parameter for UWB indoor channel profile identification,” *IEEE Trans. Wireless Commun.*, vol. 8, no. 4, pp. 1597–1602, 2009.
- [109] Q. Wang, I. Balasingham, M. Zhang, and X. Huang, “Improving RSS-based ranging in LOS-NLOS scenario using GMMs,” *IEEE Commun. Lett.*, vol. 15, no. 10, pp. 1065–1067, 2011.
- [110] H. Wymeersch, S. Marano, W. M. Gifford, and M. Z. Win, “A machine learning approach to ranging error mitigation for UWB localization,” *IEEE Trans. Commun.*, vol. 60, no. 6, pp. 1719–1728, 2012.

Bibliography

- [111] S. Maranò, W. M. Gifford, H. Wymeersch, and M. Z. Win, “NLOS identification and mitigation for localization based on UWB experimental data,” *IEEE J. Sel. Areas Commun.*, vol. 28, no. 7, pp. 1026–1035, 2010.
- [112] I. Guvenc, C.-C. Chong, F. Watanabe, and H. Inamura, “NLOS identification and weighted least-squares localization for UWB systems using multipath channel statistics,” *EURASIP J. Advances Signal Process.*, vol. 2008, no. 1, pp. 271984, 2008.

APPENDIX A

Derivation of the Zero Entries in Eqn (3.10)

The Fisher information matrix (FIM) has the form of (3.10), where **A**, **B** and **C** matrix can be expressed respectively as,

$$A^{(i,j)} = -E \left\{ \frac{\partial^2 \ln p(\mathbf{x}|\underline{\eta})}{\partial \eta_i \partial \eta_j} \right\}, \quad \eta_{i,j} \in \{\tau_1^o, \theta_1, a_1, \dots, \tau_L^o, \theta_L, a_L\}, \quad (\text{A.1})$$

$$B_e^{(i,j)} = -E \left\{ \frac{\partial^2 \ln p(\mathbf{x}|\underline{\eta})}{\partial \eta_i \partial \eta_j} \right\}, \quad \eta_{i,j} \in \underline{\gamma}^e, \quad (\text{A.2})$$

$$C_e^{(i,j)} = -E \left\{ \frac{\partial^2 \ln p(\mathbf{x}|\underline{\eta})}{\partial \eta_i \partial \eta_j} \right\}, \quad \eta_{i,j} \in \{\tau_1^o, \theta_1, a_1, \dots, \tau_L^o, \theta_L, a_L\} \cap \underline{\gamma}^e. \quad (\text{A.3})$$

Because the rays from near-field scatters to each array sensor are considered to be distribute independently, the near-field path component parameters $\underline{\gamma}^e$ at each

Appendix A

sensor are uncorrelated with each other as follows,

$$\int_{-\infty}^{+\infty} \sum_{l=L+1}^{L_e} a_l^e s(t - \tau_l^e) \sum_{l=L+1}^{L_{e'}} a_l^{e'} s(t - \tau_l^{e'}) = 0 \quad (\text{A.4})$$

where e' denotes the sensor different from e . Therefore the zero entries are induced as a result.

APPENDIX B

Derivation of Multipath Gain in Eqn(3.13)

To find out the parametric effects of a_l and a_l^e on the CRB $(\tau_1^o, \theta_1, a_1)$, three cases are considered as follows,

i) In the case of $\mathbf{A}^{(1,j)} = 0$ and $\mathbf{C}_e^{(1,j)} = 0$, and $\mathbf{C}_e^{(1,j)} = 0$ and CRB(θ_1) are respectively given in (3.21) and (3.22). The CRB(a_1) is given as follows,

$$\text{CRB}(a_1) = \frac{N_0}{2NR_s(0)} \quad (\text{B.1})$$

The CRB for the direct path is irrelevant to the a_l and a_l^e in this case.

ii) In the case of $L = L_e = 2$ and $\mathbf{C}_e^{(1,j)} = 0$, the CRB is obtained by inverting the EFIM of $\mathbf{A}^{(1,1)} - \mathbf{A}^{(1,2)}[\mathbf{A}^{(2,2)}]^{-1}[\mathbf{A}^{(1,2)}]^T$, where

$$\mathbf{A}^{(1,1)} = \frac{2}{N_0} \text{diag}\{Na_1^2\ddot{R}_s(0), a_1^2\ddot{R}_s(0) \sum_{e=1}^N (\Lambda_1^e)^2, NR_s(0)\}, \quad (\text{B.2})$$

Appendix B

$$[\mathbf{A}^{(2,2)}]^{-1} = \frac{N_0}{2} \text{diag} \left\{ \frac{1}{Na_2^2 \ddot{R}_s(0)}, \frac{1}{a_2^2 \ddot{R}_s(0) \sum_{e=1}^N (\Lambda_2^e)^2}, \frac{1}{NR_s(0)} \right\}, \quad (\text{B.3})$$

$$\mathbf{A}^{(1,2)} = \frac{2}{N_0} \begin{bmatrix} a_1 a_2 \sum_{e=1}^N \ddot{R}_s(\tau_2^e - \tau_1^e) & -a_1 a_2 \sum_{e=1}^N \ddot{R}_s(\tau_2^e - \tau_1^e) \Lambda_2^e & a_1 \sum_{e=1}^N \dot{R}_s(\tau_2^e - \tau_1^e) \\ -a_1 a_2 \sum_{e=1}^N \ddot{R}_s(\tau_2^e - \tau_1^e) \Lambda_1^e & a_1 a_2 \sum_{e=1}^N \ddot{R}_s(\tau_2^e - \tau_1^e) \Lambda_1^e \Lambda_2^e & -a_1 \sum_{e=1}^N \dot{R}_s(\tau_2^e - \tau_1^e) \Lambda_1^e \\ -a_2 \sum_{e=1}^N \dot{R}_s(\tau_2^e - \tau_1^e) & a_2 \sum_{e=1}^N \dot{R}_s(\tau_2^e - \tau_1^e) \Lambda_2^e & \sum_{e=1}^N R_s(\tau_2^e - \tau_1^e) \end{bmatrix} \quad (\text{B.4})$$

Both the $\mathbf{A}^{(1,1)}$ and the result of $\mathbf{A}^{(1,2)}[\mathbf{A}^{(2,2)}]^{-1}[\mathbf{A}^{(1,2)}]^T$ do not contain the amplitude of the second path a_2 . Therefore, the CRB for the direct path is irrelevant to the a_l and a_l^e in this case.

iii) In the case of $L = 1$, $L_e = 2$ and $\mathbf{A}^{(1,j)} = 0$, the CRB is obtained by inverting the EFIM of $[\mathbf{A}^{(1,1)} - \sum_e \mathbf{C}_e^{(1,2)}[\mathbf{B}_e^{(2,2)}]^{-1}[\mathbf{C}_e^{(1,2)}]^T]^{-1}$, where

$$[\mathbf{B}_e^{(2,2)}]^{-1} = \frac{N_0}{2} \text{diag} \left\{ \frac{1}{(a_2^e)^2 \ddot{R}_s(0)}, \frac{1}{R_s(0)} \right\}, \quad (\text{B.5})$$

$$\mathbf{C}_e^{(1,2)} = \frac{2}{N_0} \begin{bmatrix} a_1 a_2^e \ddot{R}_s(\tau_2^e - \tau_1^e) & a_1 \dot{R}_s(\tau_2^e - \tau_1^e) \\ -a_1 a_2^e \Lambda_1^e \ddot{R}_s(\tau_2^e - \tau_1^e) & -a_1 \Lambda_1^e \dot{R}_s(\tau_2^e - \tau_1^e) \\ -a_2^e \dot{R}_s(\tau_2^e - \tau_1^e) & R_s(\tau_2^e - \tau_1^e) \end{bmatrix}. \quad (\text{B.6})$$

Both the $\mathbf{A}^{(1,1)}$ and the result of $\mathbf{C}_e^{(1,2)}[\mathbf{B}_e^{(2,2)}]^{-1}[\mathbf{C}_e^{(1,2)}]^T$ do not contain the amplitude of the second path a_2^e . Therefore, the CRB for the direct path is irrelevant to the a_l and a_l^e in this case.

APPENDIX C

Derivation of Lower Error Bound of ADOA

Given the Fisher information matrix (FIM) of interest as [81],

$$\mathbf{J} = \begin{bmatrix} \mathbf{A}^{(1,1)} & \mathbf{A}^{(1,2)} \\ [\mathbf{A}^{(1,2)}]^T & \mathbf{A}^{(2,2)} \end{bmatrix} \quad (\text{C.7})$$

The $\mathbf{A}^{(i,j)}$ is defined in equation (C.2),

$$\mathbf{A}^{(i,j)} = \frac{2}{N_0} \begin{bmatrix} a_i a_j \sum_{e=1}^N \ddot{R}_s(\tau_j^e - \tau_i^e) & -a_i a_j \sum_{e=1}^N \ddot{R}_s(\tau_j^e - \tau_i^e) \Lambda_j^e & a_i \sum_{e=1}^N \dot{R}_s(\tau_j^e - \tau_i^e) \\ -a_i a_j \sum_{e=1}^N \ddot{R}_s(\tau_j^e - \tau_i^e) \Lambda_i^e & a_i a_j \sum_{e=1}^N \ddot{R}_s(\tau_j^e - \tau_i^e) \Lambda_i^e \Lambda_j^e & -a_i \sum_{e=1}^N \dot{R}_s(\tau_j^e - \tau_i^e) \Lambda_i^e \\ -a_j \sum_{e=1}^N \dot{R}_s(\tau_j^e - \tau_i^e) & a_j \sum_{e=1}^N \dot{R}_s(\tau_j^e - \tau_i^e) \Lambda_j^e & \sum_{e=1}^N R_s(\tau_j^e - \tau_i^e) \end{bmatrix} \quad (\text{C.8})$$

where

$$\tau_i^e = \tau_i - \Delta \tau^e(\theta_i) \quad (\text{C.9})$$

Appendix C

$$\Lambda_i^e = \frac{\partial \Delta \tau^e(\theta_i)}{\partial \theta_i} \quad (\text{C.10})$$

R_s and $\ddot{R}_s$ are respectively the auto-correlation function of source signal $s(t)$ and its time derivative $\dot{s}(t)$. $\dot{R}_s$ denotes the cross-correlation function of source signal and its time derivative. The Cramér-Rao bounds (CRB) of θ_1 is given by $[\mathbf{J}^{-1}]_{2,2}$, and the angle-difference-of-arrival that is defined as $\Delta\theta = \theta_1 - \theta_2$ can be evaluated by the performance bound as follows,

$$\begin{aligned} \text{Var}(\theta_1 - \theta_2) &= \text{Var}(\theta_1) + \text{Var}(\theta_2) - 2\text{Cov}(\theta_1, \theta_2) \\ &\geq [\mathbf{J}^{-1}]_{2,2} + [\mathbf{J}^{-1}]_{5,5} - 2[\mathbf{J}^{-1}]_{2,5} \end{aligned} \quad (\text{C.11})$$