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**NANYANG
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**PHASE MEASUREMENTS BASED INDOOR
VISIBLE LIGHT POSITIONING SYSTEMS**

ZHANG SHENG

SCHOOL OF ELECTRICAL & ELECTRONIC ENGINEERING

2020

**PHASE MEASUREMENTS BASED INDOOR
VISIBLE LIGHT POSITIONING SYSTEMS**

ZHANG SHENG

School of Electrical & Electronic Engineering

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

2020

Statement of Originality

I hereby certify that the work embodied in this thesis is the result of original research, is free of plagiarised materials, and has not been submitted for a higher degree to any other University or Institution.

23 August 2019

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Date

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Supervisor Declaration Statement

I have reviewed the content and presentation style of this thesis and declare it is free of plagiarism and of sufficient grammatical clarity to be examined. To the best of my knowledge, the research and writing are those of the candidate except as acknowledged in the Author Attribution Statement. I confirm that the investigations were conducted in accord with the ethics policies and integrity standards of Nanyang Technological University and that the research data are presented honestly and without prejudice.

02 March 2020

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Authorship Attribution Statement

This thesis contains material from 6 paper(s) published in the following peer-reviewed journal(s) / from papers accepted at conferences in which I am listed as an author.

The contributions of the co-authors are stated below.

1. P. Du, S. Zhang, C. Chen, A. Alphones, and W.-D. Zhong, "Demonstration of a low-complexity indoor visible light positioning system using an enhanced TDOA scheme," in *IEEE Photonics Journal*, vol. 10, no. 4, pp. 1-10, 2018. (related to Chapter III)

The contributions of the co-authors are as follows:

- P. Du conducted the experiments and wrote the main part of this paper.
 - I designed and provided the positioning algorithm and built up the simulations with MATLAB.
 - P. Du and I designed and constructed the whole hardware testbed together.
 - C. Chen revised the paper with technical details and assisted in analyzing data.
 - Prof. Alphones provided advice, revised the paper and gave suggestions for experimental design.
 - Prof. Zhong provided comments and revised the paper and gave advice and guidelines for designing the algorithm.
-
2. S. Zhang, W.-D. Zhong, P. Du, and C. Chen, "Experimental demonstration of indoor sub-decimeter accuracy VLP system using differential PDOA," in *IEEE Photonics Technology Letters*, vol. 30, no. 19, pp. 1703-1706, 2018. (related to Chapter IV and Chapter V)

The contributions of the co-authors are as follows:

- I wrote up the manuscript which was then revised by Prof. Zhong, P. Du and C. Chen.

- I designed the positioning algorithm with the suggestions from Prof. Zhong.
- I programmed and optimized the algorithm and developed the simulations with MATLAB.
- I designed the experiments and then conducted the experiments with P. Du.
- I collected, processed and analyzed the data in both simulations and experiments
- P. Du, C. Chen and Prof. Zhong provided suggestions based on the results of the experiments.

3. S. Zhang, P. Du, C. Chen, W.-D. Zhong, and A. Alphones, "Robust 3D indoor VLP system based on ANN using hybrid RSS/PDOA," in *IEEE Access*, vol. 7, pp. 47769-47780, 2019. (related to Chapter V and Chapter VI)

The contributions of the co-authors are as follows:

- I wrote the drafts of the manuscript which was then revised by Prof. Zhong, Prof. Alphones, and C. Chen.
- I designed the neural network-based DPDOA and RSS positioning system and proposed the selection strategies of the hybrid system.
- I performed the pre-training and training of the neural networks and conducted simulations.
- P. Du and I analyzed the simulation results, and P. Du provided suggestions on T-selection strategies.
- C. Chen proofread the paper and provided suggestions on V-selection strategies.
- Prof. Zhong gave guidelines in relieving the training workload of neural networks, and provided comments on the manuscripts.

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trilateration assisted by deep learning technique," in *IEEE Access*, vol. 7, pp. 93986-93997, 2019. (related to Chapter VI)

The contributions of the co-authors are as follows:

- P. Du wrote the drafts of the manuscript, and I then revised the manuscript with C. Chen and Prof. Zhong.
- P. Du and I constructed the experimental testbed together.
- P. Du and H. Yang conducted experiments and collect the data.
- I designed the neural network structure and P. Du optimized the network structure.
- I provided neural network-based algorithms and training schemes.
- Prof. Alphones, Prof. Zhong and R. Zhang provided comments on the manuscripts, and assisted in analyzing the data.
- Y. Yang gave suggestions in revising the manuscript and system design.

5. S. Zhang, W.-D. Zhong, D. Pengfei, C. Chen, and D. Wu, "PDOA based indoor visible light positioning system without local oscillators in receiver," *2017 Conference on Lasers and Electro-Optics Pacific Rim (CLEO-PR)*, Singapore, 2017. (related to Chapter IV)

The contributions of the co-authors are as follows:

- I wrote the drafts of the manuscript which was then revised by Prof. Zhong, D. Pengfei and C. Chen.
- I designed the positioning algorithm with the suggestions from Prof. Zhong and D. Wu.
- P. Du and I constructed the experimental testbed and conducted experiments together.
- P. Du and C. Chen analyzed the simulation results and provide suggestions.
- D. Wu provided suggestions on MATLAB codes for simulations.

6. S. Zhang, P. Du, C. Chen, and W.-D. Zhong, "3D indoor visible light positioning system using RSS ratio with neural network," *2018 23rd Opto-Electronics and Communications Conference (OECC)*, Jeju Island, Korea (South), 2018. (related to Chapter VI)

The contributions of the co-authors are as follows:

- I wrote the drafts of the manuscript which was then revised by Prof. Zhong, and C. Chen.
- I designed the neural network-based RSS positioning system and RSS ratio positioning system.
- P. Du and I analyzed the simulation results, and P. Du provided suggestions on RSS ratio algorithms.
- P. Du and I constructed the experimental testbed and conducted experiments.
- Prof. Zhong and C. Chen analyzed the experimental data and provide suggestions.

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Twenty-eight years ago, born as an infant, I became a family member thanks to the great effort of my dear mother and father. From an innocent and naughty boy, I grew up to a man with rationality and curiosity. I am grateful for the life my parents gave me, for the patience they held when I was willful, for the expectations and trust they have on me, for all the supports they gave in every hard time of my life. Tough thousand miles from China, they are and will always care about me, and I am always their little child whether when they are young or elder even hair getting white. I remember every time I sat on the bike when my father rode me home after school; I know they have worked so hard to save and borrow money for my milk powder. Dear mom and dad, I love you.

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In the past four years, I have experienced happiness and sorrows in both study and life.

I was not feeling well in the first one and a half year of Ph.D. study. I broke up with my ex-girlfriend, everything just like in a tragic film -- quarrels and tears. At almost the same time, my researches stuck by a case dependent error with unknown reasons. I stepped out of both the emotion and research challenges eventually. I am thankful for the relationship and the errors that stuck my life and research. Only when facing the problem, the solution will come naturally, just like life.

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Abstract

The widespread use of LED lamps in the illumination environments is witnessed from the early 21st century. Applications of LEDs in indoor communications have been gradually investigated in the last two decades. Companies like Pure-LiFi [1] and Oledcomm (with the product Li-Fi MAX and MyLiFi bidirectional desk lamp [2]), as well as many research institutes, are researching on the secure and high-speed visible light-based communication approach with good adaptivity. The fast development of visible light communication (VLC) provides a great chance for visible light positioning (VLP) systems. Moreover, researchers are seeking a feasible indoor positioning technology and developing an indoor GPS like system. As the GPS signals have severe multi-path effects and strong signal attenuations in indoor buildings, visible light with its line of sight (LOS) property and fewer reflections and diffractions gains advantages in the positioning accuracy over other RF-based techniques.

There are several positioning algorithms, the simplest one in structure is the received signal strength (RSS) which has good signal-to-noise ratio (SNR) property, but is not feasible in situations with rotations and intensity disturbance. Time difference of arrival (TDOA) is one of the complicated algorithms, with high demand in hardware, but good robustness in rotations. Among the positioning algorithms, Phase difference of arrival (PDOA) is one of the compromises. PDOA is similar to the TDOA based method in concept, however, it uses continuous sine waves rather than short pulses, reducing the hardware complexity greatly. Meanwhile, PDOA can achieve both high positioning accuracy and rotation robustness.

In this thesis, our first concern on the classical PDOA systems is the use of local oscillators (LOs). The LOs normally use hardware devices and the modulation frequencies are constrained by the multiples (harmonics) of a fundamental LO's frequency. Also, such LOs are used in both transmitting and receiving sides, causing clock precision related errors. Hence, a system with virtual LOs (VLO) is proposed in this thesis, using software-generated signals, and a new algorithm with higher frequency allocation flexibility is also proposed. Therefore, the interferences of harmonics from the modulation frequencies are avoided and less band is occupied. The proposed techniques are hence promising in the combination of the VLC and VLP systems.

Further researches reveal that PDOA systems using LOs (even with VLO) have an issue

of pseudo synchronization. In actual applications, the signals received are truncated with a random time schedule and unsynchronized to the transmitter side. This causes a confusion of phases at the receiving end with leap solutions in inverse trigonometric functions, ending up with sudden phase changes. Therefore, a novel LO irrelevant positioning scheme is further proposed. The scheme with one extra transmission frequency is added on the transmitter side, with totally five signals carrying four distance information. The proposed algorithm has two distinguished differential processes on phase extractions. The distance difference measurements are extracted from the differential of PDOA signals, hence called DPDOA algorithm. Our proposed DPDOA algorithm requires no pseudo synchronization at the receiver ends and completely removes the LOs. Experimental validations illustrate sub-decimetre level positioning accuracy.

In actual applications, the LED lamps have phase/time models different from the ideal sphere model and the performance of the PDOA/TDOA based system is hence compromised. A neural network (NN) based solution is proposed for the first time to address the onsite modeling and positioning problem in a single hidden layer NN. The proposed scheme largely reduces position solving calculations and significantly enhances the positioning performance.

After examining phase and time-based VLP systems, it is found that phase/time measurements have generally higher SNR requirements than the RSS measurements. Meanwhile, the RSS as the most cost-efficient algorithm has higher SNR tolerance when no rotation or intensity disturbance occurs. The DPDOA algorithm is capable of functioning under rotation and intensity disturbances. Hence, we propose a hybrid algorithm of using both DPDOA and RSS measurements with selection based strategies. As the DPDOA signals contain both RSS and DPDOA information, no extra cost incurs. We design the T-selection and the V-selection strategies using hybrid DPDOA and RSS measurements as fundamental positioning standard, and show that the T-selection based system outperforms the V-selection based system.

List of Abbreviations

2D – 2 Dimensional

3D – 3 Dimensional

ADC – Analog to Digital Converter

AI – Artificial Intelligence

AOA – Angle of Arrival

APD – Avalanche Photo-diode

AWG – Arbitrary Waveform Generator

BPF – Band Pass Filter

DAC – Digital to Analog Converter

DC – Direct Current

DDOA – Distance Difference of Arrival

DOA – Distance of Arrival

DPDOA – Differential PDOA

FFT – Fast Fourier Transition

FOV – Field of View

IOT – Internet of Things

ITD – Initial Time Delay

KF – Kalman Filtering

LBS – Location-based Service

LED – Light Emitting Diode

Li-Fi – Light Fidelity

LO – Local Oscillator

LOS – Line of Sight

LPF – Low Pass Filter

MSE – Mean Square Error

NN – Neural Network

PD – Photo-detector

PDOA – Phase Difference of Arrival

RF – Radio Frequency

RMS – Root Mean Square

RSS – Received Signal Strength

SNR – Signal to Noise Ratio

TD – Time Difference

TDOA – Time Difference of Arrival

TOF – Time of Flight

UWB – Ultra-Wide-Band

VLC – Visible Light Communication

VLO – Virtual Local Oscillator

VLP – Visible Light Positioning

Wi-Fi – Wireless Fidelity

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Chapter I Introduction

1.1 Backgrounds and Motivations

In the era of Internet of Things(IoT) and Artificial Intelligence (AI), it's an unstoppable trend to make all the devices (including lamps, cleaning robots, indoor vehicles, etc.) connected to indoor private networks, providing better quality of life and efficiency in the industry [3], [4]. Services like temperature controlling, aged care, house cleaning, safety checking, cargo tracking, etc. will be soon realized through indoor robots, remote controlling and smart managing. Most of these services are based on the location information and interacting through either central or distributed management.

Location-based services (LBSs) are crucial not only in realizing the smart city and smart living but also in public indoor facilities. In transportation interchanges, airports, large shopping malls, libraries with complicated structures, indoor tracking, and navigations are valuable services for the convince of customers and the traffic management of operators. Moreover, LBSs provide assistance in emergencies like evacuations in a fire, children\elders get lost, and tracking of critical objects.

However, indoor positioning services are currently less developed as the current GPS suffers severe multi-path effects and does not suit in indoor environments. In outdoor environments, after complicated compensations, GPS can achieve accuracies in the order of a meter. However, the attenuation of the building structures as well as multipath effects (reflections, refraction, etc.), causing large positioning error (tens of meters) in indoor scenarios. Also, the requirement for the nanosecond level of clock synchronization makes the GPS costly[5], [6].

In recent years, techniques with radio frequency(RF) based indoor LBS solutions are reported based on Wi-Fi, Bluetooth, radio frequency identification (RFID) and Ultra Wide Band (UWB) carriers [7]–[10]. Among them, the UWB is the one that possesses the highest accuracy, while Wi-Fi and Bluetooth are widely researched as their hardware are widely applied with no extra costs. Wi-Fi, Bluetooth, and RFID solutions usually have positioning accuracy around a few decimeters to meter level [11]. While UWB is capable of achieving a sub-decimeter level accuracy in an empty space thanks to its high time resolutions and modulation frequencies. Such RF-based techniques have good penetration capabilities through walls, and hence they usually have good coverages of

tens of square meters. However, in spaces with occlusions, they face severe diffractions and reflections named multi-path effects, which leads to errors of decimeters to meters [12]. And hence, for indoor applications, sources/carriers with less multipath effects are much desired for high accuracy indoor positioning applications. The visible light carrier then comes to light with its line-of-sight (LOS) property. Moreover, RF-based solutions with around gigahertz bandwidth are currently clean in indoor channels. But in the coming years, the 5G signals are likely to occupy the band which will be noisy for providing LBSs. Furthermore, RF-based methods are not applicable to places like hospitals and laboratories with instruments that are sensitive to RF signals.

The idea of visible light sources as carriers is firstly introduced to the public (in a TED talk) by the researcher Harald Haas from the University of Edinburgh in the year 2011 [13]. The efficiency of the Light Emitting Diode (LED) chips, with the commercially available product from Philips and other companies, in recent years has reached over 170lm/w [14]. The energy efficiency of LED is over three times better than fluorescent light bulbs or tubes. Meanwhile, LEDs have a much longer lifetime, theoretically up to 50,000 hours [15]. Hence, LED lamps are widely applied in all kinds of indoor and outdoor lighting environments.

Besides the high energy efficiency, the good response speed is another distinguished advantages in visible light communication (VLC) and visible light positioning (VLP) applications. Comparing with other illumination sources with only kilohertz modulation bandwidth, off-the-shelf LED products are capable of modulating signals of several megahertz [16], [17]. Moreover, with the same level of luminous, LED chips take much less space and are easier in forming an array of uniform and moderate illumination conditions. This property provides good SNR for the testbed and convenient layout designs for LED arrays in communication and positioning.

The visible light-based carriers also relieve potential health concerns with RF radiations, especially for babies, expectant mothers, patients, and elders. Hence the widespread use of LED lamps in indoor illuminations with high brightness and good power efficiency become the alternative, as the signal transmitters, to perform radiation-free localization and communication services.

There are several techniques being used for positioning, including the received signal strength (RSS), angle of arrival (AOA), time difference of arrival (TDOA) and phase

difference of arrival (PDOA). Among these positioning techniques, RSS based system is the most cost-efficient one. However, rotation and tilting is a crucial problem as the intensity received by the receiver differs greatly as incident angle varies leading to inaccuracy. AOA algorithms are usually calibration-free, however, the accuracy is highly dependent on the resolution of image sensors, the quality of picture captured and the image processing algorithms. AOA techniques usually demand both hardware and software complexities. TDOA techniques have a high theoretical performance of centimeter-level positioning accuracy. However, the TDOA measurements are very sensitive to noises and short pulses generation (generally the shorter pulse width the fewer interferences) is limited by the bandwidth of LED. Phase difference of arrival (PDOA) techniques are the alternative version of TDOA, instead of generating short pulses, periodically sinewave signals are used to extract phase/time information. Compared with TDOA techniques, PDOA has lower requirements in modulation bandwidth, and the resolution can be increased by using longer signal sequences, leading to reduced hardware complexity. Among them, to achieve sub-decimeter level accuracy with reasonable system complexity and good robustness under rotations, the phase-based approach is hence the most promising solution in visible light-based positioning.

1.2 Objectives

The main objectives of this work are to investigate, analyze and develop PDOA-based VLP systems that can achieve high positioning accuracy with low hardware complexity and are robust to noises and disturbances. New positioning techniques and algorithms are to be proposed and analyzed. Both simulation and experiments are to be conducted to evaluate the performances of the proposed positioning techniques and algorithms.

High positioning accuracy:

As the development of smart robots is crucial to smart city and smart livings, an accurate indoor positioning plan is most desirable in the near future. Hence, a decimeter or even sub-decimeter level accuracy for indoor positioning applications is most wanted. Usually, the root-mean-square (RMS) error is used to evaluate the positioning accuracy in Euclidean distance between the true positions and the estimated positions. There are many potential factors influencing the positioning accuracy, including:

- 1) Signal quality (or SNR), affected by the noises from the environments, hardware as well as the algorithms used for denoising (such as filtering, differential, etc.)
- 2) Signal resolution, in many time/phase-based algorithms the resolution of the signal is crucial. To ensure the quality after multiple signal processing, signals are digitally sampled directly upon receiving or after simple filtering and amplification. The analog signals become discrete samples. Upon time/phase information extraction, the time density of the samples will affect the ambiguity of extraction;
- 3) Modeling, as the most fundamental part of position estimations. In all the geometrical based position estimations, there are a few assumptions in models. Intensity-based estimations rely on the irradiation pattern and propagation model, time-based estimations rely on the time-of-flight model, image-based estimations rely on the pinhole camera model. Without precise models, the estimations have no solid foundations.

Therefore, designing and building an actual testbed with high positioning accuracy requires plenty of considerations and efforts. To enhance the SNR, accumulations of signals are applied in our work to reduce the phase noises, and selecting a photodetector with a larger sensor area also helps. As for the resolution, in phase/time based systems, we employ the interpolation techniques to compensate for the resolution of the lower sampling rate. Normally, the intensity model is based on the Lambertian irradiation model and little time distribution model is researched. Hence, we construct a better fitting of these models with neural networks (NNs) to reduce the 3D positioning errors on a large scale.

Low system complexity:

In cost-sensitive markets, systems are required to work under low hardware complexity using less computational powers. Hardware complexity includes the costs of setting up the testbed: high-speed LEDs or the off-the-shelf LEDs, signal generators and digitizers of GHz level or MHz level, etc. Computational complexity is related to signal processing algorithms, positioning algorithms, etc. The off-line workload in calibrations and model corrections are also included.

In classical PDOA systems, LOs are commonly used in both transmitter and receiver ends. However, a pseudo-synchronization is required when capturing the signal, posing a high demand on the sampling rate. To reduce the system complexity, we propose

modified PDOA techniques without LOs through multi-level differentials. As for the computations, the iterative numerical solver for quadratic equation groups has high computational complexity. Hence, we provide a solution with the NN for positioning. Moreover, using pre-training techniques in the neural network also reduces the off-line workloads in precise calibrations on the intensity/time models.

Robust positioning:

Also, many unavoidable factors may influence the performance of the positioning systems under indoor scenarios. For example, the instability in transmitting power line, non-ideal AC to DC driver, dimming as LED life span increases, tilting\rotation in receivers, etc. All these factors have influences on the received signals' intensity. Also, the shape of the diffuser of lamps and the design of reflectors (used for light enhancement downwards) have influences on the model of light irradiations. Hence, a robust and highly adaptive positioning scheme is desirable for general applications and various indoor environments.

To be robust to noises and intensity disturbances, phase-based measurements are applied with its intensity irrelevant property. Moreover, the error induced by the model difference between individual LED lamps can be mitigated through the adaptive modeling method. Also, we propose a hybrid system structure with a fusion of modified PDOA and RSS positioning techniques to increase the system robustness.

1.3 Major contributions

We aim to develop a robust high accuracy indoor positioning system based on the phase measurement approaches. The phase measurement is highly sensitive and hence has great potential in achieving high accuracy with proper design.

To begin with, the drawbacks of the local oscillator (LO) in conventional PDOA algorithms are observed. The LO based conventional PDOA positioning system is optimized to relieve the frequency allocation constraints (due to the nonlinearity of LED and harmonics of LO's frequencies) and to mitigate errors by avoiding the hardware LOs. The geometrical influences of the PDOA systems are examined by simulations. Moreover, a decimeter level real-time PDOA system is experimentally demonstrated for the first time.

To fully avoid the disadvantages of LOs, we propose for the first time, a PDOA based positioning algorithm without using LOs named as DPDOA algorithm. The algorithm is theoretically derived and validated through simulations. The properties of the system are further studied and optimized through simulations. A 2D experimental demonstration of the sub-decimeter level of the DPDOA system with low complexity is also achieved.

Moreover, we observed the non-spherical initial time delay distribution (ITD) of LED chips through experiments for the first time. The ITD induced interferences on positioning accuracy are then investigated for time/phase-based positioning systems through simulations. A neural network (NN) based pre-experimental calibration and distortion mitigation solution is proposed.

We, for the first time, propose to use a single hidden layer NN for distortion corrections and positioning, with DPDOA measurements, to mitigate model induced distortions and get rid of iterative numerical position solver. The system requires no prior knowledge of the LED lamps' layouts and much faster in position solving. This design with pre-training techniques has greatly reduced the offline workload as well as increased the on-line processing speed.

A hybrid RSS/PDOA system is then proposed for the first time to address the robustness and accuracy issues. Selection strategies are also proposed in the hybrid system, taking advantage of both the rotation and intensity robustness of PDOA systems and the good SNR performance of RSS based systems. Evaluations on the robustness under intensity variation and random rotations of the receiver are conducted through simulations.

1.4 Organization of the Thesis

In Chapter I, a brief introduction to this thesis is given, addressing the importance and motivations of studying the PDOA based positioning systems. The objectives and contributions of the research works are presented in this chapter.

In Chapter II, the developments and details of all kinds of indoor positioning systems and algorithms are introduced. Indoor positioning systems via different media with different types of measurements and various position calculation techniques are discussed.

Chapter III presents the work of an optimized PDOA based positioning system with virtual LOs with simulations and real-time experimental demonstrations. The system models are introduced and geometrical constraints of PDOA based systems are studied through simulations in this chapter. Sampling parameters are also optimized through experiments.

In Chapter IV, a modified PDOA system without LOs is proposed and validated through simulations and experiments. The hardware parameters are researched and the ITD model is proposed and analyzed in this chapter. A real-time DPDOA system with decimeter level accuracy under practical coverage is presented, including experimental results.

In Chapter V, an NN based distortion mitigation is proposed to address the non-ideal ITD induced shifting error in the DPDOA system. Moreover, a pure NN-based positioning scheme is proposed to relieve both distortions and computational complexity. Pre-training technique is also applied to enhance the adaptivity and reduce the off-line workload.

In Chapter VI, a hybrid RSS/PDOA system is presented. Selection based strategies are proposed to fuse the RSS and PDOA based position estimations. Simulations are provided with various levels of intensity variations and rotations to evaluate the performance of the proposed system.

Chapter VII is the conclusion and recommendation for future works. A summary of the thesis is given, demonstrating the relationship between the research works. Several possible approaches are also listed in the recommendation of future works.

Chapter II Literature survey

2.1 Indoor positioning systems

The most famous positioning system is the Global Positioning System (GPS), which is originally a satellite-based navigation system through radios owned by the US air force [18]. The GPS provides location and time information to the GPS receivers near the surface of the earth where no obscuration (including buildings, mountains, etc.) of at least four satellites are required. GPS broadcasts the signals (requiring no uplink connections) and can perform independently with the cell phone network. The positioning accuracy of GPS was achieved within 5m in the year 2000 [19], and a decimeter-level of accuracy can be achieved with dual-frequency boosted GPS in open space [20]. Such high accuracy is supported by the highly synchronized atomic clocks with the ground clocks, with high time resolution the time of flights or their differences can be estimated accurately.

Different from GPS, Indoor Positioning Systems aim at the circumstances with relatively small coverage, however higher accuracy requirements in applications for both human and objects (e.g. vehicles and robots). Scenarios like airports, subway stations, shopping malls, hospitals, schools, factories, and apartments, require accurate positioning for robotic managements and indoor navigations in decimeter levels. In this chapter, a review will be given for the development of indoor positioning techniques.

2.1.1 Indoor positioning systems via different media

IPS via Radio Frequency

The theoretical researches on indoor positioning systems started over two decades ago. In the 1990s, researchers started to apply the positioning techniques into the indoor environment. In the year 1998, J. Werb and C. Lanzl proposed a potential local positioning system (LPS) scheme as an indoor extension of GPS named 3D-iD [21]. The proposal used 2 to 6 GHz radio frequencies (RF) as carriers, which is a license-free band for personal uses, modulated with positioning signals at tens of Megahertz. The flowchart of the scheme is shown in Fig 2.1, and the accuracy of such a scheme is designed to be less than 2m in the fine application scenes. In this work, the most

Figure 2.1 Schematic of LPS scheme: 3D-iD [21]

commonly addressed concerns like the multipath effects, clock precision, and delayed retransmissions are discussed and considered in the detailed application plan of the scheme.

At the same time, researchers started to seek the possibilities of indoor positioning systems with RF medium. K. Pahlavan and P. Krishnamurthy [22] researched on the indoor channel model of wideband radio signals in indoor geolocation applications. His research pointed out that the frequency-selective multipath fading characteristics is the main challenge of designing an RF-based indoor positioning system. And such effect is most severe in time-based positioning methods such as time of arrival (TOA) and time difference of arrival (TDOA) approaches. Also, some benchmarks are provided [23] to evaluate the performance of the LPS, such as coverage, capacity, accuracy, blocking rate, reliability, hardware & computational complexity, and delay.

In the year of 2000, P. Bahl and V. N. Padmanabhan from Microsoft experimentally demoed an RF-based in-building location and tracking system [24]. They built a large LPS inside a lab of 22.5m by 43.5m space, with an average accuracy of 2 to 3 meters in 2D positioning.

RFID system

An RFID based positioning system consists of RFID readers, RFID tags, and the communication channel. These components communicate via low frequency, high frequency, ultra-high frequency, and microwave frequencies. The RFID reader reads

the data transmitted from RFID tags via radio frequencies. Protocols are proposed for the data transmitting and receiving [25].

The passive RFID tags reflect signals transmitted from the reader and modulate their own ID on the reflected signal. These passive tags have a smaller size and fewer weights with no battery driving and cheaper than active RFID tags. The active RFID tags, alternatively, broadcast their ID and other data periodically. The active tags have generally larger coverage as the signal is stronger broadcasting a longer range.

Figure 2.2 SpotON multi-tags RFIF with the influence of partitions [26]

The SpotON RFID technology introduces a multi-tag 3D location sensing system [26] as shown in Fig. 2.2. The strength of the signals received by the tags is used for estimating the distances between multiple tags. Multiple distance estimations are cooperated to calculate the most possible 3D locations and achieve better accuracy. However, a large positioning error occurs with the blockages of physical partitions.

Cellular Network systems

Indoor positioning using a cellular network is majorly focused on mobile phone users with strong cellular signals. Signal strength fingerprints are the commonly used method with GSM-based indoor positioning systems. In this method, the signal strength readings from multiple GSM cells are used to calculate the neighbor stations with known locations to achieve the accuracy of about 2.5 m [27].

UWB system

As UWB systems have wide-band and high operating frequency, ultra-short pulses of less than 1ns in duration with a low duty cycle (typically 1:1000) are capable of being sent by the transmitters[28]. These UWB tags consume less power as the pulse duration is very short and operate in a broader spectrum. UWB is suitable in close proximity to other systems with low interference, as the spectrum occupied is different from conventional devices. The UWB signal passes easily through walls and clothing, however, liquid and metallic material cause interferences. Though in space with obstructions, multipath effects are still severe. Also, algorithms with accurate clock synchronization and short pulses sampling are crucial in the positioning performances [29].

Wireless Local Area Network (WLAN) Systems

The midrange WLAN normally operating in 2.4 GHz ISM band (the WLAN services, normally known as Wi-Fi), is widely applied in indoor communication environments and hence, as an already commonly placed server, a WLAN based positioning system is a cost-efficient solution [30]. Normally, round trip time of flight (TOF) measurements are used to estimate the distance between the WLAN nodes [31]. Then with the distance information, the locations of the mobile nodes (user) are calculated.

Besides using the time information, the RSS information is also carried in the WLANs. Hence, the intensity-based distance estimations are also a possible approach. Additionally, the radio-map of the RSS can be composed and using fingerprinting methods to estimate positions. Such mapping takes the reflection and diffractions of the wall, floor, door, and other objects, hence improving the accuracy to 2-3m level.

IPS via Lightwave carriers

All lightwave based positioning systems require a LOS channel as the lightwave is less diffractive and penetrative in conventional indoor scenarios. As lightwave carriers have very high frequency (THz level), the intensity modulation is the most commonly used approach.

Infrared (IR) systems

Commercially available tracking systems based on IR are majorly focused on medical and motion capture applications like the products ‘Firefly’ [32] and ‘Optotrak Certus’

[33]. Users usually carry an ID tag with IR transmitters which broadcasting the location information periodically and the receivers are mounted on the ceiling or walls receiving the signals and calculate the actual position through geometrical relationships [34], [35]. As IR is not visible to human, the application of IR transmitters can operate at night without disturbing the human activities.

Visible Light systems

Visible light as carriers occurs quite recently for about just one or two decades, after the idea of using light as a communication medium. Different from IR systems, visible light carriers have existing transmitters with LED illumination widely placed in all indoor environments. With similar techniques as IR, LED can be modulated to transmit signals and perform localizations as the extra functions. With high-frequency modulations (MHz level) and moderate extinction ratio (modulation with biased voltages adequate for lighting up the LED), the illumination function is fully maintained [36]. Generally, the visible light-based system is easier in implementations however less flexible in placements as the visible light may cause disturbances in the eyesight.

2.1.2 Indoor positioning techniques

Fundamental positioning principles

Positioning algorithms can be generally divided into two categories [37]. One is based on the mathematical and geometrical relationships between the objects and the preset anchors (LED lamps in VLP cases), which are known as range-based algorithms (trilateration and triangulation algorithms). Another type is range-free algorithms, such as positioning based on ID matching and machine vision, which relies on the labeled targets to locate the targets.

Range-based approaches

Distance of arrival

The most frequently used range-based method is the distance of arrival (DOA) based trilateration method, as illustrated in Fig. 2.3. The distance (d_1 , d_2 , d_3 in Fig 2.3) information from three pre-known anchors (x_i , y_i) to the receiver (x , y) is required for 2D positioning in such method. The distances from the receiver to individual anchors are expressed as:

$$\begin{cases} (x - x_1)^2 + (y - y_1)^2 = d_1^2 \\ (x - x_2)^2 + (y - y_2)^2 = d_2^2 \\ (x - x_3)^2 + (y - y_3)^2 = d_3^2 \end{cases} \quad (2.1)$$

There are three quadratic equations with two variables, using any two of the three equations ends up in two symmetrical solutions, and only three equations are able to uniquely determine the receiver's location [38]. When considering the measuring error, the distance information constrains the receiver's location in a certain range (circles as shown in Fig 2.3) of the transmitters, and the overlapping of the three circles can determine the possible location of the receiver (as the shadowed area in Fig 2.3).

Figure 2.3 The illustration of basic principle of DOA

In 3D cases, the circles used for limiting the receiver's position have evolved to spheres with the anchors as the centers. Theoretically, distances from the receiver to the four anchors are required. The distance information forms four equations, as shown below:

$$\begin{cases} (x - x_1)^2 + (y - y_1)^2 + (z - z_1)^2 = d_1^2 \\ (x - x_2)^2 + (y - y_2)^2 + (z - z_2)^2 = d_2^2 \\ (x - x_3)^2 + (y - y_3)^2 + (z - z_3)^2 = d_3^2 \\ (x - x_4)^2 + (y - y_4)^2 + (z - z_4)^2 = d_4^2 \end{cases} \quad (2.2)$$

However, when the anchors are mounted on the ceiling, the extra solution can be excluded above ceiling height. When using any two of the above equations, the solutions are placed on a circle. If using any three of the equations (corresponding to three anchors), two solutions symmetrically distributed at each side of the plane formed by the three chosen anchors. In conventional cases the anchors are placed on the ceiling, hence the solution above the ceiling is not valid (i.e. $z < 0$), resulting in a unique position.

Angle of arrival

The angle of arrival (AOA) is another type of triangulation method, which uses only the angle information from the receiver (x, y) to different transmitters (x_i, y_i) to calculate the actual position of the receiver. As shown in Fig 2.4 is the principle schematic of 2D AOA positioning. Three angles $(\theta_1, \theta_2 \text{ and } \theta_3)$ relative to a predetermined coordinate, as shown in Fig. 2.4, are known from measurements and calculations. These angles represent the angles of transmission, and corresponding to three sectors (the area between the rays with the same color due to variation of measurements) are defined to estimate the possible locating area of the receiver, as the shadowed area in Fig. 2.4.

Figure 2.4 The illustration of basic principle of AOA

The angle related equations are as follows:

$$\frac{x-x_i}{d_i} = \cos(\theta_i), \quad \frac{y-y_i}{d_i} = \sin(\theta_i) \quad i = 1, 2, 3 \quad (2.3)$$

With the cosine and sine values of the irradiation angles (θ_i) , the values are distinguished in the region $(-\pi, \pi)$. As these equations contain the distance terms (i.e. $d_i = \sqrt{(x-x_i)^2 + (y-y_i)^2}$), they are also quadratic equations. In 2D cases, these equations are solvable with at least three equations. While in 3D cases, an extra angle is introduced as the pitch angle decomposing the angle in 3D space by two angles: θ in x-y plane and φ in the x-z plane. Also taking advantages of the LED lamps facing down, the φ value is only valid in the range $(-\frac{\pi}{2}, \frac{\pi}{2})$. The φ value is calculated in a similar manner as in 2D x-z plane:

$$\begin{cases} \frac{x-x_i}{\sqrt{(x-x_i)^2+(z-z_i)^2}} = \cos(\varphi_i) \\ \frac{z-z_i}{\sqrt{(x-x_i)^2+(z-z_i)^2}} = \sin(\varphi_i) \end{cases} \quad i = 1, 2, 3 \quad (2.4)$$

Then, the position can be solved through all 6 equations. Noticing there is a hidden assumption that the receiver has no rotation. Otherwise, not only the three-position variables (x, y, z) but also the rotations of the receiver (α, β, γ) have to be solved. Hence, these six equations are not sufficient and another two anchors are required if the rotations are not avoidable.

Figure 2.5 The illustration of basic principle of DDOA

Distance difference of arrival

The third type of range-based method is the hyperbolic positioning based method [39], which is based on the distance difference of arrival (DDOA). Such a method requires two pairs of measurements of distance difference between two different transmitters to the receiver in a 2D positioning case. As shown in Fig 2.5 $d_1'-d_2'$ and $d_2'-d_3'$ are measurements, however, the individual values of d_1' , d_2' and d_3' are unknown parameters.

$$\begin{cases} d_1' - d_2' = \sqrt{(x-x_1)^2 + (y-y_1)^2} - \sqrt{(x-x_2)^2 + (y-y_2)^2} \\ d_2' - d_3' = \sqrt{(x-x_2)^2 + (y-y_2)^2} - \sqrt{(x-x_3)^2 + (y-y_3)^2} \end{cases} \quad (2.5)$$

From these two equations, a unique solution is obtained. To visually understand the solution, it is known that a point has a fixed distance difference to two fixed points, forming a trace on one branch of a hyperbola (the same color hyperbolas shows the system error induced variations, in Fig 2.5). Assuming $d_2' - d_3'$ and $d_1' - d_2'$ are positive, the intersection of two sets of hyperbola branches determines an area in a 2D plane, which is corresponding to the shadowed section.

It's obvious that solving the DDOA equations are more complicated than the DOA based equations. Also, the distance difference measurements are relatively hard to obtain than the distance measurements. The reason for using DDOA is mainly about its differential processes which mitigate common mode induced errors and reduces part of the noises contained in the signal.

Range-free approaches

Range-free approaches usually have relatively less accuracy, since most of the schemes depend on the density of the pre-experimental positioning samples [40]. Range-free based approaches usually have a low positioning accuracy with relatively low costs and can be used in applications where high positioning accuracy is not required.

Fingerprinting

The simplest approach is using ID matching or fingerprinting [41], [42]. ID matching is to use transmitters periodically broadcast the individual ID information, which forms a map of ID among the area; the receiver then checks the map accordingly to determine the position within the grid of transmitters.

Figure 2.6 Person detection and identification [46]

The fingerprinting method uses relatively fixed samples or labels among the space to perform database matching obtaining the location of the receiver [43]. The receiver uses the fingerprint information (e.g. intensity map) to find the neighborhoods and estimate

the possibility in the covered areas, by overlapping these possibilities the position is provided within the most likely areas.

Computer Vision

Computer vision based on convolutional neural network (CNN) is widely studied for human detection, face recognition and motion detection applications [44], [45]. These techniques are generally using camera-based image classifications and comparisons. As shown in Fig.2.6, A CNN based on Res-Net [46] or other multilayer CNN networks are applied to detect the bounding box of human and extract the feature of individual person [47]. The bounding box is a frame of estimating the approximate location of each person and extracting the features to re-identify the person if another camera also captures highly similar features. And hence continuous tracking among a large coverage can be performed.

2.2 Visible light based indoor positioning system

The visible light is firstly studied as an indoor communication strategy providing radiation-free and secure communication. Before turning into special applications on the indoor positioning, the indoor communication system based on visible light is firstly discussed.

Figure 2.7 Spectrum of white LED chips. a) Spectrum of RGB LEDs; b) Spectrum of phosphor based LEDs

2.2.1 Visible light communication system

The main property of visible light is its line-of-sight propagation (LOS). On one hand,

the LOS property makes signals easily get blocked, however, on the other hand, it is good in avoiding the multi-path effect which keeps the communication users inside the vision where no one can tap your communication through walls [48]. Also, the potential bandwidth of the visible light is as large as hundreds of gigahertz, though currently, the available bandwidth is around 1-3MHz (3dB bandwidth) for commercial chips. Many researchers have proposed and experimentally demonstrated high speed LED chips for communication applications, achieving a few hundreds of MHz bandwidth [49]. The white LED chips have two different designs; one is RGB which uses three LED color chips with red, green and blue to compose a white light; another approach is to use the blue LED chip as the base with phosphor to compose the white light. The spectra of the two types of LEDs are shown in Fig.2.7, and it is manifest that RGB LEDs have a much clear spectrum, however more expensive than phosphor-based white LEDs. Many works on VLC of Gbps transmission rate have been presented in the past decade [50]. Several high-speed research works are conducted with lens and precise tilting facing the transmitter [51]. As for the demonstrations in commercial usages, the transmission rate of hundreds of Mbps is achieved in conventional coverages. Though the development of VLC depends on the hardware property like the bandwidth of LED chips and the sensitivity of photodetectors, the currently achievable communication rate is sufficient for the positioning applications.

As time passes by, the LED lamps are dominating the illumination function of the current market, which is much energy efficient and easy placement and eco-friendly. Hence, should the LED lamps become the positioning satellites for indoor GPS, the overall bandwidth burden to the VLC system will be little and the positioning can be easily and widely covered in indoor spaces.

2.2.2 Visible light positioning system

In the VLC systems, the bandwidth of LED chips is the main limitation of transmission speed and the uplink transmission is a hidden problem. However, the same structure is quite abundant for positioning services. The VLP system, as a promising approach of indoor positioning based services, has been gradually studied in the past decade [52].

A VLP system consists of three main parts: transmitter, indoor channel, and receiver. On the transmitter side, to drive the LED chips with envelope modulated signals, the

system involves signal generators, amplifiers, signal mixers, and a DC driver. In whichever method, techniques have to be applied to identify different LED lamps and using it to provide a relative location (similar to the map of satellites in the GPS). A typical way of assigning ID is to generate sine wave signals with frequency-division multiplexing (FDM). To fully use the bandwidth while maintaining enough signal quality (usually evaluated by signal to noise ratio (SNR)), a generator is used with bandwidth from a few kilohertz to a few megahertz depending on the specific requirements on cost, accuracy, and complexity. The signals generated are then buffed by amplifiers to support the power driving the variation of LEDs' intensity. To ensure the normal illumination function, the extinction ratio is around 70%, the duty ratio is over 50% and the frequency of the signal should be above 60Hz (avoid flashings in human eyes and usually far over 1000Hz). It's also important to consider the details of the LED lamps, the irradiation of the LED is not uniform in all directions, typically it follows the Lambertian irradiation model [53]. However, with reflectors and diffusers, the Lambertian pattern is highly affected and many works have investigated the correction of the Lambertian model. Besides the intensity distribution of the LED chips, when studying time/phase-based positioning approaches, the initial time delay distribution of the LED chips is normally considered to be spherical (with the same time delay in all directions).

The signal channel is simply the indoor space, and the lightwave propagates in all directions which follow the intensity fading and time consumption (i.e., Time-of-Flight (TOF)) in the following manner:

$$TOF = \frac{Distance}{Speed\ of\ Light} \quad and \quad Intesity \propto \frac{1}{(Distance)^2}$$

The receiver part consists of a photodetector (PD), a digitization unit and a signal processing unit. PD is the most crucial component as the signal source of the processing algorithms in the receiver end. The better the signal quality the PD provides, the fewer noises will be induced in the positioning results. The digitization unit determines the resolution of the signal, the high sampling rate is costly, and low sampling rate can induce inaccuracy. The signal processing unit is in charge of digital filtering, convolution, and fulfilling positioning algorithms.

2.3 Commonly used range based VLP schemes

2.3.1 DOA schemes

For DOA based approaches, to obtain the distance information, several approaches are most commonly used, including Received Signal Strength (RSS) and the Time of Arrival (TOA).

RSS approach

The RSS method uses the light intensity distribution of the modulated signals among the space to calculate the individual distances from the respective anchors (LED lamps) to the receiver [54]. The relationship between the transmitted signal RSS and the received RSS is expressed as follow [55]:

$$R_{received} = \frac{(m+1)A}{2\pi d^2} \cos^m(\varphi) \cos(\Psi) \times R_{transmitted} \quad (2.6)$$

, where m is the Lambertian order which is different in different LED chips/lamps, d is the distance between the transmitter and the receiver, φ and Ψ are the irradiation angle and incident angle respectively.

Such method suffers most when the transmitted light power and radiation pattern are unknown within the room or not capable of modeling with the Lambertian model, the positioning error of such method is more than 50cm in normal room conditions (around 3m height). Also, the angle of light incident to the receiver has to be either fixed or pre-known.

TOA approach

In the TOA method, pulses are sent from the transmitting lamps, and the time of flight of each pulse is then measured for the calculation of distances [56]. The bandwidth limitation of the off-the-shelf LED chips makes the length of the pulse to be much longer than $0.1 \mu s$, while pulses in UWB systems are generally $\sim 1ns$ to achieve high positioning accuracy.

TOA is a method of high theoretical accuracy, however with high synchronization requirements between transmitters and receivers. The TOF is calculated through correlations between the pulse traveling through space and the pulse directly obtained from the transmitter [57].

The extraction process of the TOF is shown in Fig.2.8, with one pulse obtained from the transmitter side through synchronization and the other from the receiver passing the indoor channel. The correlation result of two square pulses is a triangular pulse, with a width of twice the pulse width of the original pulse and the peak locating at where the time difference of the pulses is. Worth noticing that, in finding the peak of the correlation waveform, the noises may induce disturbances, resulting in a few nanosecond variations. Such variation is less if the system has a higher time resolution and better signal quality.

Figure 2.8 Illustration of TOF extraction through a correlation process

Since the light travels at high speed, a nanosecond error can lead to a few decimeter positioning errors, which poses a stringent device demand in synchronization. The error of the TOA method is also limited to 30cm and above, in normal conditions [58].

Figure 2.9 Illustration of image based AOA positioning

2.3.2 AOA schemes

Imaging approach

To estimate the AOA, several methods are reported. One is to use image sensors to estimate the incident angle from image distortion, using geometric optics and imaging theory [59]–[61]. As shown in Fig. 2.9, the lamps as transmitters ($T_{1,2,3}$) have their individual images ($i_{1,2,3}$) on the camera sensor.

The rotation matrix of the receiver is denoted as $\mathbf{R}$ (containing yaw, pitch, raw angles which present the posture of the camera [62]). When the receiver has no rotations, the geometry of the transmitters is considered as the amplification of the geometry in the image by the amplification factor K . After amplifying the image to the scale of transmitters, the distance (in 3D) between the amplified image to the transmitters is denoted as $\mathbf{T}$. Hence the following equation presents the relationship between the lamps and their images [59]:

$$\begin{bmatrix} x_0 & x_1 & \dots & x_{N-1} \\ y_0 & y_1 & \dots & y_{N-1} \\ z_0 & y_1 & \dots & z_{N-1} \end{bmatrix} = \mathbf{R} \times K \begin{bmatrix} a_0 & a_1 & \dots & a_{N-1} \\ b_0 & b_1 & \dots & b_{N-1} \\ c_0 & c_1 & \dots & c_{N-1} \end{bmatrix} + \mathbf{T} \quad (2.7)$$

where the (x, y, z) are the coordinates of the lamps and (a, b, c) are the coordinates of their corresponding image on the image plane and c is usually fixed as the focal length. With at least five lamps the equations are solvable, however, with at least three lamps, the approximate position can be determined.

This method requires massive calculation in image processing, and the accuracy relies on the high resolution of the imaging picture. Furthermore, there are assumptions based on the pinhole model that neglects the distortions caused by the optical structures. Settings on the picture capturing like exposure time and contrast will also have influences on the accuracy.

Intensity approach

Another AOA approach uses a receiver with multiple PDs (as in Fig. 2.10) with designed structures is also able to estimate the incident angle [63], [64]. The signal power received among PDs are firstly extracted, then the difference of the received signal power is calculated accordingly. As the PDs are close, the power difference is mainly related to the incident angle and the design of the receiver. Hence the incident angle can be solved

from the power difference. As angle calculation is only related to the property of the multi-PD receiver, this approach is highly adaptive when the LED characteristics are different [65].

Figure 2.10 Multi-PD based AOA receiver for incident angle estimation [64]

2.3.3 DDOA schemes

DDOA schemes have two different variations: Time Difference of Arrival (TDOA) and Phase Difference of Arrival (PDOA). Though the substance of PDOA is still calculating the time difference (TD), the major differences are the way of modulations and the process of extracting the TD information.

TDOA approach

TDOA approach is similar to the TOA mentioned above. Different from the TOA, TDOA requires no synchronization in the transmitter side, as the differential algorithm eliminates the common clock bias between signals. Correlation is applied to calculate the time difference of each pair of received pulses and then obtain the distance differences [66], [67]. Such a positioning scheme usually relies on the pulse precision, where the sampling rate and the clock precision of the system is the major bottleneck. Since in standard LED chips, the modulation bandwidth is a few megahertz and the commercially used analog to digital converter (ADC) has a sampling rate far less than 500Msa/s. However, 500Msa/s sampling rate corresponds to a resolution of $\sim 60\text{cm}$, since the minimum error is constrained to $1/500\text{M}$ seconds during which light travels 0.6m . To further enhance accuracy, the equivalent time sampling method is used. However, the positioning accuracy of within 20cm is still hard to reach [29].

PDOA approach

With the PDOA method, a long sequence ($\sim 1\text{ms}$) of sine waves with different frequencies are modulated to different LED transmitters, and the phase differences between different transmitted sine waves are then extracted. Subsequently, the corresponding distance differences are calculated. As in Fig. 2.11, the flowchart of a phase difference based positioning system is presented with multiples of oscillators in both transmitter and receiver sides [68]. The multiplied frequencies (f_1, f_2, f_3) on the transmitter side are higher than the ones on the receiver side. Such a fixed frequency difference is used to extract the phase differences through multiplications and filtering.

Figure 2.11 VLP system based on phase difference detections [68]

The major difference between PDOA and TDOA method is that the PDOA uses a long sequence to estimate the distance difference, which can reduce the demand on the sampling rate and time resolution, meanwhile, it is less sensitive to signal distortion and offers higher accuracy.

2.3.4 Hybrid positioning system

To achieve higher accuracy, more than one approaches can be used in one positioning system to reduce estimation error and system complexity. Researches on the hybrid of AOA & RSS are conducted recently.

An approach that uses three receivers and a single lamp was recently proposed by Yang [64], which reduces the requirement to the LED lamp arrangement and increases the robustness of the system. This approach combines AOA and RSS to achieve the localization, which is examined theoretically. Another research also based on AOA and RSS techniques was reported in [69], which uses hybrid sensors, including an image sensor for angle measurement and a Photo Diode (PD) for intensity detection, to locate the receiver, which achieves an averaged positioning error around 10cm in a room of $2\text{m} \times 2\text{m} \times 2.5\text{m}$.

Figure 2.12 Fingerprinting based VLP system [71]. a) system configuration; b) RSS fingerprints at different grid points.

2.4 Indoor VLP system without ranging

2.4.1 Fingerprinting

As for positioning based on building and checking maps, one approach is to pre-label the testing space prior to actual applications. Such a method is also known as fingerprinting. The most common approach achieving this is to use RSS based fingerprints [70]. Multiple RSS fingerprints from different transmitters with IDs are collected by the receiver, and then the receiver's location is estimated through classifications.

A normal fingerprinting based unit consists of three or more lamps are depicted in Fig. 2.12 (a). Before performing the positioning, the testbed is a grid with known positions, and at each position, the profile of the RSS fingerprints is taken as in Fig. 2.12 (b). Four lamps are identified by different frequencies, and hundreds of measurements of the

whole testbed are prepared for feature generation. These features are used by a classifier to identify the receiver's rough location to a few grid points. During the experimental tests, the pre-generated classifier receives the RSS fingerprints and gives the likelihood at grid points as outputs. Then, a weighted sum of the position of these grid points is calculated to enhance the accuracy of the positioning [71].

2.4.2 Vision based Simultaneous localization and mapping (SLAM)

Another type of possible mapping strategy is to perform simultaneous localization and mapping (SLAM) [72], such mapping is based on visions from camera images to detect and rebuild the surroundings digitally, the accuracy is around ~5cm level.

Figure 2.13 Computer vision based building map construction with landmarks [73]

In [73], a SLAM robot with a single camera was reported. This SLAM robot worked with a camera and a gyroscope to compute and build the map within a 0.75m radius circle. Their research shows that the more loops the robot performs SLAM in the testbed the better accuracy (maximum ~2cm error) is achieved (within the first few loops). As in Fig. 2.13, a schematic of the surroundings is established through 2D camera pictures. Such a system is robust in general environments without any preset instrument in the testbed. However, extra high calculation power is required as massive graphical data are continuously processed, and the 3D model of the whole environment is stored and continuously updated.

2.5 Factors affecting the positioning performances

Coverage

A positioning system generally consists of multiple positioning units to cover a large

space by switching one unit to another. Each individual positioning unit covers a certain area, out of which the positioning performance degrades sharply. The coverage of a unit depends on several factors, such as the field of view (FOV) and the signal to noise ratio (SNR).

The FOV is the hardware property of a transmitter or receiver, as illustrated by the yellow (transmitter) and blue (receiver) field in Fig. 2.14, respectively. The FOV normally refers to the angle range of half maximum performance to the direction of the maximum. The intensity of lamps is reduced by half or the receivers' responsivity decreases to half at the angle of the FOV. If the light incident or irradiate within such angle, the signal's quality is generally acceptable.

Figure 2.14 Illustration of FOV of LED and PD

Multi-path effect

An indoor channel is normally located in an indoor place with a high density of objects. These objects (including walls, mirrors, desks, windows, etc.) have reflections/refractions/diffractions to the signal generated by transmitters. In this case, the signal propagates from a transmitter may have multiple ways to reach the receiver, which is called the multi-path effect.

The multi-path effect is harmful to the accuracy of positioning, as these signals from other paths are in band noises. For an RSS system, the channel model usually has no considerations of the multi-path effect. Hence distance estimations are distorted. Also, the multi-path effect may arbitrarily distribute, and the Lambertian model may not able to fit it through calibrations.

For time/phase-based systems (TOA, TDOA, and PDOA), the multi-path signals will delay the whole waveform and directly affect the estimations of time/phase differences.

In consequence, the accuracy of position estimation is compromised.

Fortunately, the multi-path effect of visible light is not as severe as that of the radiofrequency system, as little diffraction and refraction occur in conventional objects. The reflection signals are very likely to be outside the FOV. Therefore, the multipath effect is rarely considered in the visible light-based system.

Resolutions

Resolution is the hardware property related to the process of taking measurements. For RSS signals, resolution of the amplitude (e.g. a minimum scale of 5mV is better than 10mV) in the digitization process is of high importance. As for the TOA, TDOA, and PDOA, the time resolutions (sampling rate) of the digitizer are much crucial. For image-based AOA, the pixel density of the picture and the brightness of the pixels are the crucial resolutions. All these resolutions have great effects on the performance of the positioning systems.

2.6 Summary

In this chapter, the indoor positioning systems are reviewed and discussed. Firstly, indoor positioning systems operating over different media are presented, with their respective benefits and drawbacks. Then, the commonly used techniques to calculate positions in indoor scenarios are explained. The emerging of the VLP system with its potential and expectation is presented. The VLP systems based on different techniques are discussed by the range-based and range-free categories. Finally, several factors affecting the performance of positioning systems are briefly introduced.

Chapter III Phase difference of arrival (PDOA) based indoor positioning system via visible light carrier

3.1 Introduction

As discussed in Chapter 2, VLP systems have advantages in negligible multi-path effects and pre-set transmitters (LED lamps) over RF-based schemes. As the indoor applications (with various objects in a relatively small space) require high accuracy, VLP system is a promising solution. RSS, AOA, TDOA, and PDOA are the common approaches in realizing VLP systems. Among these approaches, RSS is the most cost-efficient approach but with strict constraints in rotations. The AOA approach, on the other end, is robust and usually requires no calibrations. However, AOA has higher system complexities and usually lower accuracy. As for the TDOA approach, high accuracy is generally claimed also with good robustness [67]. However, the TDOA approach normally yells high demands in the time resolution of the whole system, and little experimental demonstration is reported. PDOA approach has moderate complexity with relatively good robustness (intensity irrelevant property) [74]. For these causes, the PDOA approach is preferred, in our view, to be the most promising solution for the high accuracy indoor VLP system with acceptable complexity.

The reported PDOA system usually requires LOs, which provide local phase references to extract the phase/time information [68]. However, the usage of real LOs induces constraints in frequency allocations by the multiples of the oscillator. Moreover, to avoid the interferences of the second-order harmonics (induced by nonlinearity) the frequency selection is further limited. The synchronization between the LOs also needs to be ensured at the receiver side.

In this chapter, a modified scheme is proposed, using virtual LOs (VLOs) and a frequency-flexible phase extraction algorithm to address the issues mentioned above. As VLOs are generated through software saved in a digital form, the synchronization between LOs is ensured. We also improve the algorithm to relieve the constraints on the frequencies and hence the bandwidth is better allocated without influences of harmonics. The proposed scheme is validated and studied through simulations. Moreover, an experimental demonstration of less than 10cm average accuracy is presented in the area of 1.2m by 1.2m with no more than 500MSa/s in sampling rate. Our proposal achieves

good positioning accuracy with lower complexity and better bandwidth usage. This chapter is related to the work we published in [75].

Figure 3.1 System architecture of 3D PDOA based VLP system

3.2 System architecture

Fig. 3.1 shows one unit of the proposed PDOA based VLP system [76], [77]. The entire positioning system covering a large area such as a factory/workshop, or a supermarket or a large hall can be formed by multiple cellular VLP units. Each VLP unit can cover an area of $X_m \times Y_m \times h$, where h is the height of the receiver plane from the ceiling.

As shown in Fig. 3.1, each VLP unit consists of 4 LED lamps (L_1 to L_4) as transmitters (in 3D positioning cases), which are arranged in a triangle shape, hanging on the ceiling of the room. Three of the transmitters are placed in the vertexes of an equilateral triangle while one lamp is placed in the center of the triangle. Such an arrangement has advantages of circular symmetry which will achieve a uniform error distribution in all directions. Objects (O) can be robots or other targets that are required to be accurately localized, each of which carries a suitable receiver such as a PD or an avalanche photodiode (APD). Let d_i be the distance between the object to the i -th LED lamp in the VLP unit.

As shown in Fig. 3.2, four RF signals f_1 to f_4 (continuous sine waves with angular frequency ω_1 to ω_4 accordingly) are modulated into these 4 LED lamps respectively. A DC source is applied to ensure normal illumination. Signals are modulated to the intensity of the light irradiated from lamps. And then travel through the indoor free space channel from the LED lamps to the receiver (PIN diode or Avalanche Photo-diode (APD)). The received signal is captured/truncated with digital acquisitions and processed by the computer (or other digital signal processors).

Figure 3.2 The flowchart of LO based PDOA positioning scheme

3.3 System models

3.3.1 Optical channel model

As per [78], [79], the light irradiance of each LED lamp is modeled as the Lambertian radiation pattern, the channel gain is represented in the following equation:

$$H_{Los}(0) = \frac{(m+1)A}{2\pi d^2} \cos^m(\varphi) T_s(\psi) g(\psi) \cos(\psi), \quad 0 \leq \psi \leq \psi_c \quad (3.1)$$

where the m is the order of Lambertian emission, A is the physical area of the PD, and d is the distance between the LED and the PD. φ is the angle of irradiance defined by the geometric relationship shown in Fig 3.3. φ is given by:

$$\varphi = \arcsin(h/d) \quad (3.2)$$

where h is the height of the receiver h , and d is the distance between the transmitter (LED lamp) and the receiver. ψ is the angle of incidence (refer to Fig. 3.3), $T_s(\psi)$ is the

gain of an optical filter and $g(\psi)$ is the gain of an optical concentrator (optical lens), and ψ_c is the field of view (FOV) of the concentrator. The order of Lambertian emission m is given as (3.3), where $\varphi_{1/2}$ is the transmitter semi-angle at half power:

$$m = -\left(\ln 2 \left(\ln(\cos \varphi_{1/2})\right)^{-1}\right) \quad (3.3)$$

Figure 3.3 illustration of irradiation angle and incident angle within the FOV

In the experiment, the concentrator is not used, so $g(\psi) = 1$, also the Lambertian order is given by the producer or calculated from onsite measurements (to be $m=1$ in our case). Further assuming that the receiver plane is parallel to the transmitter plane, which makes $\varphi = \psi$. The blue color filter used is assumed to be angle irrelevant, i.e., $T_s(\psi) = 1$. The final optical channel DC gain can be simplified as:

$$H_{Los}(0) = \frac{(m+1)A}{2\pi d^2} \cos^2(\varphi) \quad (3.4)$$

3.3.2 Noise model

The APD photocurrent is affected by two noise processes [80]. a) the shot noise, i.e., fluctuation in the photocurrent due to the incident optical power ($P_{rSignal}$) consisting of the desired signal and ambient light sources; and b) thermal noise, i.e., fluctuation in the photocurrent due to the random motion of electrons, and changes with the absolute temperature of the electrical circuit. These noises are assumed to be white Gaussian noise, and the total noise deviation can be expressed [81]:

$$\sigma_{noise}^2 = \sigma_{shot}^2 + \sigma_{thermal}^2 \quad (3.5)$$

The shot noise variance is given by:

$$\sigma_{shot}^2 = 2q\gamma P_{rSignal}B + 2qI_{bg}I_2B \quad (3.6)$$

where q is the electronic charge, and B is equivalent noise bandwidth, I_{bg} is the background current, I_2 is the noise band factor.

The thermal noise variance is given by:

$$\sigma_{thermal}^2 = \frac{8\pi kT_K}{G}\eta AI_2B^2 + \frac{16\pi^2 kT_K\Gamma}{g_m}\eta^2 A^2 I_3B^3 \quad (3.7)$$

where k is the Boltzmann's constant, G is referred to as the open-loop voltage gain, T_K is the temperature in (K), η represents the capacitance of PD per unit area, Γ is a noise factor related to FET, g_m is the trans-conductance of FET, and I_3 is usually given as 0.0868.

Figure 3.4 Intensity modulation property of the LED chip [83]

3.3.3 Nonlinear modulation model

The nonlinearity of LED lamps in intensity modulation also has influences on both positioning and communication for indoor applications [82]. Nonlinear effects will induce harmonics and difference frequency components. If the second or third order difference frequency components fall into the signal bands, they will induce severe interferences. Hence it is necessary to simulate the nonlinearity effects of LEDs on the system performance.

Taking the LED (Luxeon Rebel LXML-PWC1 [83]) employed in our experiments as an example, Fig. 3.4 shows the relationship between the forward current and the

normalized luminous flux of the LED chip. It is observed from the experiment when a sine wave together with a DC bias is modulated to the LED, and the sine wave is compressed at the peaks observed from the output of the APD as the modulation depth increases. A polynomial model is introduced to simulate this effect. Using the model, we can have the following result in Fig 3.5. From the polynomial model, we can observe a good match to the datasheet. The formulation of this given graph is:

$$y = 7.045 \times 10^{-10} x^3 - 2.016 \times 10^{-6} x^2 + 3.378 \times 10^{-3} x + 0.03484 \quad (3.8)$$

The equation above indicates that, if $x(t)$ is in the form of $\sin(\omega t)$, y will have terms which include frequencies like $2\omega, 3\omega$. Furthermore, if x is a multi-frequency signal (ω_2, ω_1) , terms of difference and sum between modulated frequencies like $\omega_2 \pm \omega_1$, will appear in the light intensity envelope due to the nonlinear effects. This phenomenon will affect the frequencies selection and arrangement fundamentally. Avoiding these signal bands in the experiment can enhance the signal quality and induce less error among the signal processing.

Figure 3.5 Nonlinearity of LED chip fitted under polynomial model

3.4 Positioning principles

Signals are transmitted from different LED lamps sharing the same signal generator to ensure the synchronization on the transmitter side. Without loss of generality, we assume that signals transmitted from LED lamps are synchronized and the LED lamps are not synchronized to the receivers. The ideal received signal is composed of multiple frequency components from ω_1 to ω_4 , each of which has a different light path from different LED lamps to the receiver. The distance from LED lamp i to the receiver is

denoted as d_i . Hence the TOF in each path is expressed as follows:

$$t_i = \frac{d_i}{c} \quad (i = 1 \text{ to } 4) \quad (3.9)$$

The signal captured by the PD is given below:

$$Rx = \sum_{i=1}^4 H_{Los,i} \sin(\omega_i(t + t_i + T_{rand})) \quad (3.10)$$

After passing through BPFs, different frequency components are separated. Since the transmitting and receiving are two isolated systems, the clock is not synchronized and a random time parameter is introduced as T_{rand} . This random time difference between the transmitter side and receiver side is caused by non-synchronized signal collection in the receiver side. The separated frequency components are noted as:

$$Rx_i = H_{Los,i} \sin(\omega_i(t + t_i + T_{rand})) \quad i = (1,2,3,4) \quad (3.11)$$

It is noticed that these expressions are in the view of the receiver's clock.

To extract, the time components whiling avoiding the random time constant T_{rand} appears in the results, a differential process has to be taken. Here local oscillators(LOs) are introduced to assist the extraction process of the t_i ($i=1$ to 4):

$$\begin{cases} Los_i = \sin(\omega_i t) \\ Loc_i = \cos(\omega_i t) \end{cases} \quad (i = 1 \text{ to } 4) \quad (3.12)$$

In the receiver's view, LOs have zero time-delay at all time and they are virtual (only in digital data). Through multiplications between Los_i and Rx_i , the following equations can be obtained:

$$Dfs_i = Rx_i \times Los_i = H_{Los,i} \sin(\omega_i(t + t_i + T_{rand})) \times \sin(\omega_i t) \quad (3.13)$$

After simplification with prosthaphaeresis formulas [84], we have:

$$Dfs_i = -H_{Los,i} \frac{\cos(2\omega_i(t+t_i/2+T_{rand}/2)) - \cos(\omega_i(t_i+T_{rand}))}{2} \quad (3.14)$$

As can be observed in Dfs_i , the time term t_i can be extracted by simply applying a low pass filter (which extracts the DC component). After passing through the low pass filter (LPF), we have:

$$Lfs_i = H_{Los,i} \frac{\cos(\omega_i(t_i+T_{rand}))}{2} \quad (3.15)$$

Similarly, multiplying Rx_i with Loc_i , we obtain the phase related term in sine form:

$$Lfc_i = H_{Los,i} \frac{\sin(\omega_i(t_i + T_{rand}))}{2} \quad (3.16)$$

Hence the intensity irrelevant (by neutralizing $H_{Los,i}$) phase term can be extracted from:

$$Ph_i = \omega_i(t_i + T_{rand}) = \arctan\left(\frac{Lfc_i}{Lfs_i}\right) \quad (3.17)$$

Notice that, when the phase value varies around $\pm \pi/2$, the output Ph_i may suffer a jump in phase. Worth to notice that, when T_{rand} varies, such phase jump is more likely to happen and result in positioning error. To avoid this error, a pseudo synchronization (with a header or peak detection to locate a fixed start point of the received signal) is required in the process of signal capturing.

Here the issue left is the T_{rand} which is not predictable and non-constant in different received signals, hence the cancellation of T_{rand} is necessary with a differential process to obtain the time difference (TD) as follows:

$$\begin{aligned} Dp_i &= \frac{Ph_{i+1}}{\omega_{i+1}} - \frac{Ph_i}{\omega_i} = \frac{\omega_{i+1}(t_{i+1} + T_{rand})}{\omega_{i+1}} - \frac{\omega_i(t_i + T_{rand})}{\omega_i} \\ &= t_{i+1} + T_{rand} - (t_i + T_{rand}) = t_{i+1} - t_i \end{aligned} \quad (3.18)$$

It is noticed that $t_i = \frac{d_i}{c}$ and hence the expression can be presented:

$$Dp_i = \frac{(d_{i+1} - d_i)}{c}, \quad i = 1 \text{ to } 3 \quad (3.19)$$

with all three equations, an equation group is then formed. There are four unknown variables d_i ($i = 1 \text{ to } 4$) with only three equations. These variables are related to LED lamps' locations and the receiver's position as follows:

$$d_i = \overline{Po Pl_i} = \sqrt{(x - x_i)^2 + (y - y_i)^2 + (z - z_i)^2} \quad (3.20)$$

where the LED lamps' locations are pre-measured as $Pl_i (x_i, y_i, z_i), i = 1 \text{ to } 4$, and the receiver's position is $Po (x, y, z)$. By solving the above equations, the receiver's position $Po(x, y, z)$ can be obtained.

3.5 Simulations

To start the simulation, a testing space (normally the illuminated space is a cone shape) is firstly defined. Here one VLP unit has a general coverage of around 3m by 3m with 2m height. To research on the system performance, the room size is hence 4m by 4m

with a 2.5m height. As discussed in section 2.2.1, the LED's modulation bandwidth is around 1-3Mhz (3dB bandwidth). The signal quality will decrease as the frequency increases. Through several tryouts, 8Mhz is finally chosen. For correlation calculations, in general case, the longer the sequence the higher the resolution may achieve. Hence 2ms are taken in each signal sequence. The signal is sampled at 50 - 200Msa/s, which influences the resolution of the distance measurements as well. The testing space is gridded with manually set coordinates spaced at 20cm. Specifications of the simulation are listed in the following table:

TABLE 3.1 DEFAULT SIMULATION PARAMETERS

Modulation Frequencies	8 MHz to 8.6 MHz, with 0.2 MHz gap
Signal sampling rate	200 MSa/s
Sampling duration	2 ms per measurement
Room size	4m x 4m x 2.5m
Measured positions	11 by 11 points equally spaced at 40 cm

The default layout of LEDs is depicted in Fig 3.6 (a) with L_1 at the geometrical center of an equilateral triangle with a radius of 0.6 m and the other three lamps are approximately at the vertexes. The layout is placed at the center of the testbed, and the coordinates of the lamps are pre-determined or measured. The according SNR distribution of the test space is illustrated in Fig. 3.6 (b). The SNR is much higher in the central area and decreases sharply in the area outside the FOV of LED lamps.

Figure 3.6 LED lamp's layout and SNR distribution. a) LED lamps' layout at 2.5m height; b) SNR distribution on the ground level

3.5.1 Pseudo synchronization induced error

As explained in the principle section, a pseudo synchronization is introduced to avoid phase confusion. To performance pseudo synchronization, the peak is detected as the fixed start point for phase extraction. This process requires a relatively high time resolution and good signal quality.

Figure 3.7 Examples of a received waveform. a) received signal with multiple periods; b) one period of received signal (with 10^{-7} s delay introduced to the waveform in red).

As presented in Fig 3.7 (b), a time-shifting of the whole waveform by 10^{-7} s is introduced. At the sampling rate of 200Mbps, 10^{-7} s is the duration of 20 samples, which can be easily missed (in peak detection) under noises. Such a short error in time results in distance differences from $(-0.35, 0.75, -0.56)$ to $(-1.26, -0.12, -1.38)$ (with the format $(d_1 - d_2, d_2 - d_3, d_3 - d_4)$ in meters) and position estimation error from $(-2.10, -2.10, 2.66)$ to $(-0.39, -0.06, 0.00)$ (with format (x, y, z) in meter).

Figure 3.8 PDOA based position estimations. a) estimations in x-y view of the testbed; b) estimations in x-z view of the testbed

Hence, in this approach, a pseudo synchronization has to be applied after filtering and with a higher sampling rate. Normally, a header is used and identified with cross-correlations to ensure a fixed start point. In this work, we consider an alternative approach whereby the peak of the signal is detected and marked as the starting point.

3.5.2 Simulation with the default setup

With the default setting, we validate the positioning theory with LOs assistances. As can be seen in Fig 3.6 (b), the SNR is measured in the whole test space at 2.5m height, with minimum SNR of 8dB at the corners and around 26dB in the center area. The positioning results in the X-Y view are shown in Fig 3.8 (a). The positioning performance generally follows the SNR distribution. Fig 3.8 (b) presents the position estimation result of X-Z view. As the height grows the positioning accuracy generally decreases and edge area has a relatively larger error than the central region. Moreover, the spreading of the estimations forms a cone shape.

Figure 3.9 RMS positioning error at different heights to LED plane. a) 1m; b) 1.5m; c) 2m; d) 2.5m;

The positioning error is evaluated in the rooted mean square (RMS) error. As depicted

in Fig 3.9, the RMS errors are provided at different heights (varying from 1m to 2.5m with a step of 50cm). It's observed that as the height increases the high accuracy area (in deep blue) firstly increases and then decreases. There are two factors influencing the RMS error: one is the SNR decreases as height grows (along the Z-axis), another is the irradiation pattern induced SNR decreasing as the irradiation angle and incident angle increase (along X-Y plane). Hence the coverage increases as the cone area grows with the height, while the SNR decreases proportionally to the square of the distance.

3.5.3 Geometrical effects of LED lamps' layout

To further research the geometrical influence on the positioning accuracy, the performances of different layouts are analyzed at 2m height (still with 3D positioning algorithm) only.

Figure 3.10 RMS positioning error with quadrilateral LED layouts. a) Square layout; b) Isosceles trapezoid layout; c) Oblique trapezoid layout; d) ordinary quadrilateral layout. (lamps are placed at red dots)

The most common layouts of four LED lamps are square-like shapes, as depicted in Fig 3.10 (a) with red circles. However, this over symmetrical layout ends up with high noise

sensitivity along the symmetrical axes ($x=0$ and $y=0$). As depicted in Fig 3.10 (b), we remove one symmetrical axis by applying an isosceles trapezoid layout. Hence this high error only occurs in the X-axis. We remove the other symmetrical axis by using an oblique trapezoid layout, as in Fig 3.10 (c). The RMS error of this layout is just more sensitive around low SNR areas. Further reducing the symmetry use ordinary quadrilateral layout, as in Fig 3.10 (d). The RMS error is further reduced even in the area with relatively lower SNR. And better positioning coverage is hence achieved.

As for the layout with triangular structures shown in Fig. 3.11, similar to the default layout, the performance is much better than quadrilateral ones due to its non-pair-symmetrical property (i.e. two pairs of lamps are symmetrical to a common axis). Placing the LED in the center to the middle point of the bottom edge, as depicted in 3.11 (a), the overall RMS errors are slightly increased and a larger error occurs at the bottom area of the testbed. When replacing with an isosceles triangle with a smaller span, as shown in 3.11 (b), the error performance is worse around the edge area of the whole testbed. If the middle LED is away from the center, as in 3.11 (c), the RMS error performance of the whole testbed increases evidently.

Figure 3.11 RMS positioning error with triangular LED layouts. a) equilateral triangle layout; b) isosceles triangle; c) equilateral triangle with one LED at the side of the bottom edge. (lamps are placed at red dots)

From these simulations, it can be inferred that the symmetry of pairs of LEDs is a harmful layout in the current system and using triangular based layouts is able to address the problem effectively. Among triangular layouts, within the adequate SNR range, the larger span can provide better accuracy in the whole testbed.

3.6 Experiments

3.6.1 Testbed setup

The experiment is conducted with commercially available devices as listed in Table 3.2 [75]. On the transmitter side, commercially available LED chips are used as transmitters with self-made Bias-Tees used to add the sinewave signals to DC driving currents. The signal generator contains a four-channel arbitrary waveform generator (AWG) which is tunable in sampling rate when generating the signal sequences.

TABLE 3.2 HARDWARE PARAMETERS AND MODELS

Hardware/Parameter	Model/Value
LED chips	Philips Cool White LUXEON Rebel ES LED, 40mm Round 7-Up Base
FOV of LED optics	51 °(Half Angle)
Waveform Generator	Tabor Electronics WW2074, @200Mbits/s
Power Booster	AD811 and BUF634
Photo-detector	Hamamatsu C12907
Oscilloscope	Tektronix MSO3102 (up to 5Gsaps)

As presented in the signal flow in Fig.3.12 (a), signals generated by the AWG pass-through current boosters and are then modulated on the DC-drive LED chips through Bias-Tees. Through the indoor free-space optical channel, an APD is used to collect the optical signal and the signal intensity (photocurrent) is then measured. The oscilloscope acting as an analog to digital converter (ADC) provides for digital signal processing.

The illustration of the experimental testbed is shown in Fig.3.12 (b), where a polycarbonate board with aluminum bones is LED plane and signals are modulated to the LED lamps through cables. The APD as the optical receiver is placed on a rail to ensure precise location measurements with height adjustable rods.

The positions of LED lamps are pre-determined during the setup process. The coordinate is arranged as per the left-thumb rule, shown in Fig.3.11 (b). The three lamps form an isosceles triangle with coordinates LED₁: (0.675,0.125,0), LED₂: (0.225,0.125,0) and LED₃: (0.425,0.475,0) (all units are in meters).

Figure 3.12 Experimental setups. a) Signal flows of the experimental process; b) Illustration of experimental testbed

3.6.2 Parametric optimizations

In this section, we utilize the proof-of-concept VLP system to determine the optimal parameters including the original sampling rate, the data length for correlation and the interpolation factor, which can help to further reduce the ADCs sampling rate and the memory size required for correlation while maintaining a reasonable localization performance. In this optimization experiment, only the central positions are used for data collections. These six positions are 20cm spaced in both X and Y directions forming a $20 \times 40 \text{ cm}^2$ area at the receiver plane (i.e. when $Z=2.06\text{m}$). For each chosen position, the data is collected at different sampling rates of 500 MSa/s, 1 GSa/s, and 2.5 GSa/s. The original data has 1 M points, and we also truncate the data length for correlation to see the acceptable minimum data length for PDOA estimation.

Interpolation is also applied during the experiment to generate a larger amount of data without distorting the phase information contained in the samples. The interpolation method is based on the cubic spline interpolation method [85], which assisted in enhancing the time resolution during extraction. Between adjacent original samples, virtual samples are hence generated to increase the sampling rate by L (denoted as

interpolation factor) times.

Figure 3.13 Positioning performance analysis on. (a) the interpolation factors under different original sampling rates and (b) the data length for correlation under 500 MSa/s with interpolation factor of 100.

As shown in Fig. 3.13 (a), the effect of interpolation is evident. When little interpolation applied, the sample rate has a manifest effect influencing the positioning error, as the time resolution gets worse when sampling rate decreases. By applying the interpolation, such gap of positioning error is sharply reduced by over 20cm when more and more virtual samples introduced with a larger interpolation factor. The positioning accuracy generally follows the value of multiplications of the original sampling rate and the interpolation factor. When the multiplication is more than 50GSa/s, positioning error no longer decreases. This is due to that the interpolation can enhance the time resolution to identify the TOF value but cannot effectively compensate the measured TOF value itself which inherently contains the digitization error and fluctuations caused by all kinds of noises from practical hardware settings.

Also, the accuracy is influenced by the length of samples, as in Fig.3.13 (b). The waveform data with 500MSa/s and the interpolation factor of 100 are tested. A sudden accuracy jump occurs when the length of the waveform is lower than 250k. This is possibly related to that the capability of suppressing the zero-mean noise in the cross-correlations process is dependent on the data length [86]. When the data length falls below a certain value, the rising noise in the correlation function will distort the peak of the correlation function hence affecting the judgment of TOF. In our case, the dramatic increase of positioning error occurs near 250k samples when the data length reduced from 1000k samples to 50k samples. In one word, the acceptable minimum data length can be as low as 250k sample points. All these optimal parameters will be directly employed in the following experimental demonstration.

It is noteworthy that the robustness of the optimization results is ensured only if the span of SNR in the optimization experiment represents the span of SNR in actual usage. In accordance with this rule, the test points in the optimization experiment have to be adjusted depending on different coverage areas. For example, if the coverage is an expanded version from the following experiment in the actual usage, the distance between the test points has to be increased and the number of test points is necessarily increased to ensure the reliability of the optimization.

3.6.3 Testbed evaluation

The feasibility of our proposed system is verified by the evaluation of the positioning accuracy. Also, the impact of the VLO and cubic spline interpolation techniques are studied in comparison with the existing conventional systems. Based on the obtained optimization results, here we set the sampling rate as 500 MSa/s, the interpolation factor as 100 and the data length for correlation as 250k, as shown in Table 3.3. Fig.3.14 depicts the measured TD values in one of the positions to be localized. The measurement variation is 0.0096 ns, and the estimation error is less than 0.03 ns.

TABLE 3.3 EXPERIMENTAL PARAMETERS

Parameter	Value
Testbed size	2-D 1.2m $\times$ 1.2m at 2.06m
Grids	0.2m spacing
Interpolation Factor	100
Waveform data length	250kpts
Measurements	25 times each position
Sampling rate	500 MSa/s

Fig. 3.15 (a) shows the position estimation results. Each position is estimated 25 times in order to ensure the reliability of the measurements. As can be seen, the estimations are consistent and close to the true position. Due to the geometric layout of the LEDs placed at the edge of the coverage shown in Fig. 3.15 (a), we can expect a similar localization performance at the opposite area, i.e. 0 to 1.2 m in the X direction and 0.3 to 1.5 m in the Y direction. Therefore, a much larger coverage can be achieved in practice in the demonstrated VLP system, which is at least 2m $\times$ 1.2m.

Figure 3.14 Time difference (TD) estimations. (At the position $(0.2560, -0.0034, 2.0600)$)

Generally, it is possible to further expand the coverage of the prototype by increasing the SNR of the received signal at the edge of coverage. There are many ways to achieve this goal, such as to increase the modulation index and the optical power of the modulated signal and to use a photodetector with a higher responsivity or a larger active area. Since the modulation index currently set is 0.5 and the optical power of the modulated signal is no more than 1 W, the prototype system has a large potential for expanded coverage. Apart from that, we can also duplicate the prototype unit to form a cellular network with multiple units to cover a much larger coverage in actual usage.

Figure 3.15 Experimental results. (a) Positioning estimation results. (b) CDF plot of the RMS positioning error. (VLO: virtual local oscillator, RLO: real local oscillator, L: interpolation factor.)

It should be noted that the positioning error is small in the central area while there exist relatively large positioning shifting errors at the edge of the coverage. This is due to two factors: 1) the bias error of time delay measurements introduced by the practical implementation of the hardware; 2) the calibration process on the initial time delay (ITD)

at all LED transmitters. The bias error of ITD measurement is common in a practical system which is particularly caused by the accuracy and the instability of the measurement equipment [76]. Worse still, the calibration process before the launch of the system operation in principle will amplify the bias error of ITD measurements at the edge of the coverage. In the calibration process, the ITD caused by the hardware is obtained by subtracting the true ITD from the measured ITD at a reference position right below the transmitter whose true position is already known. During the operation of the VLP system, all the ITD measurements will be calibrated by removing the calculated ITD. Hence, the bias error of ITD measurement will be accumulated for those positions to be localized away from the reference point in the center. Consequently, the positioning shifting error is relatively larger at the edge of the coverage.

Fig. 3.15 (b) depicts the cumulative distribution function (CDF) curves of the estimation results shown in Fig. 3.15 (a). It can be found that the positioning error of the proposed system is less than 18 cm at the confidence of 95% and that the average positioning accuracy is 9.2 cm. As can be seen from Fig. 3.15 (b), the proposed system using VLO has slightly higher positioning accuracy than that using real LO. This is due to that the additional instability is introduced where the real LO is mimicked in the demonstration by means of transmitting a real local signal via a cable from the AWG to the oscilloscope. The impedance of the cable carrying the real local signal slightly changes with the bending and rotation of the cable, hence causing slightly different ITD at different positions which are generally assumed to be constant. Consequently, it can be concluded that the proposed system applying the VLO technique can successfully reduce the hardware components such as real LOs and still maintain equivalent or even higher positioning accuracy.

Fig. 3.15 (b) further demonstrates the positive impacts from the cubic spline interpolation applied to the cross-correlation based time difference (TD) measurement. We compare the estimation results under three configuration settings: 1) a sampling rate of 500 MSa/s and an interpolation factor of 100; 2) a sampling rate of 5GSa/s and an interpolation factor of 10; 3) a sampling rate of 500 MSa/s without interpolation. It can be found that the positioning error is as high as 3 m at 90% confidence when using a sampling rate of 500 MSa/s without interpolation. However, when interpolation with a factor of 100 is adopted, the positioning error can be significantly reduced, verifying the feasibility of applying interpolation to enhance the positioning accuracy of PDOA-based

VLP systems. Hence, it can be concluded that the applied interpolation technique helps to significantly reduce the system requirement on the sampling rate of ADC by increasing the time-resolution of cross-correlation in software. Moreover, comparing the dataset with configuration 1) and 2), it can be observed that the data with a lower sampling rate and a higher interpolation factor reveals slightly better localization performance, even they have the same sampling rate after interpolation. This effect is mainly caused by the relationship between the performance of the digital filter and the sampling rate. The frequency resolution of the digital BPF is higher if the sampling rate is lower, which implies that the filtered data used for TD estimation has much less noise remained. Therefore, the TD calculation is more accurate when the sampling rate is relatively lower.

3.6.4 Comparisons

To give a better view of our proposed system, we summarize the accuracy, methodology, advantages, and disadvantages in comparison with the existing VLP works reported in the literature in Table 3.4. As we can see from Table 3.4, among the works verified in conditions close to the actual usage, our proposed system achieves relatively high accuracy while retaining the feature of relatively low hardware complexity and ease of usage [87] [88].

TABLE 3.4 COMPARISONS BETWEEN VLP WORKS

Ref No.	Lin et al. [87]	Zhang et al. [88]	Yasir et al. [80]	Our system
Average accuracy(m)	0.017	0.07	0.25	0.092
Positioning principle	RSS	Pin-hole Camera Model	RSS	PDOA
Coverage Area (m ²)	0.2×0.2	1×1	2×1.4	1.2×1.2
Experimental Demo	No	Yes	Yes	Yes
Hardware Complexity	Low	High	High	Low
Rotation Sensitivity	Yes	No	No	No
Offline Preparation	Tedious	Minor	Minor	Moderate

3.7 Summary

In this chapter, an optimized VLO based VLP system is proposed. Instead of using real LOs, VLOs are employed, which reduces the system complexity and enhances the

flexibility of frequency allocations. Simulations are conducted to validate and analyze the performance of the proposed system. The system performance related to the LED's layouts is also studied through simulation. Experiments are carried out to demonstrate the VLO based VLP system and optimize the sampling rate to be 500Msa/s and interpolation factors of 100. With the optimized parameters, experimental results show that an averaging RMS error of 9.2cm is achieved in the testbed of 1.2m by 1.2m with the height of 2m.

Chapter IV DPDOA positioning system

4.1 Introduction

In the previous chapter, the system using VLOs is investigated and discussed. The use of VLO can enhance flexibility and reduce the overall complexity of the system. When LOs/VLOs are used for phase/time extractions, there is a time difference (T_{rand} in eq. 3.10) between the received signal and the LOs/VLO, which varies in each capture of the signal, since the receiver and transmitters are not synchronized. As this time difference causes confusion in phase extraction and ends up with multiple phase solutions. To resolve this problem, the pseudo synchronization is introduced with a header or peak detection, which is explained in Chapter 3. However, using pseudo synchronization techniques requires a good peak detection or header alignment to $\sim 1\text{ns}$ level [75].

In this chapter, a novel technique is proposed to circumvent the LOs/VLOs on the receiver side. Simulations are conducted for the validation of the proposed technique. Further investigations on the performance related to the hardware parameters are also performed through simulations. Finally, an experimental testbed is constructed, where the average positioning accuracy of decimeter level is achieved in a coverage area of over 2m by 2m. Besides, Kalman Filtering (KF) is also adopted to mitigate the noise-induced variations on the distance difference measurements. This chapter is related to the works we published in [76], [77].

4.2 System architecture

A similar architecture as in Section 3.2 is used in the study. However, a different frequency allocation strategy and positioning principle are proposed for the first time. As depicted in Fig.4.1, there are five frequencies generated (f_1 to f_5 and respective angular frequency ω_1 to ω_5) from the AWG, two of which are combined in one channel. These signals from four channels are amplified and modulated to four LED lamps individually.

On the receiving end, the signal is received by an APD and digitized by an oscilloscope without using headers for pseudo-synchronization. Moreover, the VLO used for phase extraction in the previous chapter is removed by using a novel phase difference

extraction algorithm. And finally, a numerical solver is applied for position estimation.

Figure 4.1 System schematic of DPDOA positioning system without LOs

4.3 Principle

The received signal is different from that of the conventional PDOA method as two frequency components are allocated to one of the four LED lamps. Without loss of generality, the received composite signal can be expressed as:

$$Rx(t) = A_1 \sin(\omega_1(t + t_1)) + A_1 \sin(\omega_5(t + t_1)) + \sum_{i=2}^4 A_i \sin(\omega_i(t + t_i)) \quad (4.1)$$

Here A_i is the amplitude associated with the i -th channel. As each of the frequency components propagates through the indoor free space channel, a time delay t_i will be induced, which is related to d_i and the speed of light c and given by:

$$t_i = d_i/c \quad (4.2)$$

t_i is associated with the phase of the received signal as:

$$\varphi_i = \omega_i t_i \quad (4.3)$$

Here we assume that these sine wave signals are synchronized at the transmitter side, and the initial phases are the same in all irradiation angles, and hence the time delay is only related to the flight distance and is location irrelevant.

As shown in Fig. 4.1, after passing through respective BPFs, the received composite signal is separated into five frequency components each with only in-band noise, expressed as follows (note that ω_1 and ω_5 are modulated to the same lamp):

$$Rx_i(t) = \begin{cases} A_i \sin(\omega_i(t + t_i + T_{rand})) & i = 1 \text{ to } 4 \\ A_1 \sin(\omega_i(t + t_1 + T_{rand})) & i = 5 \end{cases} \quad (4.4)$$

where, T_{rand} is the signal capture induced time delay (related to asynchronization between transmitter and receiver).

Also, notice that the frequencies allocated are arranged in an arithmetic progression:

$$\omega_5 - \omega_4 = \omega_4 - \omega_3 = \omega_3 - \omega_2 = \omega_2 - \omega_1 = \Delta\omega \quad (4.5)$$

Multiplying $Rx_i(t) \times Rx_{i+1}(t)$ ($i = 1 \text{ to } 4$), take $i=1$ as an example:

$$\begin{aligned} Rx_1(t) \times Rx_2(t) &= A_1 \sin(\omega_1(t + t_1 + T_{rand})) \times A_2 \sin(\omega_2(t + t_2 + T_{rand})) \\ &= -\frac{A_1 A_2}{2} [\cos(\omega_1(t + t_1 + T_{rand}) + \omega_2(t + t_2 + T_{rand})) \\ &\quad - \cos(\omega_1(t + t_1 + T_{rand}) - \omega_2(t + t_2 + T_{rand}))] \end{aligned} \quad (4.6)$$

Observing the above equation, the second term with frequency $\Delta\omega$ and the difference of phase between LED 1 and 2, with a BPF at $\Delta\omega$, we can extract the second term individually. Denoting the filtered term as $Dx_i(t)$ and the first round of differential is completed, taking $i=1$ and 2 as an example:

$$Dx_1(t) = \frac{A_1 A_2}{2} \cos(\Delta\omega(t + T_{rand}) - \omega_1 t_1 + \omega_2 t_2) \quad (4.7)$$

$$Dx_2(t) = \frac{A_2 A_3}{2} \cos(\Delta\omega(t + T_{rand}) - \omega_2 t_2 + \omega_3 t_3) \quad (4.8)$$

Multiplying $Dx_i(t) \times Dx_{i+1}(t)$, $i = 1, 2, 3$. A similar process of the differential is then formed:

$$\begin{aligned} Dx_1(t) \times Dx_2(t) &= \frac{A_1 A_2^2 A_3}{8} [\cos(2\Delta\omega(t + T_{rand}) - \omega_1 t_1 + \omega_2 t_2 - \omega_2 t_2 + \omega_3 t_3) \\ &\quad + \cos(-\omega_1 t_1 + \omega_2 t_2 - (-\omega_2 t_2 + \omega_3 t_3))] \end{aligned} \quad (4.9)$$

As can be observed that, the second term includes a difference of the phase differences, to extract the second term an LPF is then applied and the DDx_i is obtained:

$$DDx_1 = \frac{A_1 A_2^2 A_3}{8} \cos(\omega_1 t_1 + \omega_3 t_3 - 2\omega_2 t_2) \quad (4.10)$$

$$DDx_2 = \frac{A_2 A_3^2 A_4}{8} \cos(\omega_2 t_2 + \omega_4 t_4 - 2\omega_3 t_3) \quad (4.11)$$

$$DDx_3 = \frac{A_3 A_4^2 A_1}{8} \cos(\omega_3 t_3 + \omega_5 t_1 - 2\omega_4 t_4) \quad (4.12)$$

Notice that, the T_{rand} is neutralized by this step which causes no phase jump as happened in Section 3.4.

However, the intensity and the arccos() function can cause confusion and errors, an in-

phase and quadratic phase method is then used to extract the phase term by the Hilbert transform: $Dx_i(t) \times \text{Hilb}(Dx_{i+1}(t)), i = 1, 2, 3$:

$$Dx_1(t) \times \text{Hilb}(Dx_2(t)) = \frac{A_1 A_2^2 A_3}{8} [\sin(2\Delta\omega(t + T_{rand}) - \omega_1 t_1 + \omega_3 t_3) + \sin(\Delta\omega t - \omega_1 t_1 + \omega_2 t_2 - (\Delta\omega t - \omega_2 t_2 + \omega_3 t_3))] \quad (4.13)$$

Using LPF in a similarly way:

$$DDS_1 = \frac{A_1 A_2^2 A_3}{8} \sin(\omega_1 t_1 + \omega_3 t_3 - 2\omega_2 t_2) \quad (4.14)$$

$$DDS_2 = \frac{A_2 A_3^2 A_4}{8} \sin(\omega_2 t_2 + \omega_4 t_4 - 2\omega_3 t_3) \quad (4.15)$$

$$DDS_3 = \frac{A_3 A_4^2 A_1}{8} \sin(\omega_3 t_3 + \omega_5 t_1 - 2\omega_4 t_4) \quad (4.16)$$

It is worth to notice that, not like the precious algorithm with LOs, such algorithm avoids problems induced by the random capture time T_{rand} caused by asynchronization between transmitters and receiver. Taking ratio as $\frac{DDS_i}{DDx_i}$ ($i = 1, 2, 3$), the amplitude terms are canceled, leading to a $\tan()$ based phase term. Extracting the dual differential of phases with $Dph_i = \arctan(\frac{DDS_i}{DDx_i})$, we have:

$$\omega_1 t_1 + \omega_3 t_3 - 2\omega_2 t_2 = Dph_1 \quad (4.17)$$

$$\omega_2 t_2 + \omega_4 t_4 - 2\omega_3 t_3 = Dph_2 \quad (4.18)$$

$$\omega_3 t_3 + \omega_5 t_1 - 2\omega_4 t_4 = Dph_3 \quad (4.19)$$

The above equation groups can be solved by the following matrix:

$$\begin{pmatrix} \omega_1 & -\omega_3 & 0 \\ 0 & \omega_2 & -\omega_4 \\ \omega_5 & \omega_5 & \omega_5 + \omega_3 \end{pmatrix} \begin{pmatrix} d_1 - d_2 \\ d_2 - d_3 \\ d_3 - d_4 \end{pmatrix} = c \begin{pmatrix} Dph_1 \\ Dph_2 \\ Dph_3 \end{pmatrix} \quad (4.20)$$

where t_i is replaced by d_i through $t_i = d_i/c$, and all the Dph_i are knowns. Considering $d_i - d_{i+1}$ as a variable, we have a rank three equation capable of solving these distance differences variables. To calculate the receiver's position (x, y, z) , the relationship : $d_i = \sqrt{((x - x_i)^2 + (y - y_i)^2 + (z - z_i)^2)}$ is used.

4.4 Simulations

4.4.1 Validation of the proposed scheme

Simulations are conducted with the same default parameters as mentioned in Section 3.5. It is noted that the SNR is relatively lower (around 3dB less) due to that the energy allocated to the channel of two frequencies is lower than that of a single frequency (the overall modulation power are roughly the same).

Figure 4.2 Positioning results under default simulation setup. a) SNR distribution on the ground level (2.5m from LED plane); b) RMS error distribution; c) X-Z view of estimation results; d) X-Y view of estimation results.

The SNR distribution roughly determines the positioning accuracy distribution under the default settings as shown in Fig. 4.2 (a) and (b). As the distance increases the estimation is less accurate, especially at the edges of the testbed. Measurements are taken within a 2m by 2m space at the locations of 40cm spaced grids, as depicted in Fig.4.2 (c) (d) with red dashed gridlines. Observing the X-Z view of the positioning scatters in Fig. 4.2(c), the coverage area grows from 1m to 1.5 m height since the

irradiation angle dominates the accuracy. Beyond 1.5m height from the LED plane, the accuracy is then dominated by the distance.

4.4.2 Influences of hardware parameters

As known, the optimal positioning system should be fast (real-time) and simple (low computational and hardware complexity). And the most complicated hardware is the ADC and the DAC, the higher the sampling rate is the more complex the system is. However, a trade-off between the phase resolution and sampling rate constrains the overall system performance. Also, to be fast in updating estimations, the sampling duration matters as well, which in turns influences the resolution. The modulation frequency also needs to be well-chosen, and the higher frequency means the shorter wavelength and better phase resolution. However, using high modulation frequency also place requirements for the sampling frequency in both ends.

Figure 4.3 RMS error vs. different modulation frequencies and sampling rates. a) Sampling rate ranging from 5 to 50Mbps; b) Sampling rate ranging from 55 to 100Mbps (pairs with RMS error over 10cm are marked in red)

Influences of sampling rate and modulation frequency

To begin with, the modulation frequency is set to as low as possible with proper sampling time. Specifically, to achieve an averaged estimation RMS error less than 10cm, the modulation frequency is changed from 1Mhz to 10Mhz, and the sampling rate varies between 5 to 100Mbps. As presented in Fig. 4.3 (a) and (b), the red squares are the modulation and sampling pairs that have RMS positioning error larger than 10cm or

do not follow the Nyquist sampling law. From Fig. 4.3, we can observe that: the higher modulation frequency the more accurate positioning estimations are; the sampling rate is not crucial as long as sampling frequency is higher than two times the modulation frequency. It can also be inferred that when the sampling frequency is a multiple of any modulated frequencies the accuracy will be compromised. This may be caused by a fixed sampling pattern in a periodical waveform, leading to information loss.

Influences of sampling rate and sampling duration

Here the trade-off between sampling rate (the same setting for both ADC and DAC) and sampling duration versus estimation accuracy is researched and optimized. The modulation frequency is set at 8MHz. As previously analyzed, sampling rate lower than 50Mbps may have great constraints, which may compromise the analysis of the sampling duration. Hence the sampling rate is set from 50 Mbps to 100 Mbps.

Figure 4.4 Factors analysis on positioning performance. a) Sampling rate and duration; b) Averaging based sample reductions. (at 100Mbps sampling rate)

The trade-off between sampling duration (length\number of sample points) and the sampling rate is shown in Fig. 4.4 (a). It is manifest that the RMS error reduces as the duration of samples increases. When the sample duration is over 250Kpts the accuracy is not evidently improved. This effect has two factors: one is the resolution increases in the frequency domain leading to less in-band noises; the other is due to higher spatial resolution can be achieved when more samples are involved in the correlation process. However, evident time consumption is imposed as the length of sample duration increases. The time is increased by multiple times as the signal sequence is processed through fast Fourier transform (FFT) and finite impulse filtering digitally. Hence great

times of multiplications and summations between signals are conducted.

Averaging method	Complexity: reduced by over 10m times
<ul style="list-style-type: none"> ▪ Read waveform sample (mN points) from the digitizer and truncate into N samples for m segments (contains integer periods of the composite signal). ▪ Accumulate the segments by adding up the aligned segments to form Signal_A. ▪ Filtering the Signal_A by multiple BPFs to extract the respective frequency components (denoted as Rx_i for the i-th frequency component). ▪ Extracting the phase difference information from Rx_i as stated in section 4.3, and then obtain distance differences. ▪ Newton's method based numerical solver applied to solve position (x, y, z) as stated in section 4.3. 	

To reduce the duration of the received signal, an averaging method is proposed (as stated above) to mitigate the in-band noises by using the random distributed (zero mean) property of the noise. Even the received signal sequence of 500Kpts long, as the periodical property of the received signal, averaging the signal to 10Kpts can be achieved easily. If the waveform sequence is accumulated by m folds, the computational complexity (summations and multiplications) in signal processing is consequently reduced by over **10 × m** times.

The averaging method mentioned above is applied to reduce the sample duration into the length of averaging as shown in Fig. 4.4 (b). As depicted in Fig. 4.4 (b), the received signal sequence is accumulated in 5Kpts to 50Kpts accordingly versus the received sample duration of 50Kpts to 500Kpts length (with 100Mbps sampling rate). When the number of sample points is less than 200Kpts, the sequence length is the main constraints to the results. Beyond 200Kpts, by averaging/accumulating the sequence to even 5Kpts have little influences on the estimation accuracy.

4.4.3 Initial time delay modeling

As stated in the principle section, the analysis of the PDOA based system is based on a sphere initial phase/time delay model (where time delay measurements are irradiation angles irrelevant). However, it is found that the terms t_i in eq.4.4 are different at different irradiation angles which would induce fixed errors to distance difference

measurements and result in non-negligible shifting errors in the position estimations. In Fig.4.5, several different initial time distributions (ITD) are demonstrated, as the initial phase distribution of the lamps can be affected by factors like the defect in LED chip production, lamp diffuser, back reflector, phosphor, etc.

Figure 4.5 Evaluations on ITD. a) Test setup; b) ITD distribution of different LED chips

The distribution of the ITD (in 2D) is measured in the manner depicted in Fig. 4.5 (a). The LED lamp is placed in the center, and then we measure the time difference between a LO and the received signal from the APD at a fixed distance. Denoting the ITD at θ° irradiation angle as θns , the time delay distributions of 3 LED chips are recorded and shown in Fig. 4.5 (b). In Fig. 4.5 (b), the solid green curve is the ideal ITD distribution with no divergence in irradiation angles (as assumed in principle). While the LED 1 curve is a fitting curve based on the measurements in a blue light LED chip (no phosphor), and the LED 3 curve is fitted based on the measurements of a white phosphor LED chip. The LED 2 curve falls in the middle between the LED 1 and LED 3 curves, and has a medium level of ITD. A common property among the ITDs is the differences between the ideal ITD and the measured ITDs increase as the irradiation angle grows.

Figure 4.6 3D position estimations with different ITD distribution. with Ideal LED ITD distribution a) X-Y; b) X-Z view; with LED 1 ITD distribution c) X-Y view; d) X-Z view; with LED 2 ITD distribution e) X-Y view; f) X-Z view; with LED 3 ITD distribution g) X-Y view; h) X-Z view.

Using these four ITD distributions, simulations are conducted in a test space of 2m by 2m with the height varying 1m to 2.5m. Notice that in the simulation we assume the 2D ITD measurements are feasible in 3D situations in a circular symmetry manner.

With the ideal assumption of the LED lamps having the same time delay in all directions, under the default simulation setups, simulation results on the position estimations are shown in Fig.4.6 (a) and (b) with X-Y and X-Z views. Shown in Fig.4.6 (a), distortions are observed at the corners of the testbed due to signal attenuation induced SNR decreases. In Fig.4.6 (b), the simulation shows variations increases as the height grows. In all X-Y view figures in Fig. 4.6, a red dotted square is marked as the boundary of our actual position (with a fixed space of 40cm). And in all the X-Z view figures, red dotted lines are marked at 1m to 2.5m heights with 50cm spaced where the measurements are taken. Then ITD distributions of LED 1, LED 2 and LED 3, as shown in Fig. 4.5 (b), are evaluated separately through simulation. Simulation results are demonstrated respectively in Fig. 4.6 (c)&(d) (with the ITD of LED 1), (e) & (f) (with the ITD of LED 2), and (g) & (h) (with the ITD of LED 3).

Comparing Fig. 4.6 (c), (e), (g) with (a), when the ITD value become larger (i.e. LED 3 > LED 2 > LED 1 in ITD value) the positioning coverage decreases (i.e. in Fig. 4.6 (g) < (e) < (c) in coverage). In the X-Z view, as shown in Fig. 4.6 (b), (d), (f) and (h), the distortion (shifting) in the Z direction is much larger than that in the X-Y plane, where the severity is (h) > (f) > (d) > (b). In the most severe case (h), the shifting in Z direction is over 0.6m with bending distortions appearing at the edges.

It can be concluded that the ITD distribution of a few nanoseconds is capable of distorting the positioning estimations evidently (especially in Z direction). Hence it is crucial to ensure the ITD distribution to be uniform in all irradiation directions (3D) through pre-experimental calibrations.

4.5 Experiments

4.5.1 Testbed setup

The experimental setup of the indoor VLP system is depicted in Fig.4.7 (a). Three modulation signals are generated offline using MATLAB with $f_1 = 8$ MHz and $\Delta f = 0.2$ MHz, which are then uploaded to an AWG (Tabor WW2074). The output signals of

the AWG are amplified and three DC biases are added via bias tees. The resultant signals are used to modulate three white LEDs (Lumileds LXML-PWCI).

After propagating through the free space and passing through a blue filter, the light is detected by an APD (Hamamatsu C12702-5361). The received signal is sampled by a digital oscilloscope (Tektronix MDO3104) with a sampling rate of 100 MSa/s. The obtained digital signal is processed in real-time, and the position estimation is updated about three times per second. Fig.4.7 (b) shows an example of the received mixed signal waveform. A calibration process at a reference position with known actual distance differences is firstly conducted to eliminate the different time delay induced by hardware (cables, circuits).

Fig. 4.7 (c) shows the photo of the experimental testbed for 2D VLP. Three LED lamps are mounted on a polycarbonate ceiling board and a triangular layout is adopted due to the setting of our testbed. The impact of different LED layouts has been analyzed in the previous chapter 3.5.3. The height between the ceiling and the receiving plane is 2 m. The coordinates of LED₁, LED₂ and LED₃ are (0.425, 0.475, 2), (0.21, 0.125, 2) and (0.675, 0.125, 2), respectively, and all the units are meters.

Figure 4.7 Experimental architectures. (a) System hardware schematic; (b) An example of waveform; (c) Testbed photo.

4.5.2 Kalman filtering

Due to the poor signal quality in practical environments, the fluctuation of the phase measurements is severe. Hence the position estimations at the far end of the testbed variate is a large with position resolution worse than 30cm (see Fig. 4.9 (a)). Therefore, the KF method is applied to address this problem. The KF estimates the joint probability distribution of the variables $(d_i - d_{i+1})$ over a small number of measurements and gives estimations based on the distribution so as to reduce the statistical noise [89], [90].

Kalman Filtering Algorithm	Complexity: $O(n^2)$
<p>Define the movement-related distance differences at the state k with $\mathbf{x}_k$ (with dimension n), and assume that $\mathbf{x}_k$ is a time-related transition ($\mathbf{F}_k$) from the previous state $\mathbf{x}_{k-1}$:</p> $\mathbf{x}_k = \mathbf{F}_k \mathbf{x}_{k-1} + \mathbf{w}_k$ <p>, where $\mathbf{w}_k$ (with the covariance $\mathbf{Q}_k$) is the noise generated in the moving process with zero mean.</p> <p>$\mathbf{z}_k$ is from the actual measurements with measurement noises $\mathbf{v}_k$ (with covariance $\mathbf{R}_k$):</p> $\mathbf{z}_k = \mathbf{x}_k + \mathbf{v}_k$ <p>The KF estimates the next state (k) from the previous state ($k-1$) iteratively:</p> $\hat{\mathbf{x}}_{k k-1} = \mathbf{F}_k \hat{\mathbf{x}}_{k-1 k-1}$ $\mathbf{P}_{k k-1} = \mathbf{F}_k \mathbf{P}_{k-1 k-1} \mathbf{F}_k^T + \mathbf{Q}_k$ <p>where $\mathbf{P}_k$ is the estimated accuracy of the state estimation.</p> <p>To update the state, the following parameters are calculated:</p> <p>Measurement residual: $\tilde{\mathbf{y}}_k = \mathbf{z}_k - \hat{\mathbf{x}}_{k k-1}$</p> <p>Residual covariance: $\mathbf{S}_k = \mathbf{P}_{k k-1} + \mathbf{R}_k$</p> <p>Optimal Kalman gain: $\mathbf{K}_k = \mathbf{P}_{k k-1} \mathbf{S}_k^{-1}$</p> <p>These parameters are then used to update the new variables $\mathbf{x}$ and $\mathbf{P}$:</p> <p>Update state estimate: $\hat{\mathbf{x}}_{k k} = \hat{\mathbf{x}}_{k k-1} + \mathbf{K}_k \tilde{\mathbf{y}}_k$</p> <p>Update estimate covariance: $\mathbf{P}_{k k} = (\mathbf{I} - \mathbf{K}_k) \mathbf{P}_{k k-1}$</p>	

From the algorithm of the KF, it can be concluded that the prediction of the next measurement is based on the statistical distribution of the previous measurements. As our distance differences measurements suffer consistent noise with consistent distribution, the KF algorithm is highly effective in reducing the variations in the position estimations. Moreover, KF is capable of operating in real-time, the complexity is mainly relevant to the input dimension of the data ($O(n^2)$) [91]. In our application, the

dimension n is 2 or 3 (in 2D or 3D cases respectively) which merely requires a small number of calculations. Hence applying the KF method involves little burden to the proposed DPDOA system

Figure 4.8 Distance difference measurements w/ and w/o KF. a) measurements of d_1-d_2 ; b) measurements of d_2-d_3

Fig. 4.8 shows the distance difference measurements without and with KF for both (d_1-d_2) and (d_2-d_3) . It can be seen that the distance differences fluctuate significantly without using KF. However, with KF, the fluctuation of the distance difference is substantially reduced and relatively stable distance difference measurements for both (d_1-d_2) and (d_2-d_3) can be obtained. It should be noted that certain fluctuations are found at the first several measurements after applying KF. As the KF method requires a few measurements in the beginning to acquire a stable joint probability distribution through iterative updating.

Figure 4.9 Position estimations results. a) raw measurements; b) measurements with KF based denoising.

4.5.3 Positioning results

Finally, the experimental results are presented in Fig. 4.9 where the three green circles denote the positions of three LED lamps and the measurements are performed in a 6×7 rectangular grid, achieving coverage of $1 \times 1.2 \text{ m}^2$. Fig. 4.9 (a) shows the original measurements without applying the KF. It can be seen that relatively accurate estimations can be achieved when the receiver is close to the central area of the LEDs' layout. When measuring the positions at far from the center, the positioning variations increase to up to $\sim 20\text{cm}$ (in radius). Moreover, as the receiver is moved away from the center, the estimations suffer significant shifting errors.

The variation of estimations induced by the additive noise can also be substantially reduced when the KF method is adopted. Shown in Fig. 4.9 (b), the estimations are based on the distance difference measurements with KF. The noises are greatly suppressed with KF by over 4 times among the whole testbed.

Figure 4.10 RMS Positioning error CDF with or without w/ and w/o the Kalman Filter

Fig. 4.10 further compares the cumulative distribution functions (CDFs) of the root mean square positioning error (RMSPE) for different cases. As we can see, the obtained positioning error is relatively large when KF is not applied, with an average (ave.) RMSPE of 10 cm and a maximum (max.) RMSPE of 37 cm. At 80% of the CDF confidence, RMSPE of raw measurements is around 15cm while RMSPE of KF based measurements is around 10cm. Beyond 80%, the performance of KF based estimations is similar to raw measurements, as the shifting error dominates the error causing the stair-like effect in the CDF plot. However, such shifting errors are not removable through statistical methods.

It should be noted that the actual achievable coverage of our VLP system should be much larger than the reported $1 \times 1.2 \text{ m}^2$ since only part of the area (about one quarter) is under test as can be observed from Fig. 4.9, which is mainly due to the limitations of our experimental testbed.

4.5.4 Comparisons

In Chapter III, we have present an optimized PDOA system with LOs. And in this Chapter, we propose a novel algorithm to avoid using the LOs. Comparisons between the two approaches are shown in Table 4.1

TABLE 4.1 COMPARISONS ON THE USE OF LOs

Property	with LOs	without LOs
Sampling rate	$> 500\text{Ms/s}$	$>50\text{Ms/s}$
Algorithm	Interpolation required	Two differential process
SNR	Uniform with all frequencies	SNR in f_1 and f_5 are $\sim 3\text{dB}$ Less

Without LOs, a 10 times lower sampling rate is required as the header is no longer needed. Moreover, the interpolation method applied when using LOs leads to higher computational complexity. While the algorithm of extracting phase without LOs has slightly high complexity as two differential processes are applied. As for SNR property, the scheme with LOs has better overall SNR as each lamp carries only one frequency. In the scheme without LOs, two frequencies are carried in one of the lamps, which have $\sim 3\text{dB}$ less SNR as the power is shared by two frequency components.

A comparison of our work with other experimental works is given in Table 4.2. RSS based systems are usually tilting sensitive. Even though machine learning (ML) is applied in this work [92], the error in X-Y plane is 4cm and tolerance in height is 15cm. The coverage is constrained to a small area (an equilateral triangle space) due to the sharp decreases of intensity at larger irradiation angles. Compared with the work in [88], the coverage of our proposal is larger as the FOV of camera-based imaging system is constrained. The work in [75] claims the coverage of 1.2 by 1.2m in which the measurements are taken in around half of the testbed space, i.e., the expected coverage of 1.2 by 2.4m. And our measurements/experiments are conducted in around a quarter area of the testbed, i.e., the expected coverage of over 2m by 2m. Even with a larger coverage, the average RMSPE is comparable with that reported in [75]. However, the

shifting errors at the far end of our testbed result in large maximum RMSPE.

TABLE 4.2 COMPARISONS BETWEEN VLP WORKS

Reference No.	[92]	[88]	[75]	Our Work
Principle	RSS+ML	AOA	TDOA	DPDOA
Dimension	2D	3D	2D	2D
Receiver Type	PD	Camera	PD	PD
Coverage (m ²)	0.5	1×1	1.2×1.2	1×1.2
Height (m)	2.5	1.2-1.6	2	2
Ave. RMSPE (cm)	4	7	9.2	8
Max. RMSPE (cm)	9	14	20	35
Offline workload	Moderate	Moderate	Moderate	Low
Notes	Tilting sensitive	Small coverage	Half coverage	Quarter coverage

4.6 Summary

In this chapter, we have proposed a novel system with a modified PDOA algorithm called DPDOA and presented the detailed dual differential phase difference extraction principle. Through simulations, the influences of sampling hardware parameters are studied, and the ITD distribution obtained from experiments and its impact on positioning accuracy are investigated through simulations. The effects of sampling rate, modulation frequency, and sampling duration are studied to figure out the trade-offs and optimal combinations. Different ITD distributions are observed based on experimental measurements, which are used to predict the distortions.

Furthermore, we have also experimentally demonstrated a sub-decimetres accuracy indoor VLP system. By using the DPDOA algorithm, no LOs are required at the receiver side, due to the use of differential phase difference measurements. A KF based method is also adapted to reduce the variation of distance difference measurements. The obtained experimental results show that an average RMSPE of 8 cm can be achieved in the proposed VLP system with a coverage of 1×1.2 m² and a height of 2 m. To the best of our knowledge, it is the first time a sub-decimetres accuracy phase-based indoor VLP system with a sampling rate of 100Msa/s and practical coverage is experimentally demonstrated.

Chapter V Neural Network based DPDOA indoor VLP system

5.1 Introduction

In PDOA based VLP systems, several models have been taken into considerations as introduced in Chapter 3. However, early works assume the ideal ITD distribution of LED lamps and do not take into account the actual ITD distribution which is LED lamp dependent, as discussed in Chapter 4. The ideal assumption on the ITD distribution results in severe shifting errors which are presented in the experimental section of Chapter 4. Usually, these models are calibrated before actual experiments. Normally, the higher the accuracy required the more calibration works are required. As the coverage of the testing space increases, the more measurements are required in the calibration process.

Moreover, in either PDOA or DPDOA based VLP system, iteration based numerical position solvers are generally applied as in Chapter 3 and Chapter 4. The time consumption of such solvers is highly dependent on the initial guess and the quality of the inputs. With distortions and high noises, these inputs are poor and result in bad position estimation and high time consumption.

In this chapter, neural network-based methods are proposed to address the issues mentioned above. Firstly, a NN is introduced to deal with non-ideal ITD distribution induced shifting errors in position estimations. With the NN, the shifting error caused by non-ideal ITD distribution is mitigated on a large scale. To further reduce the complexity, both the shifting correction and the position solving are achieved in a single NN. Simulations are conducted to further study the performance of the NN based DPDOA system. The experimental results are presented to validate the feasibility of the proposed scheme. Moreover, the robustness of the scheme is illustrated through experimental comparison with RSS based VLP system. This chapter is related to the work we published in [76], [93].

5.2 Neural network basics

Neural network (NN) as a newly emerging technique is widely applied in many fields.

The NN is capable of fitting functions accurately through training [94]. A fundamental element of the NN is a neuron with multiple inputs and one output as in Fig.5.1 (a) [95]. A neuron consists of two parts: an adder, which sums up all the inputs ($\mathbf{p}$) with corresponding weights ($\mathbf{w}$: adjustable in training process) and biases ($\mathbf{b}$); an activation function f , which constrains the output in a certain region (usually 0 to 1) and increases the nonlinearity of the output to the inputs. Hence, the output is related to all the inputs with nonlinearity, which offers the capability of approximate arbitrary functions. The activation function has different designs of which the commonly used are *sigmoid*, *tanh*, and *ReLU*, as shown in Fig. 5.1 (b). *Sigmoid* is a smooth and slow function which is flat when the Y value close to 1 and 0, hence before the training, the inputs should be normalized. Comparatively, *tanh* is faster in convergence. While *ReLU* function truncates the negative inputs and much simpler than the other two in calculation and derivations, however, the partial linearity property is more suitable in classification instead of fitting in the shallow network.

Figure 5.1 Fundamental elements of NN. a) Structure of a multi-input neuron [95]; b) Illustration of different activation functions f

5.2.1 Neural network with a single hidden layer

Fig. 5.2 shows a simple NN consisting of an input layer, an output layer, and only one hidden layer. The number of neurons in the hidden layer and the type of activation functions are not adjustable in training the NN. The NN is fully connected (all possible connections) between each neuron across the layer. Hence the relationship between inputs and outputs is expressed as:

$$\mathbf{a} = f_2(\mathbf{w}_{st} f_1(\mathbf{w}_{Rs} \mathbf{p} + \mathbf{b}_1) + \mathbf{b}_2)$$

Backpropagation and weight adjustment

A cost function (F) is first set up as a goal of training. Cost function constrains not only the mean square error (MSE) between the NN outputs and the target values but also the distribution of weights by giving a penalty to extremely high or low weights (regularization) [96].

The target of training is to minimize the cost function (F), through iterative weight adjustment. The weight adjustment of the k -th iteration in the weights of the j -th neuron at the i -th layer can be expressed as [95]:

$$\begin{cases} w_{i,j}^m(k+1) = w_{i,j}^m(k) - \alpha \frac{\partial \hat{F}}{\partial w_{i,j}^m} \\ b_i^m(k+1) = b_i^m(k) - \alpha \frac{\partial \hat{F}}{\partial b_i^m} \end{cases}$$

where α is the learning rate. With the chain rule, the cost function related errors propagate layer by layer backward to adjust all the weights, and this process is called gradient-based backpropagation.

Figure 5.2 Neural Network with single hidden layer

Neural Network Training Process

The NN is designed with random initiated weights w and biases b , these weights and biases are optimized and adjusted through training epochs. A set of {inputs, targets} pairs are given for the training process to offer the best estimations in outputs and a good generalization in new data. A basic flow of training the NN is shown below:

- To begin with, several pairs of $\{\mathbf{I}_{qS}, \mathbf{t}_q\}$ (in the form of {inputs, targets}) are given as pre-known.
- The dataset is randomly shuffled and divided into training\testing\validation sets.
(The testing set is used to evaluate the performance after the training complete, and no test data allowed to be involved in the training.)

Iteration starts

- Calculate the cost function F with the training set
- Adjust weights through backpropagation to minimize the cost.
- Calculate the performance (usually MSE) on the validation set.
(usually, learning rate α is also tuned accordingly in this step)
- Check the stopping criteria.
(Commonly used criteria: MSE of the validation set starts to increase; reaching the maximum number of iterations)

Iteration ends

- Calculate MSE on the testing set, to evaluate the performance of the trained model.

5.2.2 Overfitting & under-fitting

The training process carries two tasks, one is to minimize the error between the outputs of the model and the targets, another is to ensure the model is general enough for inputs outside the training set.

Overfitting can be observed as the trained model is able to achieve small error on the training set, however, performs badly in the testing set. When overfitting occurs, the NN is lack of generality. Under-fitting means the situation where both the training and testing sets have a large error. Normally, overfitting issue is caused by the high degree of freedom in the NN structure, while under-fitting is normally caused by lacking training data or given too few degrees of freedom in the NN structure. To overcome these issues, L1-regularization and L2-regularization are normally used to introduce weight penalties [97].

5.2.3 NN structure determination

Continued to relieve the overfitting and under-fitting situations, the structure (number of layers, number of neurons in each layer, activation function) is the most crucial part. Here *sigmoid* activation function is chosen for our task.

To define the number of neurons and layers of the NN, a try-out strategy is usually used when the number of inputs and outputs are small:

- Training starts from 1 hidden layer with the number of neurons being equal to the sum of the inputs and outputs. If the training results indicate overfitting, the number of neurons can be reduced. If under-fitting indication appears, the number of neurons is increased in the next phase of training.
- Repeat the former steps until no overfitting indications and the training error is less than 5% to 10% of the targets' value.
- If under-fitting continues for several adjustments, add one more hidden layer. The same adjustments repeated in the newly added layer until no over-fitting and under-fitting occurs.
- The structure of the NN is finally determined through such process.

5.2.4 Bayesian regularization

As our dataset (tens to a hundred of data) is relatively small (normally trained with thousands of data) the overfitting may frequently occur. To overcome the overfitting during the training process, Bayesian regularization is applied by tuning a dynamic penalty on weights in the cost function ($F(\mathbf{w})$). The steps of the Bayesian optimization of the regularization parameters are given as follows [98][99]:

- 1) Initialize α, β and the weights of the network. The weights are initialized randomly and set $\alpha = 0, \beta = 1$
- 2) Take one step of the backpropagation, minimize the cost function: $F(\mathbf{w}) = \beta E_D + \alpha E_W$ (E_D is the sum of squared errors and E_W is the sum of the weights).
- 3) Compute the effective number $\gamma = n - 2\alpha \text{tr}(\mathbf{H})^{-1}$, where the Hessian matrix of $F(\mathbf{w})$ at minimum point as $\mathbf{H} = \nabla^2 F(\mathbf{w}) \approx 2\beta \mathbf{J}^T \mathbf{J} + 2\alpha \mathbf{I}_n$ is available in Levenberg-Marquardt algorithm [100], [101].

- 4) Update the estimates for cost function with parameters α, β (N is the number of parameters in the network, and n is the number of training set data):

$$\alpha = \frac{\gamma}{2E_w(\mathbf{w})} \quad \text{and} \quad \beta = \frac{n - \gamma}{2E_D(\mathbf{w})}$$

- 5) Repeating steps 2 to 4 iteratively until convergence.

In this manner, the cost function is then minimized with the Bayesian based approach. When Bayesian regularization is applied, the best results are obtained if the training data (both inputs and outputs) is initially normalized into the range $[-1,1]$ which relies on the pre-processing of the data.

5.3 Principle

To address the non-ideal ITD distribution induced distortions (as presented in section 4.4.3 and section 4.5.3), here two approaches are proposed. The first approach is to use the NN to mitigate the shifting errors through projection (in section 5.3.1). The second approach is to use NN to perform position estimations directly (in section 5.3.2).

Figure 5.3 Shifting error mitigation with NN based projection

5.3.1 Neural network based ITD induced distortion mitigation

The ITD distribution induced position shifting can be considered as a distorted positioning space. Hence we apply the NN technique to determine the projection function which can project the distorted space to the actual positioning space. As shown in Fig. 5.3, the DPDOA positioning results with distortions denoted as (X_d, Y_d, Z_d) are the inputs of the NN and the outputs are the actual location obtained from actual the measurements. The NN is then trained with experimental data to find an accurate fit to the projection function.

This is a manifest and direct approach to correct the distortions. However, adding on to the whole system described in Chapter 4, this extra module for distortion correction increases the overall workload.

5.3.2 Neural network based positioning

Instead of directly dealing with the distortions (as in section 5.3.1), the position calculation process with iterative numerical solver can be replaced by a neural network as a whole. In this manner, both the distortion induced by ITD distribution and the position solving is achieved by just one NN. The improvement in both accuracy and time consumption can be expected.

The phase extraction process is directly taken from section 4.3. Hence here we assume that the distance differences are already obtained. To be general in different hardware settings, the center point of the testbed is set to have zero distance differences, and all other locations are calibrated by the data collected at the center point. With a geometrical solution based positioning schemes, the locations of the LED lamps are required to be measured separately in centimeter-level accuracy. Here, no location measurements on the lamps are required, as the NN based positioning learns from the onsite dataset containing the LED's information.

Figure 5.4 Comparisons on classical and pre-training based NN solution

Pre-training

To accelerate the training process and overcome overfitting and under-fitting issues the pre-training techniques are introduced in our pre-training [102]. As shown in Fig. 5.4, the classical approach is using the dataset collected from testbed to train a randomly

initiated network. Hence, the performance of the network is mainly limited by the coverage and the density of the dataset. To have larger coverage and high accuracy, the scale and the density of data collection are demanded.

In the pre-training approach, as in the right part of Fig. 5.4, a simulation dataset is firstly used to train the randomly initialized network. The network trained with simulation data is called a pre-trained network. As the simulation data (which has large coverage and high sample density) is based on the ideal positioning model, in our applications, the pre-trained network only learns the basic knowledge of positioning algorithms. Then data (within a smaller coverage, and sparser samples and less off-line workloads) are required from testbed for further tuning the pre-trained network. In this step, the property of the testbed (e.g., ITD distribution of LED) is learned by the network through training. Moreover, the pre-trained network accelerates the training process and is a general model for all PDOA based systems (for repeatable usages).

Figure 5.5 Flowchart of pre-training based DPDOA indoor VLP system

Principle of NN based DPDOA positioning

The proposed positioning process flow is shown in Fig. 5.5. To begin with, a single hidden layer NN is constructed as in Fig. 5.6 with randomly initialized weights and biases. The NN has the distance difference measurements as the inputs and the actual 3D coordinates as the outputs. The activation function f chose is Sigmoid as it performs better in the fitting tasks.

After that, a simulation-based dataset with {distance differences (**Dd**), actual position ($\mathbf{x}, \mathbf{y}, \mathbf{z}$)} pairs are constructed. This dataset has a large scale testing space with dense grid points and without measurement noises. These simulated data (**L** in Fig. 5.5) are used for the pre-training process.

Then the NN is trained by the dataset generated from simulation, forming a pre-trained NN. Notice that, by this stage, the lamps' layout and the environmental influences are

not taken into consideration. Hence, a final step of training based on the onsite dataset (**S** in Fig. 5.5) is introduced. The training is based on a sparsely taken dataset (with less than 40 pairs) in the 3-D space (of 3 or 4 different heights). Finally, the network is capable of real-time position estimations in the testbed with real-time DPDOA measurements as inputs and the position estimations as outputs.

Figure 5.6 Illustration of DPDOA based position solver with a NN

5.4 Simulations

As stated in the principle section 5.3.2, the first step is to generate a larger dataset (**L**) with ideal system models and default LED layout. Here parameters and models used for the simulation are listed in Table 5.1 Using these models and parameters, the simulation provides over 300 pairs of [distance differences, actual position].

TABLE 5.1 MODELS AND SIMULATION PARAMETERS
USED FOR PERTAINING DATASET GENERATION

Model	Type	Parameters	Value
LED Intensity Model	1 st order Lambertian	Modulation Frequency	4MHz – 5MHz
LED ITD Model	Angle irrelevant	Sampling Rate	100Mbps
LED Layout	Equilateral Triangle	X-Y Coverage	4m by 4m
Emission Intensity	From measurement	Heights	1 m to 2.5m
Channel Model	Classical free space	Grids	11 by 11 by 4
		Filter bandwidth	40kHz

The obtained dataset is divided into training, testing, and validation set to train a single hidden layer neural network. Before the actual training starts, the structure of the NN is adjusted and optimized.

5.4.1 NN structure optimization

Starting with five neurons in a single hidden layer NN, the accuracy is evaluated as the number of neurons increases. The training and testing mean square errors (MSE) and converging epochs (maximum epochs set at 1000) are recorded in Table 5.2.

TABLE 5.2 NEURAL NETWORK PERFORMANCE ANALYSIS

Number of Neurons	5	10	15	20	25	30
Maximum Training MSE (cm)	5.8	2.7	0.7	0.4	0.2	0.1
Maximum Testing MSE (cm)	6.4	2.8	1.0	0.4	0.4	0.6
Converging epochs	40	100	230	570	700	1000

As can be observed, the number of epochs for training MSE convergence increases as the number of neurons grows. Besides, the training MSE decreases as the number of neurons increases. On the other hand, the testing MSE drops at the beginning until reaching 20 neurons and afterward the testing MSE grows instead. It can be inferred that when there are less than 15 neurons the network doesn't have enough freedom to fit such positioning model while over 20 neurons the overfitting effects become severe. Hence, the number of neurons should be chosen between 15 to 20, and 18 neurons are eventually selected as it's testing accuracy outperforms the others.

Till here, the pre-trained network is formed by 18 neurons for DPDOA based positioning. However, the simulation scenario is quite different from the actual environment, meaning that the pre-trained NN is not able to be directly applied to setups in which LED layout and ITD distribution are different. Hence a further step of training with the data collected from the field is needed.

5.4.2 Comparisons of the DPDOA VLP system without NN and DPDOA VLP system with NN without pre-training

To research on the performance of pre-training, another dataset with different lamp layouts and ITD distribution model from experimental measurements is introduced. The following parameters in Table 5.3 are used to simulate an actual testbed environment.

TABLE 5.3 SIMULATION PARAMETERS OF ONSITE DATASET GENERATION

Model	Type	Parameters	Value
LED Intensity Model	1 st order Lambertian	Modulation Frequency	4MHz – 5MHz
LED ITD Model	<u>Actual measurements</u>	Sampling Rate	100Mbps
LED Layout	<u>Isosceles Triangle</u>	X-Y Coverage	3m by 3m
Emission Intensity	From measurement	Heights	1 m to 2.5m
Channel Model	Classical free space	Grids	7 by 7 by 4
Noise Level	<u>Actual measurements</u>	Filter bandwidth	40kHz

ITD distortion and accuracy

Fig. 5.7 (a) and (b), shows the positioning estimations under ITD distortions with the classical PDOA system where dashed red arrows indicate the trend of distortions. As can be observed, only around the central 2m by 2m space in X-Y plane, the RMS positioning error (RMSPE) is less than 20cm. Moreover, in X-Z plane, a clear bending of the positioning space occurs as well as shifting upwards. Such effects become severe as the irradiation angle increases. This severe distortion is a result of no consideration of the ITD distribution.

Figure 5.7 Position estimations under simulated test space with ITD distortions. DPDOA estimations w/o NN, a) X-Z view; b) X-Y view; with NN without pre-training c) X-Z view; d) X-Y view.

As for estimations with NN based position estimator shown in Fig. 5.7 (c) and (d) (without pre-training), the distortions are mitigated as the training process of the NN

already taken the ITD and other environmental factors into consideration. Only slight bending can be observed in the X-Z view and minor distortions occur in the X-Y plane. Hence, the overall accuracy of the system is greatly improved, and the overall distortion-free coverage is increased by over 4 times.

Computational time of the real-time system

Another major advantage of using NN for position estimation is the lower consumption of computational power. As is known, the time consumption in solving function with the Newton-Raphson method is complexity dependent and relies on the initial guess. While the complexity of a trained NN in real-time performance is just related to the number of inputs, outputs, neurons, and layers. The time consumption of the DPDOA system with NN is significantly reduced as compared to the DPDOA system without NN.

TABLE 5.4 TIME CONSUMPTION COMPARISON FOR
DPDOA SYSTEMS WITH AND WITHOUT NN

Rounds	1	10	50	100	200
Time used DPDOA w/o NN (s)	0.178	0.52	1.208	2.584	8.3382
Time used DPDOA with NN (s)	0.0005	0.0044	0.0129	0.0241	0.0408
Ratio	356	118.182	93.6434	107.22	204.368

Through extensive simulations at different locations in the test space, and a total of 200 measurements are taken for a fair comparison between NN based DPDOA and classical DPDOA position estimations. The results are given in Table 5.4, the computational improvement of the NN based DPDOA is about two orders of magnitude, which is very significant. This is because of the classical DPDOA using Newton's method faces long iterations when noises are high. And hence, the classical DPDOA system does not perform uniformly in time consumption.

Though training is required for NN in our experiments, the NN is trained with the dataset of 16 pairs and the time consumption of the training process is ~5s. Moreover, this training process induces no on-line burdens.

5.4.3 Comparisons of NN based DPDOA systems with/without pre-training

The pre-training process is introduced to provide prior-knowledge for DPDOA based

position estimations. Since we already have the pre-trained NN based on DPDOA measurements, fewer samples are required for further weights adjustments. The training error is generally better when pre-training is applied, as the training starts at a better point (instead of randomly). Also, the converging speed of the pre-training based NN is faster by around half of the epochs usage as compared to the case without pre-training.

Figure 5.8 Position estimations on NN built w/ and w/o pre-training. NN without pre-training. a) X-Y view; b) X-Z view; pre-training based NN; c) X-Y view; d) X-Z view.

Fig. 5.8 compares estimation results between the NN based positioning with and without pre-training. These simulations are conducted in a much larger test space than that of the training data collected (5m by 5m vs. 3m by 3m space). Comparing Fig. 5.8 (a) and (c), the system with pre-training based NN provides position estimations with fewer distortions and larger coverage in the X-Y plane. While in the X-Z plane as shown in Fig. 5.8 (b) and (d), the distortions at the ends are mitigated by using the pre-training based NN at all heights. From Fig. 5.8, we can infer that the pre-training process provides knowledge beyond the area (3m by 3m) collecting the training data and hence the

positioning performance is not degraded as the classical approach. It can be concluded that the pre-training based NN is helpful in both the performance of the positioning and relieving the efforts of data collection and training.

5.5 Experiments

5.5.1 ITD distribution induced distortion mitigation with NN

Addressing the significant position shifting error observed in the raw estimation results, as previously shown in Fig. 4.9 (a) and (b), a NN is applied to correct the distortions during position estimations. Using the Neural Network Design TOOLBOX [95], totally four known reference positions over the receiving plane are used to train the NN which has two inputs (estimated positions), two outputs (actual positions) and one hidden layer with 6 neurons. Here, the NN based distortion mitigation is applied and the results are shown in Fig 5.9 (a) and (b) accordingly.

Figure 5.9 Experimental results with NN based shifting correction. a) Estimations with only NN; b) Estimations with both KF and NN. (a quarter of $2\text{m} \times 2\text{m}$ testing area at 2m height)

Fig. 5.9 (a) shows the position estimation results based on raw measurements with NN based distortion correction. The average RMSPE is around 6cm, and the maximum RMSPE is reduced from 37cm to 17cm. Similarly, at the far end of the test space, the variations are large.

By applying KF technique and NN-based distortion correction, the average positioning error is greatly reduced to around 1.8cm with a maximum positioning error of $\sim 8\text{cm}$, as shown in 5.9 (b). The improvements in the positioning performance validate the effect of NN in the experimental scenarios.

Figure 5.10 Positioning performance w/ and w/o NN error mitigations and KF

Fig. 5.10 shows the RMSE CDF distributions with and without NN-based distortion mitigation and/or KF. As shown in Fig. 5.10, there are significant improvements in positioning error by ~10cm by employing NN based distortion mitigation. Also with the NN based distortion mitigation, the stair-like effect (refer to the yellow curve in Fig. 5.10) is no longer present.

Figure 5.11 Experimental validations of NN based DPDOA positioning results. a) 3D positioning results for a quarter of the test space; b) RMS positioning error distribution

5.5.2 Validations on NN based DPDOA positioning system

Experimental validations and evaluations

We set up the NN based DPDOA system with similar setups as in Chapter 4. An experiment is conducted to validate the feasibility of the NN based DPDOA system. A quarter of the test space is chosen to conduct the positioning test, and the results of the 3D positioning with NN based DPDOA are presented in Fig. 5.11 (a).

The center of the whole test space is located on the origin, and hence the best performance in positioning error also occurs around the center. The measurements in a single location illustrate an eclipse distribution with the error ranging from 5cm to 15cm, depending on the height and distance to the origin. Generally, the longer the distance to the center of the LED lamps, the larger error appears and the error is more evident along the Z direction. From Fig. 5.11 (b) we can observe the error distribution of these testing samples. The average RMS error is around 5cm, and the maximum error is around 15cm in this 3D NN based DPDOA validation experiment.

Figure 5.12 Measurements under tilting and attenuation tests. a) distance differences from DPDOA; b) intensity measurements from RSS.

Robustness test under tilting and attenuation

In actual testbed, the tilting and attenuations caused by power source are not ignorable. Though, in theory, tilting would only affect the intensity rather than the phase information. Similarly, the attenuation in the intensity on the power source or along the channels is also considered as phase irrelevant. An experiment is conducted to qualitatively evaluate the robustness of the NN based DPDOA system in slight rotation and intensity attenuation.

Here two tests each of 100 samples at a fixed location are conducted with rotation and attenuation respectively, as illustrated in Fig.5.12. The measurements of distance differences (Fig. 5.12 (a)) and RSS (Fig. 5.12 (b)) are recorded, where the first 50 samples are under the normal condition without rotation and blockage and the next 50 samples are under rotation and attenuation. The rotation is around 15 degrees and the attenuation is induced by a thin paper. There are three observations: 1) both DPDOA and RSS measurements are affected by rotation and attenuation; 2) RSS measurements are more sensitive in the attenuation test; 3) RSS measurements are superior in SNR

under all circumstances than DPDOA measurements.

Figure 5.13 Positioning results under rotation and attenuation tests. a) positioning results of NN-DPDOA system; b) positioning results of NN-RSS

Based on these measurements, the position estimations are given in Fig 5.13 through calculations. In Fig.5.13 the blue dots represent the normal measurements at individual locations, the red dots present the results of rotation experiments and the green ones present the results of attenuation experiments. There are also several observations: 1) Both NN-DPDOA and NN-RSS systems are influenced by both rotation and attenuation; 2) The influences on RSS based estimations are much larger than DPDOA ones; 3) Attenuation induced errors are not acceptable in RSS based position estimations; 4) RSS based estimations are more consistent (with little variations) comparing with DPDOA based estimations. The experiments have demonstrated that the NN based DPDOA system can achieve better robustness than RSS based system.

TABLE 5.5 COMPARISONS AMONG STATE-OF-THE-ART WORKS

Literature	[103]	[75]	[104]	This work
Method	RSS/WKNN	TDOA	Imaging	DPDOA NN
Intensity Model	Fingerprinting	N.A.	N.A.	N.A.
Time delay model	N.A.	No	N.A	NN fitted
2D/3D	2D	2D	3D	3D
Accuracy	6cm	17cm	6cm	12cm
off-line workload	High (20cm grids)	Low (1 or 2 point)	No	Medium (50cm grids)
Notice	Intensity Sensitive	Calibration required	Small coverage	Training required

5.5.3 Comparisons with the state-of-the-art works

Several state-of-the-art works are listed in Table 5.5. We can observe that works considering real system models generally perform better in accuracy like the ref. [103], while with less calibration the error tends to be higher [75]. However, accurate modeling requires heavy off-line workloads, with pre-training our work reduces the offline workload evidently. In comparison with the work in [103], the density of off-line samples is saved by over a half. Moreover, in our work with NN based positioning, triangulation and modeling are realized in the same single layer NN, which is over 100 times faster than solving quadratic equations. In comparison with image-based positioning [104] (the whole testbed is 1m by 1m by 0.8m height), our proposed system can provide a much larger in coverage (a quarter of the testbed is 0.8m by 0.8m by 2m height).

5.6 Summary

In this chapter, a NN based ITD distribution induced distortion mitigation scheme and a NN based DPDOA positioning system are proposed.

The NN based ITD distribution induced distortion mitigation scheme is achieved by using a single hidden layer NN with 6 neurons. By adding on this NN, the severe shifting errors are evidently mitigated, achieving a 2D positioning average RMS error of 1.8cm and the maximum RMS error of 8cm.

The proposed NN based DPDOA scheme is composed of a single hidden layer of 18 neurons. Simulations are conducted to determine the structure of the NN so that the overfitting and under-fitting issues can be dealt with. To reduce the complexity of the system, we propose the pre-training based method to assist the training process which significantly relaxes the data acquisition efforts. The pre-training technique is proved to improve the coverage and reduce distortions. The ITD model induced errors are also naturally solved through the training process with onsite data, meanwhile, the actual locations of LED lamps are no longer required to be pre-knowns.

Experimental demonstrations are conducted to validate the feasibility of the NN-DPDOA scheme. The average RMS poisoning error in the 3D positioning tests is about 5cm in the testing space of 0.8m by 0.8m with a height varying from 1m to 2m to the

LED plane. The experiments also demonstrate that the NN-DPDOA based positioning system can achieve better robustness in both situations with tilting and attenuation than the NN-RSS based positioning system.

Chapter VI Hybrid received signal strength(RSS) and DPDOA based positioning system

6.1 Introduction

In Section 2.3, the most commonly used range based VLP systems are reviewed. Each approach usually has its own drawbacks. The RSS based system is sensitive to rotation and intensity variations, AOA based system has relatively high complexity and PDOA based system is more sensitive to noises. Observing from the experiments in Section 5.5, using the same received signal sequences, the SNR performance of RSS measurements is much better than that of DPDOA measurements (errors are induced from inaccurate model and poor robustness).

To pursue both high accuracy and robustness, building a hybrid system is one of the options. The hybrid VLP systems using RSS and AOA are normally researched with multiple sensors (multi-PD or image sensor with PD) [64], [105]. Also, maximum likelihood estimators are commonly used in hybrid systems for the fusion of measurements.

In this chapter, we propose a hybrid PDOA/DPDOA and RSS based VLP system through selection strategies with one PD, for the first time. The measurements of RSS and PDOA are obtained from the same received signal simultaneously. Meanwhile, they are irrelevant to each other in the extraction process. To compensate for the SNR of the DPDOA system and to enhance the robustness of the RSS system, selection strategies are proposed with little burden to the whole system. The proposed hybrid system is validated through simulation, and two selection strategies are also compared. This chapter is related to the works we published in [93], [106], [107].

6.2 RSS based VLP system

6.2.1 Principle of classical RSS based VLP system

RSS is the most commonly used approach with low complexity, however sensitive to rotations and intensity changes. With the Lambertian irradiation model and the free space channel model, the LOS channel gain is expressed as below (recall from Section

3.3.1):

$$H_i = \frac{(m+1)A}{2\pi d_i^2} \cos^m(\varphi_i) \cos(\Psi_i) \quad (6.1)$$

Signals with different frequencies are allocated to individual lamps to distinguish different transmitters. These light signals are received by a PD. And after proper filtering, the received signals are separated as (for simplicity we assume the irradiation power of the lamps is 1w):

$$Rx_i(t) = H_i \sin(\omega_i(t + d_i/c)) \quad i = 1,2,3 \quad (6.2)$$

The RSS information is extracted from the received signal $Rx_i(t)$ through amplitude accumulations. Using the three extracted RSS information, distances d_i can be estimated accordingly and hence the 3D position (x, y, z) of the receiver can be obtained by using three LED lamps:

$$\begin{cases} d_1 = \sqrt{(x_1 - x)^2 + (y_1 - y)^2 + (z_1 - z)^2} \\ d_2 = \sqrt{(x_2 - x)^2 + (y_2 - y)^2 + (z_2 - z)^2} \\ d_3 = \sqrt{(x_3 - x)^2 + (y_3 - y)^2 + (z_3 - z)^2} \end{cases} \quad (6.3)$$

where (x_i, y_i, z_i) is the coordinate of the i -th LED lamp ($i=1, 2, 3$). Note that each LED lamp carries its own identified frequency ω_i accordingly.

Figure 6.1 Examples of waveform and measurements. a) a period of received waveform; b) distance difference measurements from DPDOA algorithm; c) RSS measurements

6.2.2 Comparisons between the RSS and DPDOA based VLP systems

Actual experimental testing reveals that, just as shown in section 5.5.2, the RSS based positioning system generally achieves high SNR performance and good signal quality. Fig.6.1 (a) shows an example of a period of the received waveform collected from the experiment, which contains distortions (asymmetrical in amplitude) and noises. The

corresponding measurements from experiments of distance differences and intensity are recorded in Fig.6.1 (b) and (c).

It's clear that the disturbances of the noises have more influences on distance differences rather than intensity measurements. And hence, the accuracy of the RSS based position estimations seems to outperform the distance differences (including TDOA, PDOA, and DPDOA) based estimations. However, there are several critical issues constrain the accuracy of RSS based system: inaccurate intensity model, rotation sensitivity and intensity fluctuation.

Theoretically, the Lambertian irradiation model is commonly applied as the intensity model, but even in a small coverage Lambertian model requires heavy calibrations [87][108]. The irradiation pattern is also influenced by the diffusers and reflectors (e.g. lampshade, backscatter board).

Moreover, the receiver may not always face in a fixed direction (usually assumed facing up) which influences the Ψ_i as expressed in the LOS indoor propagation model eq. 6.1. The irradiation angle φ_i varies as the receiver moves and hence the LOS gain H_i varies accordingly.

Besides that, the light intensity emitted from LED lamps may vary for the following reasons: LED driver-current ripples induced by rectification of AC to DC power source; the intensity attenuation as the operating duration increases; heating-up related intensity changes caused by the resistance variation during the warm-up stage of the LED.

And in consequence, the classic RSS based positioning techniques are only feasible for the situations where the receiver only slight tilts, with a very stable power source and in a small coverage.

Figure 6.2 Examples of waveform and measurements with intensity variations. a) An example of intensity variation at 15% level; b) RSS measurements at different variation levels; c) DPDOA measurements at different variation levels

Depicted in Fig.6.2 (a), is an example of waveform with intensity variation changing

every 2 ms. This changing of intensity is shown on the envelope of the waveform (the stair-like outline in Fig. 6.2 (a)), which is much slower than the frequency of the signal however induces noises to the measurements. The corresponding measurements on RSS and DPDOA are presented in Fig.6.2 (b) and (c) respectively. The intensity variation levels are set from 0 to 15% of the maximum amplitude, and the variations on RSS measurements are much evident than DPDOA measurements. It can be inferred that the DPDOA based algorithms are more robust in intensity variations such as receiver's rotation and LEDs' dimming situations.

6.2.3 RSS based positioning with NN

To address the inaccurate intensity model of RSS based system for 3D positioning, NN is applied to provide an accurate intensity model and an efficient position solver [107]. The flowchart of RSS based positioning system with the NN is shown in Fig.6.3.

Figure 6.3. RSS based VLP system with pre-trained NN estimator

Signals of different frequencies are generated from the same signal generator sharing a common clock. The signals from different lamps can be distinguished by their own frequency ID. Then the signals are modulated to respective LEDs (lamps) on the intensity and received by an APD. A sampling process is introduced to convert analog signals to digital ones and hence can be processed through DSP algorithms.

Since several frequency components involved in the composite received signal, several BPFs are used to separate them and to use a peak detector to extract the peaks and take the average to obtain the RSS measurements. This step is also possible to be replaced by an accumulation process, which calculates the energy of the signal and then calculates the amplitude.

Then the obtained RSS measurements are considered as the inputs to an NN which is developed on a simulation-based pre-trained NN and further optimized (train with the onsite dataset) to be feasible in the current environment (similar to the NN in Chapter

V). Then the RSS measurements based position estimations are given as the outputs.

6.3 Hybrid system principle with selection strategies

It is manifest from the above measurements that the received signal carries not only RSS information but also the phase information (assuming the LED transmitters in one VLP unit are synchronized in the clock). Hence, the respective disadvantages of RSS based positioning and DPDOA based positioning can be potentially complemented by the combination of RSS and DPDOA positioning.

To make use of both RSS and DPDOA information contained in the received signal, selection based strategies are proposed in this section. The main idea is to suppress the variations of DPDOA when SNR is high and mitigate the RSS variations under intensity disturbances.

6.3.1 Variation based selection strategy

One of the straight forward ways for the fusion of DPDOA and RSS is to select the results from the variation of measurements for a certain period. To begin with, measurements of RSS is recorded as $H_{k,n}$ for the n -th measurements with totally N times. The index of variations is defined as V :

$$V = \frac{\sqrt{\sum_{n=1}^N (H_{k,n} - \overline{H_k})^2 / N}}{\overline{H_k}} \quad (6.4)$$

The positioning results are selected with index V as:

$$\mathbf{P}_{outputs} = \begin{cases} P_{RSS} & V \leq p\% \\ P_{DPDOA} & V > p\% \end{cases} \quad (6.5)$$

There are two adjustable variables, the number of observations (N) and the threshold of selection (p). When N is larger, the response time is slower while the estimation in variations is better. Oppositely, when N is smaller, a faster prediction is obtained, however shorter observation induce larger variation in $\mathbf{P}_{outputs}$.

The disadvantage of variation based selection strategy (V-selection) is manifest that under the fixed tilting situations the variation maintains stable however position predictions may differ much from real values.

6.3.2 Position based selection strategy with t-distribution

The V-selection strategy is still constrained by the rotations of the receiver which is inherited from RSS algorithms. While the PDOA based algorithms (including DPDOA) are rotation irrelevant as discussed in Chapter 5. Hence, a DPDOA dominated selection strategy is in turn proposed. A selection index t is introduced as a typical students' t-test, and is expressed as:

$$t = \frac{|P_{DPDOA} - P_{RSS}|}{s} \quad (6.6)$$

where s is the estimated standard deviation of the DPDOA measurements (from pre-experimental measurements or using empirical values).

Figure 6.4. Illustration of Students' t distribution (with degree of freedom $\nu=2$)

A two-tailed t distribution is applied to decide which estimation of the position should be chosen. Fig. 6.4 shows a t distribution probability density with the degree of freedom $\nu=2$. The t is calculated in real-time and then the area of the red region is computed as $T(t)$. The larger difference between DPDOA and RSS based position estimations the smaller the red area is. If the red area is smaller than a pre-set threshold (α as significance level) the DPDOA based estimations are chosen, otherwise using the RSS based estimations as outputs:

$$\mathbf{P}_{outputs} = \begin{cases} P_{DPDOA} & T(t) \leq \alpha \% \\ P_{RSS} & T(t) > \alpha \% \end{cases} \quad (6.7)$$

From experiments, it is noticed that the farther from the LEDs center the worse SNR the received signal. DPDOA based solutions, comparing with that of RSS, are more sensitive to the signal quality. Hence, we should have more trust in the RSS estimations when the estimated distance from DPDOA scheme is larger. The term $\frac{d_{lim}}{d}$ is then

introduced to the selection standard to address this point:

$$t = \frac{|P_{DPDOA} - P_{RSS}|}{s} \times \frac{d_{lim}}{d} \quad (6.8)$$

where d_{lim} is a constant and d is the estimated distance through the DPDOA scheme. When d is large and t is small, more trust is given to DPDOA. Oppositely when d is small DPDOA is preferred. In this case, by adjusting d_{lim} and the significance level α the system can be adaptive to various situations.

Figure 6.5. Flowchart of pre-training based hybrid DPDOA & RSS VLP system

6.4 Simulations

To validate the ideas of the proposed selection strategies, a hybrid DPDOA & RSS positioning system together with neural networks is constructed. As shown in Fig. 6.5, a simulation based large dataset $\mathbf{L}$ (noise-free with ideal ITD distribution) containing both RSS measurements (RSSMs) and DPDOA measurements (PDMs) is generated. Two pre-trained NNs are then individually formed (from a randomly initialized NN) with the basic positioning knowledge learned from $\mathbf{L}$. After that, the RSSMs and PDMs are collected at known locations from the actual test space (with non-idea ITD distributions and noises) forming a small dataset $\mathbf{S}$. These data are used to adjust the pre-trained NNs by tuning weights, and the two NNs (one for RSS (RSS-NN) and the other DPDOA (DPDOA-NN)) are then formed for the hybrid RSS and DPDOA based positioning. As NNs are used, the computation complexity is reduced in position solving.

After the pre-experimental preparations above the RSSMs and PDMs are measured in real-time offering two individual position estimations. Based on the selection strategies proposed and discussed in the previous section, the final position estimations can be

obtained.

6.4.1 Performance analysis on DPDOA-NN and RSS-NN based VLP system

The performances of individual DPDOA-NN and RSS-NN schemes are first studied through simulations. From simulation results, a better understanding of the property of the hybrid RSS and DPDOA based positioning system with NN can be obtained.

Simulations are firstly conducted under a stable condition with no rotation on the receiver and no variation in intensity. As shown in Fig 6.6 (a)(b)(c), the RSS-NN scheme performs well from 1 to 2m heights with an average RMS positioning error around 5cm, while the DPDOA-NN scheme (in Fig 6.6 (d)(e)(f)) has an average RMS positioning error of over 9cm. As the height increases, shown in Fig. 6.6 (c)(f), the performance of DPDOA-NN scheme drops much sharper than that of RSS-NN scheme. Especially at the corners and edges of the test space, shown in Fig. 6.6 (a)(d), positioning error increases evidently in the DPDOA-NN scheme, while the RSS-NN scheme is just slightly influenced. These results indicate that, when an accurate intensity model is constructed (by the NN in this case) and no intensity disturbances involved, a better SNR performance is achieved by the RSS-NN scheme.

Figure 6.6. DPDOA-NN and RSS-NN based 3D position estimations. RSS-NN a) X-Y view; b) X-Z view; c) CDF of RMS positioning error at different heights. DPDOA-NN d) X-Y view; e) X-Z view; f) CDF of RMS positioning error at different heights.

Then we introduce some intensity variations in the transmitter side from 0 to 15%. Presented in Fig.6.7 are the RSS-NN and DPDOA-NN based position estimations under

Figure 6.7. DPDOA & RSS based position estimations with NN estimators under intensity variations. (a) DPDOA estimations X-Y view@6%; (b) RSS estimations X-Y view@6%; (c) DPDOA estimations X-Z view@6%; (d) RSS estimations X-Z view@6%; (e) DPDOA estimations X-Y view@12%; (f) RSS estimations X-Y view@12%; (g) DPDOA estimations X-Z view@12%; (h) RSS estimations X-Z view@12%;

6% and 12% intensity variation. With 6% intensity variation, RSS-NN scheme (Fig. 6.7 (b) (d)) shows better performance in X-Y directions and about the same performance achieved in the Z direction compare with DPDOA-NN scheme (Fig. 6.7 (a)(c)). When the intensity variation increases to 12%, as shown in Fig. 6.7 (e) and (g), the performance of DPDOA-NN scheme is less affected by such variations. Only at the edges of the test space, positioning error is slightly increased. While the RSS-NN scheme is strongly affected in all directions, as shown in Fig. 6.7 (f) and (h). And the overall RMS error of RSS-NN scheme grows by over two times.

Further study on the RMS positioning error distributions is conducted. Fig.6.8 shows three cumulative RMS error distributions under different intensity variations. When the variation is low (0%, 5%), the RSS based system has lower RMS positioning error (the dominant error is within 8cm) than the DPDOA-NN scheme. When the variation increases to 10% and higher, reversely, the DPDOA-NN scheme outperforms the RSS-NN scheme. It is also observed that the performance of the DPDOA-NN scheme is less affected by the intensity variation. Hence, a selection based algorithm is desired to find a balance between the good accuracy of RSS-NN scheme and the good robustness of the DPDOA-NN scheme simultaneously.

Figure 6.8. Error distributions at different intensity variation levels

6.4.2 Intensity robustness validation on proposed hybrid VLP schemes

As proposed and discussed in Section 6.3, V-selection (RSS dominated) and T-selection (DPDOA dominated) strategies are individually applied in this section. To test the

robustness of the proposed hybrid system, different levels of intensity variation are introduced.

Fig.6.9 shows the CDFs of RMS errors with different selection strategies for a different level of intensity variation. When intensity variation is lower than 5%, as shown in Fig.6.9 (a) and (b), the RSS-NN scheme performs better than DPDOA-NN scheme. Moreover, both T-selection and V-selection strategies perform close to the RSS-NN scheme.

Figure 6.9. Different selection strategies under intensity variations. a) no variation; b) 5% variation; c) 10% variation; d) 15% variation

Starting from 10% of variation and above, as in Fig.6.9 (c), (d), the performance of DPDOA-NN scheme is better than RSS-NN scheme by over 10cm at 80% confidence. At this stage, the performances of both selection strategies are closer to the DPDOA-NN scheme. These results indicate both selection strategies are effective in intensity variation and the SNR performance does not compromise in all conditions.

To compare the selection strategies, we consider the RMS estimation error at 90% confidence, on the intensity variation level from 0 to 20%. As presented in Fig.6.10, DPDOA-NN scheme is stable with the increase of intensity variation, and the RMS error

performance of RSS-NN scheme has almost linearly increased. RMS error of the V-selection strategy is similar to RSS-NN scheme when the variation is less than 6%. When the variation level is over 10% the performance of V-selection strategy is just slightly worse than that of DPDOA-NN scheme. The performance of T-selection strategy is slightly worse than that of RSS-NN scheme when intensity variation is less than 6%, beyond that level T-selection strategy is generally the best of all schemes.

Figure 6.10. Performance comparisons under intensity variations from 0 to 20%

These results prove the selection based hybrid schemes are feasible under intensity variations. And T-selection strategy is slightly better in the overall positioning performance and robustness than the V-selection strategy.

6.4.3 Rotation robustness validation on proposed hybrid VLP schemes

After the intensity variation test, both V-selection and T-selection strategies are qualified for robust and accurate positioning. However, when involving rotations on the receivers' side, the situation can be different.

Here random rotations within $\pm 2^\circ$, $\pm 5^\circ$ and $\pm 10^\circ$ are simulated respectively to emulate the situation when the receiver moves with trembling. Comparing Fig. 6.11 by columns, under random rotations within $\pm 2^\circ$ (Fig. 6.11 (a)(d)) the performance of V-selection strategy is better than T-selection strategy, especially when height increases. Under random rotations within $\pm 5^\circ$ (Fig. 6.11 (b)(e)), the performance of V-selection strategy has decreased sharply, especially at lower heights. By applying a random rotation within $\pm 10^\circ$ (Fig. 6.11 (c)(f)), the V-selection strategy fails at all heights with

RMS error larger than 40cm. While the T-selection suffers only the rotation induced SNR decreasing, the RMS error is still under 20cm.

It can be inferred from the results that, when the rotation is within $\pm 2^\circ$, the influence of SNR dominates the positioning error, hence the V-selection outperforms T-selection strategy. As the rotation further increases from 5 to 10 degrees, the V-selection strategy suffers more from the domination of RSS-NN, and T-selection, on the contrary, benefits from the domination of DPDOA-NN.

Figure 6.11. Rotation robustness comparisons between T & V selection. a) V-selection with 2-degree; b) V-selection with 5-degree; c) V-selection with 10-degree; d) T-selection with 2-degree; e) T-selection with 5-degree; f) T-selection with 10-degree.

6.5 Summary

In this chapter, we propose a new hybrid DPDOA and RSS 3D VLP system with selection strategies. The proposed system improves the robustness of conventional VLP systems under intensity variations and receiver rotations.

The performance of RSS based VLP system is first analyzed. To address the inaccurate modeling with heavy workloads, the NN technique is applied in the RSS based VLP system. To further complement the disadvantage with intensity disturbance, the DPDOA based VLP system proposed in Chapter 5 is applied to form a hybrid VLP system. We propose two selection strategies based on the position estimations of these

two independent NN based VLP schemes.

The improvements and robustness of the NN based hybrid positioning system using two different selection strategies are validated through simulations. The intensity variation is firstly taken into consideration. The hybrid positioning system using either selection strategy illustrates good intensity robustness and positioning accuracy than the VLP system using only DPDOA-NN or RSS-NN alone. The V-selection strategy provides slightly better accuracy when intensity variation is less than 6%, elsewhere T-selection outperforms V-selection strategy. We also compare the performance of T-selection and V-selection strategy under the random rotation of the receiver. When the random rotation of the receiver is greater than 5 degrees, the T-selection strategy outperforms V-selection strategy.

In conclusion, the proposed hybrid system has high adaptivity, high robustness, and better accuracy. Among the two selection strategies, T-selection is more suitable and adaptive in practical environments considering its real-time selecting mechanism with better rotation robustness.

Chapter VII Conclusions and recommendations of future works

7.1 Conclusions

This thesis theoretically and experimentally investigates phase measurements based indoor VLP systems which offer the potential to provide highly accurate, fast and robust localization for various emerging indoor applications. Three aspects of the indoor VLP systems are studied, including the positioning accuracy, system complexity, and system robustness.

In Chapter III, an optimized VLO based VLP system is proposed. Instead of using real LOs, VLOs are employed, which can considerably reduce the system complexity and enhance the flexibility of frequency allocations to individual LED lamps. Simulations are carried out to validate and analyze the performance of the proposed system. The positioning accuracy performance related to the LED's layout is also investigated through simulation. Experiments are conducted to demonstrate the performance of the proposed VLO based VLP system and to optimize the sampling rate. The study shows that the best performance can be obtained when the sampling rate is 500Msa/s and the interpolation factor is 100. With the optimized parameters, experimental results show that an averaging RMS positioning error of 9.2cm can be achieved in the testbed of 1.2m by 1.2m with the height of 2m.

In Chapter IV, a modified PDOA algorithm called DPDOA is proposed, which can circumvent the use of LOs in the receiver and hence relieve the requirement for the synchronization between the transmitters and the receivers. The formulation of dual differential phase difference extraction is presented. Through simulations, the influences of sampling hardware parameters are studied. The ITD distribution obtained from experiments and its impact on positioning accuracy is also investigated through simulations. The effects of sampling rate, modulation frequency, and sampling duration are studied to figure out the trade-offs and optimal combinations. Different ITD distributions are observed based on experimental measurements, which are used to predict the distortions. Furthermore, we also experimentally demonstrate a sub-

decimetre accuracy indoor VLP system. By using the DPDOA algorithm, no LOs are required at the receiver side, due to the use of differential phase difference measurements. A KF technique is adapted to considerably reduce the variation of distance difference measurements. The obtained experimental results show that an average RMS positioning error of 8 cm can be achieved in the proposed VLP system with a coverage of $1 \times 1.2 \text{ m}^2$ and a height of 2 m. To the best of our knowledge, it is the first time a sub-decimetre accuracy phase-based indoor VLP system with a sampling rate of 100Msa/s and practical coverage is experimentally demonstrated.

In Chapter V, by applying the neural networking (NN) technique, a NN based ITD distribution induced distortion mitigation scheme and a NN based DPDOA positioning system are proposed. The NN based ITD distribution induced distortion mitigation scheme is achieved by using a single hidden layer NN with 6 neurons. By adding on this NN, the severe position shifting errors are evidently mitigated, achieving a 2D average RMS positioning error of 1.8cm and the maximum RMS positioning error of 8cm. The proposed NN based DPDOA is composed of a single hidden layer of 18 neurons. Simulations are conducted to determine the structure of the NN so that the overfitting and under-fitting issues can be dealt with. To reduce the complexity of the system, a pre-training based method is proposed to assist the training process which significantly relaxes the data acquisition efforts. The pre-training technique is proved to improve the coverage and reduce distortion. The ITD model induced errors are also naturally solved through the training process with onsite data, meanwhile, the actual locations of LED lamps are no longer required to be pre-known. Experimental demonstrations are conducted to validate the feasibility of the NN based DPDOA scheme. The average RMS poisoning error in the 3D positioning test is about 5cm in the testing space of 0.8m by 0.8m with a height varying from 1m to 2m to the LED plane. The experiments also demonstrate that the NN-DPDOA based positioning system can achieve better robustness in both situations with tilting and attenuation than the NN-RSS based positioning system.

In Chapter VI, a new hybrid DPDOA and RSS 3D VLP system is proposed and investigated. The proposed system improves the robustness of conventional VLP

systems under intensity variations and receiver rotations. The performance of the RSS based VLP system is first analyzed. To address the inaccurate modeling with heavy workloads, the NN technique is applied in the RSS based VLP system. Two selection strategies (T-selection and V-selection) are designed to combine the position estimations obtained from the separate RSS-NN and DPDOA-NN systems. The improvement and robustness of the NN based hybrid positioning system using two different selection strategies are validated through simulations and experiments. The intensity variation is firstly taken into consideration. The hybrid positioning system using either selection strategy illustrates better intensity robustness and positioning accuracy than the VLP system using only DPDOA-NN or RSS-NN alone. The V-selection strategy provides slightly better accuracy when intensity variation is less than 6%, elsewhere T-selection outperforms V-selection strategy. We also compare the performance of T-selection and V-selection strategy under the random rotation of the receiver. If the random rotation of the receiver is greater than 5 degrees, the T-selection strategy outperforms V-selection strategy. The proposed hybrid system has high adaptivity, high robustness, and better accuracy. Among the two selection strategies, T-selection is more suitable and adaptive in practical environments considering its real-time selecting mechanism with better rotation robustness.

Figure 7.1 Flowchart of the relationship between the work of each chapters

Fig. 7.1 illustrates the relationship between the works of the individual chapters. Through all these research works, several objectives are achieved. Firstly, the complexity of phase-based VLP systems is simplified greatly by removing the LOs. Secondly, the positioning accuracy of the phase-based VLP system is improved evidently by considering the real-world ITD model with NN. Thirdly, the processing speed and position estimation are greatly improved for real-time positioning by avoiding

numerical function solvers. Finally, the robustness of the VLP system is significantly enhanced by taking advantage of both DPDOA and RSS schemes, forming a selection based hybrid system.

7.2 Future works

7.2.1 Multi-PD PDOA

Currently, the phase-based research works we have proposed are purely based on a single PD. Making use of multiple PDs or a PD array, the SNR is possible to be further improved. As the noise induced by PD is randomly generated and device-dependent, the more PDs the better SNR can be achieved by accumulation and common mode extractions. One approach is to use a quadrant detector to receive four channels of light signals independently. After proper filtering (with zero-phase filtering), the signals are then truncated by periods and accumulated to mitigate phase noises. Moreover, the intensity ratio provided by individual channels could provide a rough incident angle of the signals. Hence a hybrid VLP system with AOA and PDOA can possibly be constructed through the use of the quadrant detector. A promising advantage of this hybrid system is the calibration-free or self-calibrated VLP system with sub-decimetre level accuracy.

7.2.2 Short period blockages

Blockages can happen from time to time. Hence, a scheme with multi-sensor cooperatively overcoming the short blockages is also interesting. The blockage problems, for a short period, are possible to be solved through recurrent neural network RNN, as the RNN learns the relationship between the past inputs with the current inputs forming a time consistent predictions. Hence, it is promising to use RNN to estimate velocity, position, and posture simultaneously to predict the trace with good confidence within short blockages.

Normally, partial blockages occur much frequently than completely blind out. In such cases, the remain information is not sufficient for positioning. However, they also provide useful information combining with the last few position estimations. However, the geometrical solution is no likely to provide such likelihood-based estimations. Here,

with deep learning techniques or statistical methods, the remained information and previous moving status can be combined to roughly or even accurately predict the trace of movements.

Moreover, a sensor fusion plan is naturally combined with such a likelihood-based algorithm. The posture information provides by the gyroscope is a complement to the posture, velocity estimations. Though the gyroscope can only provide rough position information, the fusion between the gyroscope and VLP is a promising solution to tough situations with limited VLP sources.

7.2.3 VLP network

So far, the research works are mostly focused on using an individual unit to perform positioning. However, to cover a large space, like a supermarket or a transportation terminal, hundreds of units are required to perform continuous positioning and tracking. Hence, the boundary area of the units is the main challenge.

The idea of cooperation between units is to be vague in the concept of unit. Meaning that as long as receiving signals from at least three lamps, the position is solvable regardless of units. To achieve that, the management of the VLP network map is crucial. With continuous mapping, the signal received from any unit ID is allowed to involve in the calculation of adjacent IDs. An ID assignment scheme is desired to fulfill a hexagonal or square unit coverage with all adjacent IDs. Moreover, if the signals are received from over three lamps, the calculation based on SNR with adjustable weights shall also benefit the positioning accuracy among overlapped areas.

Author's Publications

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- S. Zhang, P. Du, C. Chen, and W.-D. Zhong, "3D Indoor visible light positioning system using RSS ratio with neural network," *2018 23rd Opto-Electronics and Communications Conference (OECC)*, Jeju Island, Korea (South), 2018.
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