INDOOR LOCALIZATION SYSTEM BASED ON VISIBLE LIGHT COMMUNICATION

A Dissertation in
Electrical Engineering
by
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ABSTRACT

With the rapid development of Global Positioning Systems (GPS), the field location based services (LBS) is getting more and more attention. For indoor environments, LBS has a wide application for both civil and industrial areas. To make indoor LBS available, positioning technology has become a popular research topic in recent years. This dissertation investigates several indoor positioning topics based on visible light communication (VLC).

First, it demonstrates the motivation to realize indoor LBS. Second, several positioning approaches are introduced to provide the location information. Positioning systems such as wireless local access network (WLAN), Zigbee, Bluetooth and radio frequency identification (RFID) are addressed. Third, fundamentals of VLC technology is detailed by explaining the light emitting diode (LED) as the transmitter, the photodiode (PD) as the receiver and the channel direct current (DC) gain considering the line-of-sight (LOS) condition.

Visible light positioning systems are realized with lateration techniques based on received signal strength (RSS) information detected by PD. Two channel access methods are detailed and their advantages and disadvantages are analyzed. When height information of the receiver is unknown, three dimensional positioning is realized with an iterative algorithm based on the pre-estimation of the vertical coordinates. In order to further improve the positioning accuracy and alleviate the effect of large deviations, Kalman filter, particle filter as well as Gaussian mixture sigma point particle filter (GM-SPPF) are applied for both 2-D and 3-D scenarios. Considering the vertical accuracy
cannot be improved largely from the filtering techniques, a nonlinear estimation algorithm is proposed based on a trust region algorithm.

Multipath propagation is one of the most important factors that affects the performance of indoor positioning systems. In this dissertation, impulse response with multipath reflections are analyzed with the combined deterministic and modified Monte Carlo (CDMMC) algorithm. The received optical power from different LED bulbs and the positioning accuracy for the entire room is detailed.

Orthogonal frequency division multiplexing (OFDM) is also proposed in the positioning system, considering OFDM performs well when multipath reflections exist. Positioning performance is largely improved with OFDM compared to On-off-keying (OOK) modulation. Finally, conclusions and future works are described in Chapter 9.
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<tr>
<td>ADC</td>
<td>analog-to-digital converter</td>
</tr>
<tr>
<td>AOA</td>
<td>angle of arrival</td>
</tr>
<tr>
<td>ACO-OFDM</td>
<td>asymmetrically clipped optical-OFDM</td>
</tr>
<tr>
<td>BFSA</td>
<td>basic framed slotted ALOHA</td>
</tr>
<tr>
<td>BLE</td>
<td>Bluetooth low energy</td>
</tr>
<tr>
<td>BOF</td>
<td>beginning of flag</td>
</tr>
<tr>
<td>CDF</td>
<td>cumulative distribution function</td>
</tr>
<tr>
<td>CDMMC</td>
<td>combined deterministic and modified Monte Carlo</td>
</tr>
<tr>
<td>CP</td>
<td>cyclic prefix</td>
</tr>
<tr>
<td>CPC</td>
<td>compound parabolic concentrator</td>
</tr>
<tr>
<td>CRC</td>
<td>cyclic redundancy check</td>
</tr>
<tr>
<td>CSMA/CA</td>
<td>carrier sense multiple access/collision avoidance</td>
</tr>
<tr>
<td>CSMA/CD</td>
<td>carrier sense multiple access/collision detection</td>
</tr>
<tr>
<td>DC</td>
<td>direct current</td>
</tr>
<tr>
<td>DCO-OFDM</td>
<td>DC biased optical OFDM</td>
</tr>
<tr>
<td>DD</td>
<td>direct detection</td>
</tr>
<tr>
<td>DPIM</td>
<td>digital pulse interval modulation</td>
</tr>
<tr>
<td>EOF</td>
<td>end of flag</td>
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<tr>
<td>FCS</td>
<td>frame correction sequence</td>
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<td>FDM</td>
<td>frequency division multiplexing</td>
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<tr>
<td>FET</td>
<td>field effect transistor</td>
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<tr>
<td>FFT</td>
<td>fast Fourier transform</td>
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<tr>
<td>FOV</td>
<td>field-of-view</td>
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<tr>
<td>Acronym</td>
<td>Definition</td>
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<tr>
<td>GI</td>
<td>guard interval</td>
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<tr>
<td>GM-SPPF</td>
<td>Gaussian mixture sigma-point particle filter</td>
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<tr>
<td>GMM</td>
<td>Gaussian mixture model</td>
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<tr>
<td>GPS</td>
<td>global positioning system</td>
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<tr>
<td>ID</td>
<td>identification</td>
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<tr>
<td>IFFT</td>
<td>inverse fast Fourier transform</td>
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<tr>
<td>IM</td>
<td>intensity modulation</td>
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<tr>
<td>IMU</td>
<td>inertial measurement unit</td>
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<tr>
<td>INS</td>
<td>inertial navigation system</td>
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<tr>
<td>ISI</td>
<td>inter-symbol-interference</td>
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<tr>
<td>ISM</td>
<td>industrial, scientific and medical</td>
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<tr>
<td>k-NN</td>
<td>k-nearest neighbors</td>
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<tr>
<td>LBS</td>
<td>location-based services</td>
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<tr>
<td>LED</td>
<td>light-emitting diode</td>
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<tr>
<td>LLSE</td>
<td>linear least square estimation</td>
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<tr>
<td>LOS</td>
<td>line-of-sight</td>
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<tr>
<td>LTI</td>
<td>linear time-invariant</td>
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<tr>
<td>MMC</td>
<td>modified Monte Carlo</td>
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<tr>
<td>NLOS</td>
<td>non-line-of-sight</td>
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<td>OOK</td>
<td>on-off-keying</td>
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<tr>
<td>OFDM</td>
<td>orthogonal frequency-division multiplexing</td>
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<tr>
<td>PAM-DMT</td>
<td>pulse-amplitude-modulated discrete multitone modulation</td>
</tr>
<tr>
<td>PAPR</td>
<td>peak to average power ratio</td>
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<tr>
<td>PD</td>
<td>photodiode</td>
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<tr>
<td>PDA</td>
<td>personal digital assistant</td>
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<tr>
<td>Abbreviation</td>
<td>Description</td>
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<tr>
<td>PDF</td>
<td>probability density function</td>
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<td>PPM</td>
<td>pulse position modulation</td>
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<tr>
<td>PSD</td>
<td>power spectrum density</td>
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<td>PSK</td>
<td>phase shift keying</td>
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<tr>
<td>RF</td>
<td>radio frequency</td>
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<tr>
<td>RFID</td>
<td>radio-frequency identification</td>
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<tr>
<td>RMS</td>
<td>root-mean-square</td>
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<td>RSS</td>
<td>received signal strength</td>
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<tr>
<td>RTOF</td>
<td>roundtrip time of flight</td>
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<td>QAM</td>
<td>quadrature amplitude modulation</td>
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<tr>
<td>SNR</td>
<td>signal-to-noise ratio</td>
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<tr>
<td>SPA</td>
<td>sigma-point approach</td>
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<tr>
<td>SVM</td>
<td>support vector machine</td>
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<tr>
<td>TDMA</td>
<td>time-division-multi-access</td>
</tr>
<tr>
<td>TDOA</td>
<td>time difference of arrival</td>
</tr>
<tr>
<td>TOA</td>
<td>time of arrival</td>
</tr>
<tr>
<td>UWB</td>
<td>ultra-wide band</td>
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<tr>
<td>VLC</td>
<td>visible light communications</td>
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<tr>
<td>VPPM</td>
<td>variable PPM</td>
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<tr>
<td>WLAN</td>
<td>wireless local area network</td>
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I would like to dedicate this dissertation to my parents, my friends, their understanding and support made this possible.

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Chapter 1

Introduction and Overview

1.1 Motivation

Location Based services (LBS) make use of the position information from the mobile devices to provide related services [1]. The global positioning system (GPS) has been developing since the 1970’s, where the precise location information is available through satellite infrastructures. Since then, LBS has been proposed and developed rapidly. From late 1990s, technologies to realize LBS began to boom when the mobile network services came into a prosperous era.

With the location data of the user, many related services can be provided to make life more convenient. For example, a user can easily get the information of social events happened in the city he/she stays; nearest business or services, such as banks, restaurants, grocery stores and shopping malls can be located; turn by turn navigation is offered and people are able to avoid traffic jam by personalizing their own routes in the aspects of cost, time consumption and distance. With the information of nearby friends, social network is easy to be built up. Location based mobile advertisements can be promoted which benefit both businesses and customers. LBS can even assist health care for
disabled people or kids. Several apps have been developed for LBS, such as yelp\textsuperscript{1}, Groupon\textsuperscript{2} and Tinder\textsuperscript{3}.

1.2 Objectives

Figure 1-1. Examples of LBS: (a) Indoor navigation on the mobile phone\textsuperscript{4}. (b) Indoor map for user guidance\textsuperscript{5}.

In recent years, many large indoor places have been constructed such as shopping malls, airports, museums and exhibition halls. It is difficult for people to find their own locations, directions and friends in these areas. Fig. 1-1 shows an example of LBS in a shopping mall. Online advertisements, coupons and discount information are provided to

\textsuperscript{1} https://en.wikipedia.org/wiki/Yelp
\textsuperscript{2} https://en.wikipedia.org/wiki/Groupon
\textsuperscript{3} https://en.wikipedia.org/wiki/Tinder_(app)
\textsuperscript{4} Citation source: https://www.broadcom.com/press/release.php?id=836818
\textsuperscript{5} Citation source: http://www.citadeloutlets.com/pdfs/directorymap.pdf
make shopping easier. In order to realize LBS, an economical and robust indoor positioning system is the key element that provides location information of users.

Indoor localization also finds its significant application in industry to assist the operation of robots. As artificial intelligent is an emerging technology in recent years, using robots to replace human beings is a tendency in current industry. In this way, production is increased, information of producing process is secured and some dangerous operations can be avoided. In order to obtain the current location of a robot, a precise localization system is indispensable [2][3].

![Figure 1-2 Attenuation of satellite signal.](image)

Although for outdoor environments, GPS can provide location [4], it cannot be appropriately applied for indoor environments for the following reasons. First, as shown in Fig. 1-2, satellite signals attenuate heavily when penetrating through solid walls, so GPS signal is not detectable in many indoor locations; Second, GPS estimates the user coordinates from the travelling time information of the signal. For indoor environments,
signals suffer severely from multipath reflections where the accuracy of time information is largely affected and the positioning performance is heavily degraded; Third, even for outdoor environments, the positioning accuracy of GPS is 7.8 m of 95% confidence interval error and 4 m of root mean square (RMS) error, which is not accurate enough for the application of indoor scenarios.

With the increasing demand of indoor location systems, several technologies have been taken into consideration such as wireless local area network (WLAN), radio frequency identification (RFID), ZigBee, Bluetooth, assisted-GPS and visible light communication (VLC) [5][6]. This dissertation focuses on VLC based indoor localization, and introduces the positioning algorithm and the system configuration. Filtering technologies and a nonlinear estimation algorithm are applied to improve the positioning accuracy and system robustness. The effect from multipath reflections is analyzed and modification approaches are detailed. In addition, orthogonal frequency-division multiplexing (OFDM) is applied to increase the immunity against multipath reflections.

1.3 Organization

As shown in Fig. 1-3, the organization of the rest of this dissertation includes four blocks. As a multi-disciplinary topic, the background knowledge include the fundamentals of positioning technology and VLC technology. Chapter 2 demonstrates positioning algorithms and current localization systems. Chapter 3 introduces VLC technology in the aspects of transmitter, receiver and optical channel.
In the second block, the realization of the positioning system with VLC technology is detailed. The system model is demonstrated and channel access methods are addressed and compared. Positioning algorithms for 2-D and 3-D scenarios are detailed based on received signal strength (RSS) information and trilateration techniques.

The third block targets improving the positioning performance in four aspects. In Chapter 5, filtering techniques including Kalman filter, particle filter and Gaussian mixture sigma point particle filter (GMSPPF) are applied to further increase the positioning accuracy and alleviate the effect of large deviations. In order to increase the vertical accuracy, Chapter 6 introduces a new positioning algorithm based on the nonlinear estimation, and the trust region reflective algorithm is the solver. Considering the complex indoor environment, the impact of multipath reflections is analyzed in Chapter 7. In Chapter 8, OFDM modulation is applied to improve the positioning performance. Finally, Chapter 9 as the fourth block concludes the dissertation and provides prospects for the future work.
Chapter 2

Positioning Algorithms and Systems

Considering the complex indoor environment, it is difficult to model the signal propagation when severe multipath reflections exist and line-of-sight (LOS) condition cannot be satisfied. Several positioning algorithms, as shown in Fig. 2-1, are developed which are mainly in three categories: triangulation, scene analysis and proximity. We will focus on the application of these algorithms on short range indoor localization. Positioning systems based on different technologies will be introduced in this chapter. Finally, the indoor positioning system based on VLC is demonstrated and recent research results in this area is detailed.

Figure 2-1 Indoor localization Methods/Algorithms
2.1 Triangulation

Coordinates of the target are estimated according to the geometric properties of triangles, and lateration and angulation are two branches of trilateration. The lateration makes use of the distance information from several reference points to the target, while angulation locates the target by analyzing the incident angles of the signals.

2.1.1 Lateration

(a) Distance estimation based on time

![Diagram of Lateration](image)

Figure 2-2 Positioning based on TOA/RTOF/RSS

The traveling time from a transmitter to a receiver is detected as time of arrival (TOA) information, therefore the distance is able to be estimated with the knowledge of
the traveling speed of the signal. In the limited indoor range, this speed is considered to be a constant. In most situations, at least three reference points are needed to realize 2-D localization. As shown in Fig. 2-2, the target location is estimated as the intersection of the three circles [7].

The GPS system is an example which utilizes the TOA information to realize localization. However, the travelling distance is short in the indoor range, so high precision is required on the detection of TOA information. What is more, synchronization between the transmitter and receiver should be achieved. TOA-based lateration can be used in the Ultra-wide band (UWB) technology [8].

Figure 2-3 Positioning based on TOA.
However, in most cases, systems using TOA information are too expensive to deploy so it is not suitable for civil application. Instead, time difference of arrival (TDOA) information is easier to be detected. As shown in Fig. 2-3, the receiver is estimated at the intersection of at least two hyperboloids [2]. Only the distance differences $R_{12}$ and $R_{13}$ should be calculated so the requirement of detection accuracy is decreased. As shown in Fig. 2-2, the system based on roundtrip-time-of-flight (RTOF) information does not require time synchronization between the transmitter and the receiver. As a conclusion, for short range indoor positioning, time-based methods are expensive to deploy and easy to be affected by time delay, reflections and measurement precision. The positioning error is up to a few meters [9].

**b) Distance estimation based on signal attenuation.**

For positioning systems with the time based distance estimation, the hardware complexity and cost is high and these systems can only be used in some specific areas. RSS information is more commonly used in lateration techniques, which is based on the relation between the path loss and the travelling distance. In addition, this relation can be modified according to the pre-estimation process in some specific scenarios. In Ref. [10], propagation models are estimated to simulate the real transmission environments, which outperforms conventional models in the RSS-based indoor localization.

### 2.1.2 Angulation

When a directional antennae or an array of antennas are used, the incident angles from several transmitters can be detected as the angle of arrival (AOA) information. By
finding out the direction line of each angle, the target can be located at the intersection.

As shown in Fig. 2-4, with the detected information $\theta_1$ and $\theta_2$, the target is estimated at the intersection point. In Ref. [11], the AOA information is detected with three antenna arrays for the RFID based system. The AOA information is combined with the TOA information in a UWB positioning system, and combined with the RSS information in a WLAN system [12] [13]. One advantage of the AOA based systems is that the posture of the receiver will not largely affect the coordinate estimation. However, complex hardware requirements and expensive detection devices are the shortcomings of AOA based systems. In addition, the accuracy of AOA information are heavily degraded by in the non-line-of-sight (NLOS) condition.

![Figure 2-4 Positioning based on AOA.](image)
2.2 Scene Analysis

The scene analysis approach as shown in Fig. 2-5 includes two stages and is usually applied in the radio frequency (RF)-based systems. In the offline stage, a site survey is conducted to collect all the corresponding features as fingerprint for each location. The RSS information from the nearby transmitters are usually considered as fingerprints. During the online stage, features of the current location are collected and matched with the fingerprints stored in the database to figure out the current coordinates. Considering RF based systems suffer from severe multipath reflections, scene analysis is an appropriate approach to resist the effect of the reflections from walls, floors and furniture since these surfaces are static. However, when there are some moving surfaces such as human bodies, the errors may increase largely unless the database can be updated fast enough, which in turn will occupy a lot of bandwidth. Pattern recognition techniques are usually employed to match the fingerprints including probabilistic methods, neural networks, k-nearest-neighbor (kNN) and support vector machine (SVM). In Ref. [14],
visual features are collected from images and scene classifications and recognitions are conducted. A novel RSS based algorithm makes use of statistical analysis on the WLAN signal to achieve high accurate localization. RMS error is reduced more than 20 percent and the number of training locations is decreased without degrading too much positioning performance [15].

2.3 Proximity

Figure 2-6. Positioning based on proximity.

Proximity is a straight-forward approach to estimate the location based on a dense grid of reference points with known coordinates. When a mobile target detects the signal from one of the transmitters, the receiver is considered to be collated with the transmitter. If more than one signals are detected, the receiver is considered to be collocated with the
reference point that sends the strongest signal. As shown in Fig. 2-6, the target is considered to share the same coordinates with reference point A. The proximity algorithm is easy to be implemented in Bluetooth, Zigbee, and RFID systems. However, the accuracy usually relies on how dense the grid is. Therefore, it is always difficult to achieve the deployment cost and the positioning accuracy at the same time. A hybrid positioning system combining light-emitting-diodes (LEDs) and Zigbee network was proposed to realize indoor localization expended up to 77 m long [16]. Ref. [17] proposed a prototype mixed-mode wireless indoor localization system based on proximity. The radio nodes of the network work in two power modes so that rough and precise positioning can be realized optionally.

2.4 Indoor positioning systems

Based on the above positioning algorithms, several systems are proposed with different technologies. Current indoor wireless positioning systems mainly include two categories [5]. The first category is to build up one's own network infrastructure which primarily focuses on localization purposes. Relatively high accuracy can be achieved while the deployment cost is high. Another category makes use of the existing network to locate a target, which is usually economical but the accuracy is not satisfactory. In the following part, an overview for these systems are demonstrated.

2.4.1 Assisted-GPS
As GPS signal attenuates dramatically when passing through solid walls, there are mainly two approaches of assisted-GPS to make it applicable for indoor environments. GPS utilizes the time-based information to estimate the distances. In one approach, the sensitivity of the receiver is improved so that the GPS signals can be detected inside of a building or even in a deep urban area. In Ref. [18], an assisted-GPS receiver is designed with reduced squaring loss so that the weak GPS signal whose strength is less than -150 dBm can be detected within 2~3 seconds. Another approach makes use of mobile station based services where a location server is employed. The satellite signals are simultaneously detected at the mobile station with a partial GPS receiver, therefore, the weak GPS signals inside a building can be detected. In Ref. [19], a roof-antenna with known location is used to get access to satellite signals in the LOS condition. The user obtains the data from the antenna through wireless network.

2.4.2 Bluetooth

As a wireless technology which covers short distances, Bluetooth utilizes the industrial, scientific and medical (ISM) band from 2.4 GHz to 2.485 GHz. Bluetooth is proposed to realize indoor localization for the following two reasons: first, Bluetooth is ubiquitously embedded in most phones, tablets and personal digital assistants (PDA), therefore in the receiver side no more hardware cost will be introduced. Second, Bluetooth signal usually ranges around 10 m to 15 m, which makes it an appropriate technique to employ proximity algorithms as the signals from different transmitters will not interfere too much with each other. Especially since Bluetooth 4.0 or Bluetooth Low Energy (BLE) was developed in recent years, the low energy consumption can be
achieved. Accordingly, the Bluetooth-based indoor localization is becoming a practical approach to locate the user who carries blue-tooth embedded devices. In one system, with the measurement of received signal strength indicator information, BLE-based localization schemes are provided by generating a small region where the object is ensured to be located rather than an arbitrary coordinate [20]. In another system, the device inquiry scheme and service discovery protocol are designed so that the connections can be robustly established. The positioning algorithm is based on scene analysis as data is trained in the first phase and location is estimated in the second phase, where the Weibull distribution model is used [21].

2.4.3 RFID

RFID readers make use of the distribution of electromagnetic field to identify and track tags which are attached to the users. Passive tags are small and inexpensive, which can operate without a battery, but their reading range is only 1~2 m. Active RFID tags can actively transmit their identification (ID) up to tens of meters. A well-known RFID positioning system is LANDMARC, which utilizes active RFID tags operating at the frequency of 308 MHz. In Ref. [22], extra tags are used so that the readers’ number can be decreased. Signal strength information is obtained and kNN method is used to locate the RFID tags. Recently, Mojix\(^6\) promoted their RFID localization system in various

\(^{6}\)http://www.mojix.com/
markets such as Retails, Oil & Gas, Manufacturing, Healthcare and Event Security & Safety.

2.4.4 Geo-Magnetism

The rapid development of sensor techniques enables the utilization of geo-magnetism in indoor localization. Theoretically speaking, the magnetic field of each point on the earth is identical, although their differences are difficult to be detected with normal devices. The structural steel elements in a building disturb the magnetic fields and enhance these differences in indoor environments. As these magnetic fields are spatially varied but temporally stable, Geo-Magnetism is appropriate to be used in indoor localization. The magnetic field is usually measured with an array of e-compasses, and then matched to a pre-acquired magnetic map. The system proposed in Ref. [23] includes a magnetic fingerprint map and a client device which detects the magnetic signature of the current position. The accuracy within 1 m in 88% of the time is experimentally demonstrated. Monte Carlo localization is proposed as the algorithm and a series of global localization experiments are conducted in four arbitrarily selected buildings to demonstrate the feasibility of the Geo-Magnetism based system [24].

2.4.5 UWB

As shown in Fig. 2-7, the bandwidth of UWB in frequency domain is ultra-wide and the pulses which are more than 500 MHz can be used for impulse modulation. Since
a wide range of frequency components are included, the possibility that the wave transmits through or around obstacles is increased. Accordingly, the system reliability is improved. As the UWB signal usually spreads over a large frequency range, i.e., from 3.1 to 10.6 GHz, the power spectral density (PSD) is decreased and the interference is reduced compared to other RF based systems. As the pulse width is just 0.5 ns, accurate TOA/TDOA information of the corresponding transmitter is able to be collected. In Ref. [25], UWB tags are combined with transmitters while the UWB reference nodes are collocated with both transmitters and receivers. Impulse radio UWB transceiver are employed as test setup and TDOA information are obtained at different positions. Cross correlation method is employed to estimate the time-delay and target coordinates [26].

![Time and Frequency property of UWB](image)

**Figure 2-7 Time and Frequency property of UWB.**

### 2.4.6 WLAN

As WLAN is a popular technology for indoor communication, currently localization based on WLAN is a hot research topic. As the WLAN signal is transmitted
in the band of 2.4 GHz, the performance is easily affected by the orientation of antennas, obstacles, positions of reference points and multipath reflections. The accuracy of the typical WLAN positioning system ranges from 3 m to 30 m, and the sampling rate is up to a few seconds. A common applied algorithm in the WLAN-based positioning system is scene analysis. A site survey is conducted first to collect RSS fingerprints and then the current location is found out with the matching algorithms. Spectral clustered time-stamped RSS data are utilized to describe the layout of indoor environments [27]. Spectral clustering is performed to classify the pre-collected RSS data, logic graphs are constructed and mapped into ground-truth graphs. In the online phase, area-level positioning can be achieved by estimating the smallest Euclidean distances between the current detected RSS information and the centers of the nodes.

2.4.7 Inertial Navigation System (INS)

INS is based on a straight-forward principle, i.e., integrate the velocity and the orientation at each time unit to obtain the current location. The platform modus contains motion sensors so that the postures such as roll, yaw and pitch angle are detected. As the components of inertial measurement unit (IMU), accelerometers are used to measure the linear acceleration, rotation sensors are applied to detect the angular velocity and magnetic sensors are utilized for calibration. INS technology has a long history and originally it is used on the vehicles such as ships, aircrafts, submarines and spacecraft. By dead reckoning the velocity and orientation, positions can be obtained with a known starting point and no external reference measurements are needed. However, all the INS
suffer from integration drift, i.e., small errors in the acceleration and the angular velocity accumulate progressively, and finally larger errors exist after a long time. Therefore, as shown in Fig. 2-8, the estimated coordinates must be calibrated periodically by the input from other localization systems. A strap-down INS is proposed containing an IMU which implements a dead reckoning algorithm. Bluetooth v4.0 technology is used to calibrate the drift errors so that the INS can deliver high accuracy positioning [28].

![Figure 2-8 Block diagram of INS.](image)

### 2.4.8 ZigBee

Based on the IEEE 802.15.4 protocol, ZigBee technology is able to set up a personal area network using small and low power radios. A ZigBee system is composed of coordinators, routers and end devices. Zigbee is a simpler and less expensive technology than Bluetooth and Wi-Fi, and is widely used in traffic control systems, smart home display and wireless switches. ZigBee network is easy to expend and the transmission distance is from 10 m to 100 m, which makes it appropriate to be used in indoor localization system. Since both WLAN and Bluetooth work under the 2.4 GHz frequency, RSS information of Zigbee signal is easily to be disturbed and positioning
accuracy will be largely affected. Therefore, two localization mechanisms are proposed and the first one is based on the localization map. All the nodes except the one collocated with the user are presumed to have fixed known coordinates. A site survey is conducted to collect the disturbed RSS fingerprints as a vector data and stored in a database. A mobile receiver estimates the current location by matching the current RSS to the fingerprint maps with k-NN algorithm. Another mechanism is to estimate the distance information with Markov chain inference, where mobile target’s behavior is estimated. Optimal decision is computed for the uncertainty of the behavior, and the estimated distance is used to update the predefined positions [29].

2.5 VLC

VLC technology utilizes fluorescent lamps and LEDs to transmit signal, the latter is more frequently used as the light signal can be modulated to a very high data rate. Compared with traditional illumination approaches, LEDs have a lot of advantages such as long life expectation, high lighting efficiency, design flexibility and environmental friendliness [30].

Considering the increasing users of multimedia services provided through cellular networks and WLAN, more and more tablets and smartphones induce exploded total capacity per cell. Electromagnetic spectrum is very crowded and more bandwidth are needed [31] [32]. One solution is to shift the bandwidth to a higher frequency, which will induce more path loss in propagation. As a result, stable connection cannot be provided. Another solution is to decease the base station spacing so the path loss becomes less
severe. By shrinking the spacing to the half of its original size, the total capacity will be increased four times and frequency reuse is more efficient. Less link margin is generated with smaller cells, therefore, the path loss induced by using higher frequency will be offset. To reach higher capacity, there is a tendency to deploy femtocells, whose size is just on the order of ten meters. However, there are several problems such as more frequent handovers, more complicated resource allocation and higher cost in the computation of reuse algorithm, etc [33].

Using VLC technology for indoor communication benefits the wireless industry since it does not occupy any RF band. Besides the avoidance of spectrum crunch, several other advantages are provided when the positioning systems are based on VLC technology. Positioning services can be offered universally wherever the lighting infrastructures exists, even in some environments that RF radiation is dangerous or even forbidden, such as hospitals with a lot of medical equipment and nucleus industries. VLC-based localization systems can fit in these RF-prohibited areas perfectly since no electromagnetic interference will be generated. In addition, as mentioned in previous section, in the two categories of current positioning systems, the systems using the existing network cannot provide satisfactory positioning accuracy while the systems using their own infrastructures bring up the deployment cost. Indoor positioning systems based on VLC technology possess both advantages of these two categories. As it utilizes the existing illumination facilities, the deployment cost is minimized. At the same time, as light wave has relatively shorter wavelength than radio wave, it suffers less effect from multipath reflections, therefore, the positioning accuracy is satisfactory.
In the light positioning system, LEDs are the reference points and a photodiode (PD) collocated with the user is the target. In Ref. [34], a TOA-based VLC positioning system is proposed, where perfect synchronization between the transmitter and the receiver is assumed. By deriving the Cramer-Rao boundary for the windowed sinusoidal waves, the theoretical limit on the estimation accuracy is analyzed. Using a coherent heterodyne detection method, a TDOA-based VLC localization system is proposed. Gaussian noise is considered for the mathematical model and three stages of estimation algorithms are used to minimize the effect from the noise [35]. RSS-based lateration systems are widely investigated due to the simplicity of the distance estimation algorithm as well as low requirements of the detection devices [6]. Angulation technique is also used to realize indoor localization in the VLC system, where an image sensor usually acts as the receiver to obtain AOA information. In order to distinguish the transmitters, the colored LEDs are used. The system was experimentally tested and the accurate positioning was enabled on a robot [36]. In a scene analysis based light positioning system, a new value named as correction sum ratio is defined [37]. These values are obtained with a site survey. When a mobile terminal (MT) knows its current value at an arbitrary location, its coordinates can be decided and the positioning accuracy around 1 cm can be delivered. In another system, proximity techniques are utilized in a small experimental area where four LEDs are the transmitters with different IDs. One hundred observed positions are tested at different heights and grouped differently to achieve high accurate localization [38].

Besides all the above methods, VLC are also combined with other technologies to further improve the system performance. Zigbee technology is combined with VLC so
that long distance positioning can be realized [16]. With the assistance of a six-axe sensor, i.e., geomagnetic sensor and gravity acceleration sensor, a switching estimated receiver positioning system is proposed to achieve high accuracy [39]. By hybridizing with an accelerometer, three dimensional light localization system can be realized without the knowledge of the receiver height [40]. Filtering techniques are utilized such as Kalman filter, particle filter and Gaussian mixture sigma point particle filter to further increase the positioning accuracy and prevent from large deviations [41][42].
Chapter 3
Fundamentals of VLC technology

As shown in Fig. 3-1, the carrier frequency of RF ranges from 30 MHz to 5 GHz, and band of VLC lies in the THz region. In RF communication systems, the wavelength of the carrier ranges from centimeter to kilometer, while in the VLC, wavelength is about several hundred nanometers. The properties of VLC will be discussed in this chapter, including the transmitter, the receiver and channel characteristics [43].

![Visible light spectrum](image)

Figure 3-1 Wavelengths and frequencies of radio and optical carriers.

3.1 Transmitter

As the transmitter, one LED bulb is composed of a number of LED chips as shown in Fig.3.2 (a). LEDs are not monochromatic, i.e., they generate lights with a broad spectrum. Fig. 3-3 shows the standard eye response curve, the warm white and ultra
white LED spectrum. The carriers of the signal are not in-phase, in other words, the emitted light is non-coherent. In addition, LEDs usually have a bandwidth ranges from 20 MHz to 100 MHz, and the output of an LED source follows a specific radiation pattern that obeys Lambertian law [44]. The spatial power distribution is expressed mathematically as:

\[ I_\theta = I_0 \cos^m \theta \]  

(3-1)

In the above equation, \( I_0 \) is the intensity in direction of the LED symmetrical axis, i.e., the normal direction. \( I_\theta \) is the intensity in the direction that has an angle of \( \theta \) with the normal direction. Parameter \( m \) represents the Lambertian order and is expressed as:

\[ m = \ln 2 / \ln(\cos(\Phi_{1/2})) \]  

(3-2)

where \( \Phi_{1/2} \) is the semi-angle of half illuminance of the LED. When \( m \) equals 1, the spatial power distribution is shown in Fig. 3-4 where each wedge represents an equal spatial angle \( d\Omega \). \( dA \) is the emitting elementary area and \( I_0 \) is the radiance with unit of photons/(s·cm²·sr). Therefore, the observer in the normal direction will receive \( I_0 d\Omega dA \) photons per second, while the observer in the direction of angle \( \theta \) to the normal receives \( I_0 \cos(\theta) d\Omega dA \) photons per second. The total intensity emitted by a source is:

\[ I = \iint_{source} I_0 \cos(\theta)dA \]  

(3-3)
Figure 3-2 (a) Transmitter (b) Receiver.

Figure 3-3 Relative spectral emission from LED (LE CWUW S2W from OSRAM)\(^7\)

---

As the LEDs are also applied for the illumination purpose, the luminance should be considered where 300 to 1500 lx (1 lx = 1 lm/m²) is usually required for the working environment [45]. The luminous flux $\Phi$ is the unit that indicates the light emitted over a solid angle, which also shows the brightness of a source.

$$\Phi = K_m \int_{\lambda_{\text{min}}}^{\lambda_{\text{max}}} V(\lambda) \Phi_e(\lambda) d\lambda , \quad (3-4)$$

where $K_m$ is the maximum visibility which is around 683 lm/W at 555 nm wavelength. $[\lambda_{\text{min}}, \lambda_{\text{max}}]$ is the wavelength range of the visible light spectrum, $V(\lambda)$ is the standard luminosity curve, and $\Phi_e(\lambda)$ is the luminous flux per wavelength.

Figure 3-4 Emission rate (photons/s) in a normal and off-normal direction.
3.2 Receiver

A PD is commonly used as the receiver in VLC. An output current or voltage is generated which is proportional to the received optical power on the detection area. PD also has a limited bandwidth which ranges from several MHz to several GHz. The larger the bandwidth is, the smaller the detection area is [46]. The responsivity $R$ of PD is one of the most important parameters that determines its performance which is expressed as:

$$R = \frac{\eta q}{h \nu} \quad (3-5)$$

---

$\eta$ is the quantum efficiency, $h\nu$ is the incident photon energy and $q$ is the electron charge. Fig. 3-5 shows the responsivity curve of a PD (APD 120A2) manufactured by Thorlabs, Inc. The responsivity is highest at 600 nm as 25 A/W and then decreases rapidly when the wavelength becomes smaller and larger. In order to achieve better communication performance, a proper PD should be selected whose responsivity curve is flat over the wavelength generated by the LED.
Figure 3-6 Optical concentrators: (a) hemisphere with planar optical filter (b) hemisphere with hemispherical optical filter (c) CPC with planar optical filter.
Figure 3-7 Receiver structures combining CPCs with bandpass optical filters to achieve different acceptance angles: (a) dielectric CPC combined with parabolic hollow CPC, (b) dielectric CPC combined with hollow CPC having a straight section.

In order to maximize the received optical power, optical filters and concentrators are used. Optical filters are usually applied to pass the signal by attenuating ambient radiations. The design of a receiver with a large detection area can decrease the effect of path loss [47][48]. As shown in Fig. 3-6 (a), a hemisphere lens is placed on a planar filter, and a PD with concentrator gain around $n_c^2$ is mounted, where $n_c$ is the concentrator’s refractive index. However, this design is not proposed since the incident angle $\psi$ will make changes on the incident angle $\theta$. As a result, the filter transmission $T_s(\psi)$ will be decreased at certain $\psi$. Another design is shown in Fig. 3-6 (b), to maximize the transmission, the filter is bonded on the hemispherical surface of the concentrator. Fig. 3-
6 (c) is the compound parabolic concentrator (CPC), which is widely used in VLC as higher gain can be achieved compared with the hemisphere concentrator. The optical filter is placed at the front surface and the gain is expressed as:

\[
g (\psi) = \begin{cases} \frac{n^2}{\sin^2(\psi_c)}, & 0 < \psi < \psi_c \\ 0, & \psi > \psi_c \end{cases}
\]  

(3-6)

However, the field of view (FOV) of a CPC is small. As shown in Fig. 3-7(a), a hollow CPC is placed on the top of a traditional CPC to achieve larger FOV. In this way, radiations from an angel of 90 degree can be accepted by the upper CPC and then transferred to the angle within the FOV of lower CPC. A modification has been proposed as shown in Fig. 3-7(b), where a straight part is added on the upper CPC, and any angle between FOV of lower CPC and 90 degree can be received.

### 3.3 Channel DC gain

Intensity Modulation (IM) is applied in VLC where the intensity of emitted light signal is modulated. Therefore, the modulated signal has to be real and positive in the baseband. PD utilizes direct detection (DD) to collect the optical signal where the current or voltage is generated proportional to the light intensity striking on the active receiving area. As shown in Fig. 3-8, Channel DC gain [48] is used to estimate the LOS link, which is expressed as:
\[
H(0) = \begin{cases} 
\frac{m+1}{2\pi d^2} A \cdot \cos^m(\phi) \cdot T_s(\psi) \cdot g(\psi) \cdot \cos(\psi), & 0 \leq \psi \leq \Psi_c \\
0, & \psi > \Psi_c 
\end{cases}
\]

(3-7)

In the above equation, \(A\) is the active receiving area of the PD, \(\phi\) is the irradiance angle of the transmitter with respect to its normal axis, \(\psi\) is the incident angle of receiver with respect to its normal axis. \(T_s(\psi)\) is the transmission of optical filter, \(g(\psi)\) is the concentrator gain, \(\Psi_c\) is the semi-angle of FOV and \(m\) is the Lamberton order. The received optical signal power \(P_r\) is expressed as: \(P_r = H(0) \cdot P_t\), where \(P_t\) denotes transmitted power.

Figure 3-8 Geometry in our DC gain calculation.
As shown in Fig. 3-9, on-off-keying (OOK) is a popular pulse amplitude based modulation scheme. Both return-to-zero and non-return-to-zero schemes are applied to modulate the intensity of the optical source [49]. An information subframe is followed by a compensation time (CT) subframe, which adjusts the “on”/”off” duration to achieve the desired dimming requirement [50].

![Figure 3-9 Two level modulation schemes.](image)

Pulse position modulation (PPM) is an orthogonal modulation approach, which can achieve high power efficiency. However, the bandwidth requirement and the device complexity are also high. There are three types of errors in this modulation scheme: the first one is erasure error. When a noise forces pulse to be below the threshold level, it cannot be detected. The second one is false alarm error, where a transmitted zero is detected as a one. The third one is wrong slot error, where a pulse is detected in a slot near to the correct one. Variable-PPM (VPPM) is a modified PPM scheme, which increases or decreases the pulse width considering the required dimming level. Digital Pulse Interval Modulation (DPIM) is another modification where the symbol length is
variable and an additional guard slot is usually added to each symbol to avoid the
adjacent zeroes [51]. There are two advantages of DPIM: first, the power efficiency or
the bandwidth efficiency is high; second, there is no synchronization requirement.

In this dissertation, we will focus on the OOK based positioning system. The noise
follows Gaussian distribution, which is composed of shot noise and thermal noise [48]. The
total variance of the noise is expressed as:

\[ N = \sigma^2_{thermal} + \sigma^2_{shot}. \]  

(3-8)

\( \sigma^2_{thermal} \) is the variance of thermal noise and expressed as:

\[ \sigma^2_{thermal} = \frac{8\pi k T_k}{G} \eta A I_2 B^2 + \frac{16\pi^2 k T_k \Gamma}{g_m} \eta^2 A^2 I_3 B^3 \]  

(3-9)

The first term at the left side of Eq. (3-9) represents the noise from the feedback-
resistor, \( T_k \) is the absolute temperature, \( k \) is the Boltzmann’s constant, \( G \) is the open-loop
gain, \( \eta \) is the fixed capacitance per unit area of the photo detector, \( I_2 \) and \( I_3 \) are the
noise bandwidth factors, \( B \) is the equivalent noise bandwidth. The second term represents
the noise from the field-effect transistor (FET) channel, \( \Gamma \) is the noise factor of FET
channel, \( g_m \) is the FET trans-conductance.

The variance of shot noise is expressed as:

\[ \sigma^2_{shot} = 2q \gamma (P_{rec}) B + 2q I_{bg} I_2 B \]  

(3-10)

, where \( q \) is the electronic charge, \( I_{bg} \) is background current and \( \gamma \) is the responsivity of a
PD. The noise from the gate leakage current is neglected considering the p-i-n/FET trans-
impedance receiver is used in the system. \( P_{rec} \) is all the received power including the
ambient light such as sunlight and other illumination light. The parameters used in this dissertation is shown in the following tables.

Table 3-1 Parameters of noise estimation.

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Absolute temperature $T_K$</td>
<td>295 K</td>
</tr>
<tr>
<td>Boltzmann’s constant $k$</td>
<td>$1.381 \times 10^{-23}$ K$^{-1}$</td>
</tr>
<tr>
<td>Open-loop voltage gain $G$</td>
<td>10</td>
</tr>
<tr>
<td>Fixed capacitance per unit area $\eta$</td>
<td>112 pF/cm$^2$</td>
</tr>
<tr>
<td>Noise bandwidth factors $I_2$</td>
<td>0.562</td>
</tr>
<tr>
<td>Noise bandwidth factors $I_3$</td>
<td>0.0868</td>
</tr>
<tr>
<td>Noise factor of FET channel $\Gamma$</td>
<td>1.5</td>
</tr>
<tr>
<td>FET trans-conductance $g_m$</td>
<td>30 mS</td>
</tr>
<tr>
<td>PD responsivity $\gamma$</td>
<td>0.54 A/W</td>
</tr>
<tr>
<td>Background current $I_{bg}$</td>
<td>5100 $\mu$A</td>
</tr>
<tr>
<td>Electronic charge $q$</td>
<td>$1.602 \times 10^{-19}$ C</td>
</tr>
</tbody>
</table>
Chapter 4
Visible light positioning system for 2-D and 3-D scenarios

4.1 System configuration and Channel Access Method

A typical optical positioning system model is shown in Fig. 4-1, where the green dots represent LEDs stalled on the ceiling at a height of 3.5 m. Considering that the entire room is symmetrical, one cell with a size of 6 m* 6m is used to analyze the positioning performance. The blue cube is the receiver located at a height of 1.2 m. The coordinates of the four LED are (2, 2), (2, 4), (4, 2) and (4, 4). Each of the transmitters is assigned with a unique ID code to denote their coordinates. A driver circuit is used to modulate the signal in OOK format. Theoretically, only three LEDs are enough for the coordinate estimation. However, considering that the traditional lighting bulbs are installed in the
square layout, the four-LED cell design will not change the basic configuration of an LED illumination system.

4.1.1 Time division multiple access (TDMA)

Since all of the LED bulbs transmit their coordinate information independently, the signals will interfere with each other in the air and cannot be retrieved correctly. Therefore, channel access methods should be addressed to solve this problem. TDMA is one of the proposed solutions. All the transmitters have synchronized frames and occupy different time slots in one frame period to send their signals. The frame structure is shown in Fig. 4-2. When one LED transmits its ID information, all the other LEDs emit constant light intensity for the illumination purpose [52].

![Frame structure of the positioning system for one period.](image)
4.1.2 Basic Framed Slotted ALOHA (BFSA)

Figure 4-3 Basic framed slotted ALOHA protocol (a) a successful transmission and (b) a transmission failure since two transmitters select the same slot.

One disadvantage of TDMA is that the synchronization is required, i.e., all the time slots of the transmitters should start at the same time and the receivers should also know the start time, which increases the deployment cost. BFSA is proposed as an asynchronous protocol where the transmitters and the receiver do not need to have the same start point of each time slot. A fixed number of time slots are defined in a frame structure for each transmitter. Each transmitter selects one slot randomly in the entire frame to delivery signals. Suppose there are \( l \) transmitters to compete for the \( L \) slots, \( L \geq l \) must be satisfied [53]. Fig 4-3 demonstrates the working principle of BFSA when \( l \) equals 4. As shown in Fig. 4-3(a), if the slots do not overlap with each other, i.e., the
receiver can separate the signals without any interference, the transmission is defined as a success. As shown in Fig. 4-3 (b), the interference happens and the receiver fails to distinguish the signals from these transmitters. As shown in Fig. 4-4, when $L$ equals 400, the average successful transmission rate is 98.5%. The problems that induced by the 1.5% failure rate can be compensated with other techniques detailed in the latter chapter.

![Probability of Successful Transmission without Synchronization](image)

**Figure 4-4** Probability of successful transmission versus number of slots per frame.

As shown in Fig. 4-5, the transmitted data assigned to each LED has a length of 160 bits, with 128 bits of ID data, 8 bits of beginning of flag (BOF), 8 bits of ending of flag (EOF) and another 16 bits of frame correction sequence (FCS). Cyclic redundancy check (CRC) is applied to ensure the reliability of the transmission.
However, the bandwidth is wasted in BFSA. With 4 LEDs and 400 slots, if the sampling period is 0.05 s, the required transmission rate is $400 \times 160 \text{ bit} / 0.05 \text{ s} = 1.28 \text{ Mbps}$. However, only $160 \text{ bits} / 0.05 \text{s} = 3.2 \text{ Kbps}$ is required for TDMA. Although both rates are easily achieved in current VLC technology, TDMA method enables the transmission of other service data.

### 4.2 Positioning Algorithm for 2-D scenario.

The transmitted power $P_t$ is pre-decided for the system, and the received power $P_{r_i}$ from $i$-th LED is detected by the PD, their relation is expressed as:

$$P_{r_i} = H(0) \cdot P_t = \frac{m+1}{2\pi d_i^2} A \cdot \cos^m(\phi) \cdot T_s(\psi) \cdot g(\psi) \cdot \cos(\psi) \cdot P_t \quad i = 1, 2, 3, 4$$  \hspace{1cm} (4-1)

In the 2-D scenario, the transmitter and the receiver are presumed to be perpendicular to the ceiling. Therefore, the following relation is obtained:

$$\cos(\phi) = \cos(\psi) = h / d_i$$  \hspace{1cm} (4-2)

where $h$ is vertical distance between the transmitter and the receiver. The estimated distance $\hat{d}_i$ between the transmitter and the receiver is estimated as:

$$\hat{d}_i = \sqrt{\frac{(m+1) \cdot h^2 \cdot A \cdot T_s(\psi) \cdot g(\psi) \cdot P_t}{2\pi \cdot P_{r_i}}}$$  \hspace{1cm} (4-3)

Therefore, the estimated horizontal distance $\hat{r}_i$ between the transmitter and receiver is
The transmitter’s coordinates \((x_i, y_i)\) are decoded from the transmitted ID data while the receiver’s coordinate \((x, y)\) is to be estimated. Based on lateration technique, the following equation groups are derived:

\[
\begin{align*}
(x_1 - x)^2 + (y_1 - y)^2 &= \hat{r}_1^2 \\
(x_2 - x)^2 + (y_2 - y)^2 &= \hat{r}_2^2 \\
(x_3 - x)^2 + (y_3 - y)^2 &= \hat{r}_3^2 \\
(x_4 - x)^2 + (y_4 - y)^2 &= \hat{r}_4^2
\end{align*}
\]  

(4-5)

By using the first equation to subtract the others, the linear equations are obtained as:

\[
\begin{align*}
(x_1 - x_i)x + (y_1 - y_i)y &= \left(\hat{r}_2^2 - \hat{r}_1^2 - x_i^2 + x_1^2 - y_i^2 + y_1^2\right)/2 \\
(x_1 - x_3)x + (y_1 - y_3)y &= \left(\hat{r}_2^2 - \hat{r}_3^2 - x_3^2 + x_1^2 - y_3^2 + y_1^2\right)/2 \\
(x_1 - x_4)x + (y_1 - y_4)y &= \left(\hat{r}_2^2 - \hat{r}_4^2 - x_4^2 + x_1^2 - y_4^2 + y_1^2\right)/2
\end{align*}
\]  

(4-6)

The matrix format is expressed as:

\[
AX = B
\]

(4-7)

where \(X = [x, y]^T\).

\[
A = \begin{bmatrix} x_2 - x_1 & y_2 - y_1 \\ x_3 - x_1 & y_3 - y_1 \\ x_4 - x_1 & y_4 - y_1 \end{bmatrix}, \quad B = \frac{1}{2} \begin{bmatrix} (\hat{r}_2^2 - \hat{r}_1^2) + (x_2^2 + y_2^2) - (x_1^2 + y_1^2) \\ (\hat{r}_2^2 - \hat{r}_3^2) + (x_3^2 + y_3^2) - (x_1^2 + y_1^2) \\ (\hat{r}_2^2 - \hat{r}_4^2) + (x_4^2 + y_4^2) - (x_1^2 + y_1^2) \end{bmatrix}.
\]
4.3 Linear Least Square Estimation (LLSE)

Eq. (4-7) is over-determined, i.e., the number of equations is more than that of variables. LLSE is proposed as a solver, where the estimation minimizes the sum of the square error of each single equation.

The squared residuals can be estimated as:

\[ S_L = \sum_{i=1}^{4} (\hat{x} - x)^2 + (\hat{y} - y)^2 = \| B - A\hat{X} \|_2^2, \quad (4-8) \]

where \( \| V \|_2 \) is the Euclidean norm \( \| V \|_2 = \sqrt{V_1^2 + \ldots + V_n^2} \), \( \hat{x} \), \( \hat{y} \) and \( \hat{X} \) are the estimations of \( x, y \) and \( X \), respectively.

\[ S_L = (B - A\hat{X})^T (B - A\hat{X}) = X^T A^T A X - 2X^T A^T B + B^T B \quad (4-9) \]

To minimize \( S_L \), the derivation of Eq. (4-9) is set to zero:

\[ 2A^T A X - 2A^T B = 0. \quad (4-10) \]

Finally, \( \hat{X} \) is obtained as

\[ \hat{X} = (A^T A)^{-1} A^T B. \quad (4-11) \]

In one cell of the model as shown in Fig. 4-1, a pseudo-Poisson path is generated by assuming a user walks across the room, which is defined as the real path. The system parameters are detailed in Table 4-1, the installation errors of LED bulbs are considered in the simulation.
Table 4-1 Parameters of the transmitter and receiver

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Area $A$:</td>
<td>$1 \times 10^{-4} , m^2$</td>
</tr>
<tr>
<td>Lambertian mode $m$:</td>
<td>1</td>
</tr>
<tr>
<td>FOV $\psi_c$:</td>
<td>$70^\circ$</td>
</tr>
<tr>
<td>$T_s(\psi)$:</td>
<td>1</td>
</tr>
<tr>
<td>Refraction index of CPC $n$:</td>
<td>1.5</td>
</tr>
<tr>
<td>Transmitted optical power for logic “1”/“0” $P_t$:</td>
<td>5 W/3W</td>
</tr>
</tbody>
</table>
As in Fig. 4-6, the real track is shown as the black line and the red circles represent the estimated values. Only small deviations exist and the RMS error is just 0.0186 m. To further assess the positioning performance and demonstrate how the system delivers a certain level of service quality, 95% confidence interval error is introduced to evaluate the performance. Cumulative distribution function (CDF) of the positioning errors is shown in Fig. 4-7, and the 95% confidence interval line is marked out. Most of the positioning errors are guaranteed within 0.0440 m.
4.4 Positioning Algorithm for 3-D scenario.

In the real scenario, a user cannot always hold the receiver at the same height level. Even for the application on the robot, the floor cannot always be flat. Therefore, some vertical variations will be generated and 3-D positioning algorithm should be proposed. In order to derive $d_i$, all the parameters in the right side of Eq. (4-3) should be known. However, in the 3-D scenario, the height $h$ is not available. A prediction based on the last estimate is made on the height of the receiver as $h^{(0)}$, then by substituting $h^{(0)}$ into Eq. (4-3), we obtain

$$
\hat{d}_{i}^{(0)} = \sqrt{\frac{(m+1) \cdot h^{(0)^2} \cdot A \cdot T_s(\psi) \cdot g(\psi) \cdot Pt}{2\pi \cdot Pr_i}}.
$$

(4-12)

The horizontal distance is estimated as

$$
\hat{r}_{i}^{(0)} = \sqrt{\frac{(m+1) \cdot h^{(0)^2} \cdot A \cdot T_s(\psi) \cdot g(\psi) \cdot Pt}{2\pi \cdot Pr_i} \cdot (h^{(0)2} - h^{(0)}2)}^{1/2}.
$$

(4-13)

When initializing $h^{(0)}$ for the first estimate, a Gaussian random variable is generated whose mean is the general hand height of human being. With the trilateration approach, the horizontal coordinates $[\hat{x}, \hat{y}]$ can be estimated as in Eq. (4-11), and the horizontal distance can be re-calculated with

$$
\hat{r}_{i}^{(1)} = \sqrt{(x_i - \hat{x})^2 + (y_i - \hat{y})^2}.
$$

(4-14)

When substituting $\hat{r}_{i}^{(1)}$ into Eq. (4-4), the height $\hat{h}$ is estimated as one solution of:

$$
\hat{h}^4 + (2\hat{r}_{i}^{(1)^2} - C) \cdot \hat{h}^2 + \hat{r}_{i}^{(1)^4} = 0,
$$

(4-15)
where \( C \) is a constant and equals \( \frac{(m+1)AT_s(\psi)g(\psi)Pt}{2\pi \cdot Pr} \). By solving the above equation, at most two positive \( \hat{h} \) are obtained within a reasonable vertical range. If there are two solutions, the one closer to \( h^{(0)} \) is selected as \( \hat{h} \). If no reasonable solution exists, \( h^{(0)} \) will be selected as \( \hat{h} \). Finally, the z-coordinate is estimated as:

\[
\hat{z} = H - \hat{h}
\]  

(4-16)

![Diagram](image)

**Figure 4-8** Flow diagram of 3-D positioning algorithms.

Fig. 4-8 shows the flow diagram of the 3-D positioning algorithm. This iteration algorithm is applicable because of the principle of trilateration as shown in Fig. 4-9. The horizontal position of the receiver is estimated in the intersection of the three circles. The difference between the presumed height and the actual height only influences the radius of
those circles, i.e., all of the circles will expand at the same time or shrink at the same time.
Therefore, the center of the intersection will remain almost unaffected. The changing ratios of these radius are different, which will make the center of the intersection shift a little.
This non-uniformity of the noisy received signals will induce positioning errors. However, considering that in the 0.05 s sampling period, the vertical movement will not be significant, this algorithm still holds valid. The vertical moving distance will be reduced if the sampling period decreases, which will contribute to higher positioning accuracy.

Figure 4-9 Principle of trilateration.
Figure 4-10 3-D Positioning result

Figure 4-11 Horizontal view of 3-D positioning result.
Figure 4-12 Vertical view of 3-D positioning result.

Table 4-2 Errors of the 3-D positioning system (m).

<table>
<thead>
<tr>
<th></th>
<th>Horizontal error</th>
<th>Vertical error</th>
<th>Total error</th>
</tr>
</thead>
<tbody>
<tr>
<td>RMS error</td>
<td>0.0735</td>
<td>0.0638</td>
<td>0.0974</td>
</tr>
<tr>
<td>95% confidence interval</td>
<td>0.1618</td>
<td>0.1333</td>
<td>0.1977</td>
</tr>
</tbody>
</table>

In the 3-D scenario, the receiver varies from 1.0 m to 1.4 m, and the positioning result is shown in Fig. 4-10. To demonstrate the result more clearly, horizontal and vertical views are plotted separately, as in Fig. 4-11 and Fig. 4-12. Although the vertical estimates have some variations, the horizontal estimates follow the real track well. Fig. 4-13 shows the CDF of the total, horizontal and vertical positioning errors. The positioning
results are summarized in Table 4-2, where the RMS error is just 0.0974 m and 95% of the errors are guaranteed within 0.1977 m.

Figure 4-13 CDF curves of the positioning errors.
Chapter 5
Filtering Techniques in Positioning

In order to improve the positioning performance, filtering techniques are applied in this chapter. Three filters are employed as Kalman filter, particle filter and Gaussian Mixture sigma point particle filter (GM-SPPF). In the positioning system, outliers may appear considering the BFSA failure case mentioned in Chapter 4. These large deviations heavily affect the positioning performance for several sequential estimates. With filtering techniques, these effects can be decreased.

5.1 Kalman Filter

5.1.1 Derivation of Kalman filter

In 1960, Rudolph E. Kalman published his well-known recursive solution for the discrete-data linear filtering problem [54]. This filter is named after him as Kalman filter. Since then, Kalman filter has been largely researched and wildly used in a lot of areas, especially in the navigation systems.

Kalman filter is described with a series of recursive equations, which provide an efficient way to estimate the state of the process so that the estimated variance can be minimized. Kalman filter can be used to estimate the previous and the current states, or even the future state, although the knowledge of the model is unknown.

For the proposed system, we use discrete Kalman filter to estimate the state
$S \in \mathbb{R}^n$ by assuming the system follows a linear process \cite{55}\cite{56}.

$$S_k = AS_{k-1} + Bu_k + w_{k-1}, \quad (5-1)$$

$A$ is state transition vector, $B$ is the input parameter on the input vector $u_k$, and $w_{k-1}$ is the process noise. The observation vector is $m_k \in \mathbb{R}^m$ who has the relation with the current state as:

$$m_k = HS_k + v_k, \quad (5-2)$$

where $H$ is the observation parameters and $v_k$ is the observation noise.

$w_k$ and $v_k$ are assumed to follow Gaussian distribution and independent, i.e.,

$$w_k \sim N(0, Q_k) \quad \text{and} \quad v_k \sim N(0, R_k).$$

$Q_k$ is the process noise covariance and $R_k$ is the measurement noise covariance.

At step $k$, $\hat{S}^- \in \mathbb{R}^n$ is the priori state estimation, and $\hat{S} \in \mathbb{R}^n$ is the posteriori state estimation after the measurement $m_k$ is given. Therefore, the priori and posteriori estimate errors are:

$$e^-_k = S_k - \hat{S}^-_k \quad (5-3a)$$

$$e_k = S_k - \hat{S}_k. \quad (5-3b)$$

The posteriori estimate is based on a linear blending of the noisy measurement and the priori estimate:

$$\hat{S}_k = \hat{S}^-_k + K_k (m_k - HS^-_k) \quad (5-4)$$
In the above equations, \( K_k \) is considered as the blending factor. In order to find the appropriate \( K_k \) that generates an optimal updated estimate, minimum mean-square error is used as the performance criterion. For the posteriori estimate, the expression for the error covariance is:

\[
P_k = E[e_k e_k^T] = E\left[ (S_k - \hat{S}_k)(S_k - \hat{S}_k)^T \right] \\
= E\left[ (S_k - \hat{S}_k - K_k(HS_k + v_k - H\hat{S}_k))(S_k - \hat{S}_k - K_k(HS_k + v_k - H\hat{S}_k))^T \right] \quad (5-5)
\]

Since \( (S_k - \hat{S}_k) \) as the priori error is uncorrelated with the measurement error \( v_k \), the following equation is obtained:

\[
P_k = E\left[ (S_k - \hat{S}_k)(I - K_k H)(S_k - \hat{S}_k)(I - K_k H)^T \right] + E\left[ (K_k v_k)(K_k v_k)^T \right] \\
= (I - K_k H)P_k^{-1}(I - K_k H)^T + K_k R_k K_k^T \\
= P_k^{-1} - K_k H P_k^{-1} - P_k^{-1} H^T K_k^T + K_k \left( H P_k^{-1} H^T + P_k \right) K_k^T \
\]

\( P_k^- \) is the estimated priori error covariance and expressed as:

\[
P_k^- = E[e_k^- e_k^{-T}] = E\left[ (S_k - \hat{S}_k^-)(S_k - \hat{S}_k^-)^T \right] . \quad (5-7)
\]

The trace of \( P_k \) is the sum of the mean square errors. Based on the assumption that when the total mean-square error is minimized, the individual error is also minimized, we differentiate the trace of \( P_k \) and then set it to zero:

\[
\frac{d}{dK_k} (\text{trace } P_k) = -2\left( H_k P_k^- \right)^T + 2K_k \left( H_k P_k^- H_k^T + R_k \right) = 0 . \quad (5-8)
\]

Therefore,
\[ K_k = P_k H^T (HP_k H^T + R)^{-1}. \]  
\[ (5-9) \]

By re-substituting Eq. (5-9) into Eq. (5-6), we obtain:

\[ P_k = P_k - P_k H^T (HP_k H^T + R)^{-1} HP_k = (I - K_k H) P_k \]  
\[ (5-10) \]

In addition, we can obtain:

\[ e_{k+1} = S_{k+1} - \hat{S}_{k+1} = AS_k + w_k - A\hat{S}_k = \Lambda e_k + w_k, \]  
\[ (5-11) \]

\[ P^e_{k+1} = E \left[ (AS_k + w_k - A\hat{S}_k)(AS_k + w_k - A\hat{S}_k)^T \right] = AP_k A + Q_k. \]  
\[ (5-12) \]

As a summary, Kalman filter can be realized in two phases as shown in Fig. 5-1.

In the time update phase, the current state \( \hat{S}_k \) and the covariance \( P_k \) are predicted based on the previous information. When \( m_k \) is available, the measurement update phase begins. Kalman gain \( K_k \) is computed and the posterior state \( \hat{S}_k \) and the covariance \( P_k \) are corrected.

**Figure 5-1 Principle of Kalman filter**
5.1.2 Kalman filter in 2-D and 3-D scenario.

In the proposed 2-D scenario, the state vector is expressed as

\[ S_k = [x_k, y_k, v_{xk}, v_{yk}] \]

where \( x_k, y_k \) is the coordinates, \( v_{xk} \) and \( v_{yk} \) are the movement speeds in x and y direction, respectively. \( u_k \) is 0 and

\[
A = \begin{bmatrix}
1 & 0 & \Delta t & 0 \\
0 & 1 & 0 & \Delta t \\
0 & 0 & 1 & 0 \\
0 & 0 & 0 & 1
\end{bmatrix},
H = \begin{bmatrix}
1 & 0 & \Delta t & 0
0 & 1 & 0 & \Delta t
\end{bmatrix},
Q = \begin{bmatrix}
\sigma_{px}^2 & 0 & 0 & 0 \\
0 & \sigma_{py}^2 & 0 & 0 \\
0 & 0 & \sigma_{vx}^2 & 0 \\
0 & 0 & 0 & \sigma_{vy}^2
\end{bmatrix},
R = \begin{bmatrix}
\sigma_{x}^2 & 0 \\
0 & \sigma_{y}^2
\end{bmatrix}.
\]

\( \Delta t \) is the sampling period. \( \sigma_{px}^2 \) and \( \sigma_{py}^2 \) are the variances of receiver movement and initialized as 0.1. \( \sigma_{vx}^2 \) and \( \sigma_{vy}^2 \) are the variances of receiver speed and initialized as 0.5. \( \sigma_{x}^2 \) and \( \sigma_{y}^2 \) are the measurement variances decided by the PD. \( K_k \) is a 4*4 matrix and initialized as

\[
K_0 = \begin{bmatrix}
2 & 0 & 0 & 0 \\
0 & 2 & 0 & 0 \\
0 & 0 & 4 & 0 \\
0 & 0 & 0 & 4
\end{bmatrix}.
\]

---

**Figure 5-2** Flow diagram of Kalman Filter for 3-D scenario.

---

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In the 3-D scenario, the receiver’s vertical movement is independent of horizontal movement, therefore, the filtering process is divided into horizontal phase and vertical phase. Kalman filter is applied on the horizontal estimation first and then the filtered results are fed back into the 3-D positioning algorithm to obtain the z-coordinate. The detailed process is shown in Fig. 5-2 and summarized as follows:

1. Initialize the $\hat{\mathbf{S}}_0 = [\hat{x}_0, \hat{y}_0]$ based on the first horizontal measurement from the LED positioning algorithm as mentioned in Chapter 4.

2. Make the prediction on the current state vector $\hat{\mathbf{S}}_k^+ = [\hat{x}_k, \hat{y}_k]$ based on the previous position $\hat{\mathbf{S}}_{k-1} = [\hat{x}_{k-1}, \hat{y}_{k-1}]$ and the movement velocity. $\mathbf{P}_k^-$ is also predicted based on last estimate.

3. Obtain the measurement value $\mathbf{m}_k = [\hat{x}, \hat{y}]$ as mentioned in Chapter 4.

4. Update $\hat{\mathbf{S}}_k = [\hat{x}_k, \hat{y}_k]$ and $\mathbf{P}_k$ with the measurement value.

5. Substitute $[\hat{x}_k, \hat{y}_k]$ back into the 3-D positioning algorithm to obtain $\hat{r}_k$, $\hat{h}_k$ and $\hat{z}_k$.

5.2 Particle Filter

5.2.1 Principle of particle filter

One drawback of the Kalman filter is that it is based on the assumption that state follows Gaussian distribution and the system is linear. For the nonlinear and non-Gaussian system, particle filter is proposed which is based on Monte Carlo estimation [57]. A set of weighted samples at k-th step has the posterior distribution as:
\[
p(S_k | m_{tk}, u_{0k}) \approx \sum_{i=1}^{N} w'_i \delta(S_k - S'_i)
\]  
(5-13)

\(N\) is the number of samples, and \(i\) is the sample index. \(\delta(\cdot)\) is the Dirac delta function and \(w'_i\) is the weight of the \(i\)-th sample.

With probability theory, the posterior distribution can be estimated as:

\[
p(S_{0:k} | m_{tk}, u_{0k-1}) = \frac{p(m_k | S_k) p(S_k | S_{k-1}, u_{k-1}) p(S_{0:k-1} | m_{tk-1}, u_{0k-2})}{p(m_k | m_{tk-1}, u_{0k-1})}
\]  
(5-14)

The normalized weight of each particle is:

\[
w'_i = C_k \ast \frac{p(S_{0:k} | m_{tk}, u_{0k-1})}{r(S_{0:k} | m_{tk}, u_{0k-1})}
\]

\[
= C_k \ast \frac{p(m_k | S_k) p(S_k | S_{k-1}, u_{k-1}) p(S_{0:k-1} | m_{tk-1}, u_{0k-2})}{r(S_{0:k} | m_{tk-1}, u_{0k-1})}
\]

(5-15)

, where \(C_k\) is a constant value of normalization. \(r(x)\) is the importance density, which is chosen with the following expression considering it should be calculated recursively:

\[
r(S_{0:k} | m_{tk}, u_{0k-1}) = r(S_{0:k} | S_{tk}, m_{tk}, u_{0k-1}) \ast r(S_{0:k-1} | m_{tk-1}, u_{0k-2})
\]

(5-16)

Therefore,

\[
w'_i = C_k \ast \frac{p(m_k | S'_k) p(S'_k | S'_{k-1}, u_{k-1}) p(S'_{0:k-1} | m_{tk-1}, u_{0k-2})}{r(S'_k | S'_{k-1}, m_k, u_{k-1}) r(S_{0:k-1} | m_{tk-1}, u_{0k-2})}
\]

\[
= C_k \ast \frac{p(m_k | S'_k) p(S'_k | S'_{k-1}, u_{k-1})}{r(S'_k | S'_{k-1}, m_k, u_{k-1})} w'_{i-1}
\]

(5-17)

If \(r(S_k | S_{k-1}, m_k, u_{k-1}) = p(S_k | S_{k-1}, u_{k-1})\), then we can get:

\[
w'_i = C_k p(m_k | S'_k) w'_{i-1}
\]

(5-18)
The state of k-th step is finally estimated as:

$$\hat{S}_k = \sum_{i=1}^{N} w^i_k S^i_k$$  \hspace{1cm} (5-19)

One disadvantage of particle filter is that the weight of some particles keep increasing during the iteration process and finally they will dominate all the other particles. This degeneracy problem can be overcome by a resampling process to make the operation of a particle filter more stable. The weights of $N$ particles are reset to the initial value as 1/$N$, and the posterior probability is:

$$p(S_k | m_{tk}, u_{0:k-1}) \approx \frac{1}{N} \sum_{i=1}^{N} \delta (S_k - S^i_k)$$ \hspace{1cm} (5-20)

5.2.2 Particle filter in 2-D and 3-D scenarios.

For the proposed 2-D system, the particle filter is applied as follows:

1. Use the first measurement to initialize $N$ particles $(x^i_0, y^i_0)$ with identical weight $w^i_0 = 1/N$ where $N$ equals 500.

2. Calculate $(x^i_k, y^i_k)$ from $(x^i_{k-1}, y^i_{k-1})$, which is based on the movement distance and direction.

3. Obtain the measurement value as $m_k = [m_{kx}, m_{ky}]$ so that the weight can be updated with the following equations:

$$p(m_k | S^i_k) = \exp \left( -\left( (m_{kx} - x^i_k)^2 + (m_{ky} - y^i_k)^2 \right)/\sigma^2 \right)$$ \hspace{1cm} (5-21)
4. Calculate \( J = 1 / \sum_{i=1}^{N} (w_{k}^{i})^{2} \) and if it is larger than a predetermined threshold value, the resampling process is conducted by setting \( w_{k}^{i} = 1 / N \).

5. Estimate the target coordinates as \( (\hat{x}_{k}, \hat{y}_{k}) = \sum_{i=1}^{N} (w_{k}^{i} x_{k}^{i}, w_{k}^{i} y_{k}^{i}) \).

6. Update the step length for each particle and generate new random movement directions.

Figure 5-3 Flow diagram of particle filter in proposed system.
For the 3-D scenario, after the horizontal coordinates \((\hat{x}_k, \hat{y}_k)\) are processed with particle filter, we substitute it into the 3-D algorithm as mentioned in Chapter 4 to obtain \(\hat{h}_k\) and then calculate \(\hat{h}_k\) and \(\hat{z}_k\). The detailed process is shown as in Fig. 5-3.

5.3 Gaussian Mixture Sigma Point Particle Filter (GM-SPPF)

5.3.1 Principle of GM-SPPF [58]

A set of particles is represented with Gaussian Mixture Model (GMM), which is a probability density function (PDF) composed of a weighted sum of Gaussian components. The posterior distribution is approximated with a set of Gaussian components to limit the number of particles and decrease the computational cost. The distribution is expressed as:

\[
p(x) = \sum_i \alpha_i \cdot g(x; \mu_i, \Sigma_i),
\]

(5-23)

where \(\alpha_i\) is the normalized weight of each component, \(g(x; \mu_i, \Sigma_i)\) is the Gaussian density component with mean \(\mu_i\), and covariance \(\Sigma_i\). In order to simplify the problem, \(\Sigma_i\) equals \(\sigma_i^2 I\), where \(I\) denotes identity matrix. The way to build up the PDF is detailed as below:

1. \(\alpha_i, \mu_i, \sigma_i^2\) is initialized with K-means method.

2. Calculate \(\beta_i(x) = \frac{\alpha_i g(x; \mu_i, \sigma_i^2)}{\sum_j \alpha_j g(x; \mu_j, \sigma_j^2)}\).

3. Evaluate \(\mu_i = \frac{\sum j \beta_i(x_j)x_j}{\sum j \beta_i(x_j)}\)
4. Update \( \sigma_i^2 = \frac{\sum_{j=1}^{n} \beta_j(x_j)(x_j - \mu_j)^T(x_j - \mu_j)}{\sum_{j=1}^{n} \beta_j(x_j)} \) and \( \alpha_i = \frac{1}{n} \sum_{j=1}^{n} \beta_i(x_j) \)

5. Estimate \( J = \sum_{i=1}^{n} \ln[\alpha_i \cdot g(x; \mu_i, \Sigma_i)] \) and then compare it with the previous \( J \). If their difference is smaller than a predetermined threshold, it is considered as a convergence. If not, then go back to Step 2 for another iteration.

![Figure 5-4 A simple example of the sigma-point approach in a 2-D system](image)

After GMM is built up as the PDF, another technique named as sigma-point approach (SPA) is employed [59]. As shown in Fig.5-4, a set of sampling points represented by green dots are selected. The mathematical expression on these points’ coordinates is summarized in Table 5-1.
Table 5-1 Selection of sigma points for each GMM.

<table>
<thead>
<tr>
<th>Position</th>
<th>Sigma-points value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Center</td>
<td>((\mu_x, \mu_y))</td>
</tr>
<tr>
<td>Left part</td>
<td>((\mu_x - \sigma_x, \mu_y))</td>
</tr>
<tr>
<td>Right part</td>
<td>((\mu_x + \sigma_x, \mu_y))</td>
</tr>
<tr>
<td>Up part</td>
<td>((\mu_x, \mu_y + \sigma_y))</td>
</tr>
<tr>
<td>Down part</td>
<td>((\mu_x, \mu_y - \sigma_y))</td>
</tr>
</tbody>
</table>

These selected points propagate through the nonlinear process and the posterior statics are evaluated. The weights are updated with the measurement value the same as particle filter and if necessary, resampling process is operated.

5.3.2 GM-SPPF in 2-D and 3-D scenario

In our system, 50 sigma points are selected for each Gaussian component, and there are totally three Gaussian components applied [42]. They propagate through the system function \(\mathbf{S}_{k+1} = f(\mathbf{S}_k)\), which relates the next step \(k+1\) to the current step \(k\) with moving distance and direction information. The detailed process is summarized as follows:

1. Initialize \(N\) particles \((x_0^i, y_0^i)\) based on the first measurement value.
2. Cluster \(N\) particles into three groups using K-means algorithm.
3. Set up GMM and then sample the sigma points considering 5 components.
4. When the measurement value is obtained from the PD, the weight is updated with Eq. (5-22) and resampling is operated if needed.
5. Estimate the target coordinates as 
\[(\hat{x}_k, \hat{y}_k) = \sum_{i=1}^{N} \left( w'_k x'_k, w'_k y'_k \right) \]

6. Update the step length for each particle and generate new random movement directions.

Figure 5-5 Flow diagram of particle filter in proposed system.
5.4 Results and Discussions

Figure 5-6 3-D positioning result.

(a) Real path  
(b) Raw measurements
Figure 5-7 Horizontal components of the positioning system.

Fig. 5-6 shows the positioning result of the 3-D scenario, and there is a large deviation as cycled out. Real path is shown as the black line and 262 raw measurement values are represented by the red dots. Large deviations may come from the failure of BFSA or the blockage of LOS link. The results of Kalman filter, particle filter and GM-SPPF are also shown in magenta, green and blue, respectively. To demonstrate the results more clearly, horizontal and vertical views are plotted separately, as shown in Fig. 5-7 and Fig.
5-8. In Fig. 5-7(b), the circled red spot shows where the large deviation is located. When the Kalman filter is applied as in Fig 5-7(c), estimations still diverge after the large deviation, and it takes several steps before the path converges again. As shown in Fig. 5-7(d) and Fig. 5-7 (e), when particle filter and GM-SPPF are applied, the paths after the large deviation are almost unaffected.

Figure 5-8 Vertical component of the positioning system.

Fig. 5-8 shows the performance of vertical components are only slightly
improved, because the filters are not directly applied on the vertical parts. The measurements are more precise in the center region than at both ends of the path. This is because light intensities are more uniform at the center of the room.

Table 5-2 RMS error of 3-D system with filtering techniques

<table>
<thead>
<tr>
<th></th>
<th>Horizontal(m)</th>
<th>Vertical(m)</th>
<th>Total(m)</th>
<th>Time(s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Raw measurement</td>
<td>0.116</td>
<td>0.086</td>
<td>0.143</td>
<td>/</td>
</tr>
<tr>
<td>Kalman filter</td>
<td>0.084</td>
<td>0.079</td>
<td>0.115</td>
<td>0.46</td>
</tr>
<tr>
<td>Particle filter</td>
<td>0.061</td>
<td>0.074</td>
<td>0.096</td>
<td>5.9</td>
</tr>
<tr>
<td>GM-SPPF</td>
<td>0.053</td>
<td>0.068</td>
<td>0.086</td>
<td>4.9</td>
</tr>
</tbody>
</table>

The RMS errors are quantitatively summarized in Table 5-2. An overall accuracy of 0.143 m is achieved, and the particle filter performs much better than Kalman filter. Although GM-SPPF only slightly improves the performance, the time consumption decreases to 4.9s.

The CDF of overall, horizontal and vertical positioning errors are shown in Fig. 5-9, Fig. 5-10 and Fig. 5-11, respectively. The performance improves a lot after filtering process for both overall and horizontal components, while only slightly improves on the vertical components.
Figure 5-9 CDF curves of 3-D positioning errors.

Figure 5-10 CDF curves of horizontal component errors.
Figure 5-11 CDF curves of vertical component errors.

The 95% confidence interval errors are summarized in Table 5-3. Before the filtering process, most of the errors are within 0.2321 m while after the filtering process, most of the errors are within 0.1742 m.

Table 5-3 95% confidence interval errors of the 3-D system and filtering techniques.

<table>
<thead>
<tr>
<th></th>
<th>Horizontal(m)</th>
<th>Vertical(m)</th>
<th>Total(m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Raw measurement</td>
<td>0.1413</td>
<td>0.1733</td>
<td>0.2321</td>
</tr>
<tr>
<td>Kalman filter</td>
<td>0.1404</td>
<td>0.1660</td>
<td>0.1931</td>
</tr>
<tr>
<td>Particle filter</td>
<td>0.1403</td>
<td>0.1483</td>
<td>0.1876</td>
</tr>
<tr>
<td>GM-SPPF</td>
<td>0.1245</td>
<td>0.1177</td>
<td>0.1742</td>
</tr>
</tbody>
</table>
Chapter 6

Three-Dimensional positioning based on nonlinear estimation

In Chapter 5, the horizontal performance is improved by the filtering techniques while the vertical performance is still not improved largely. In this chapter, nonlinear estimation is proposed to improve the positioning performance especially the vertical components.

6.1 Trust region reflective algorithm

Trust region algorithm is a popular solver in the optimization of the problem [60]:

\[
\min_{x\in\mathbb{R}^n} f(x),
\]

\[
\text{s.t. } c_i(x) = 0 \quad i = 1, 2, \ldots, m
\]

\[
c_i(x) \geq 0 \quad i = m+1, m+2, \ldots, q,
\]

where \( f(x) \) is a nonlinear function. If \( m=q=0 \), Eq. (6-1) is an unconstrained problem.

Assuming an approximate solution \( x_k \) is available at \( k-th \) iteration, a new point \( x_{k+1} \) is found in a “trusted” region near the current solution. Generally speaking, the trust region is enlarged when the current solution fit the problem well; otherwise, it is shrinked. The iteration stops until the convergence condition is satisfied. The most important part of a trust region algorithm is to find out the trial step, which can be solved by Levenberg-Marquardt method [61]. The step is:

\[
d_k = -\left( J(x_k) J(x_k)^T + \lambda_k I \right)^{-1} J(x_k) f(x_k),
\]

(6-2)
where $J(x)$ is the Jacobi matrix of $f(x)$ and $\lambda_k \geq 0$ is updated for each iteration.

The general steps are as follows: first, a trust region is initialized; second, an approximate model is set up and the trial step $s_k$ is solved within the trust region; third, a cost function is applied to update the next trust region and select new points. For 2-D situation, the problem is given as [62]:

1. Set up the 2-D trust-region sub-problem as

$$\min \left\{ \frac{1}{2} S^T HS + S^T g \right\} \quad \text{s.t.} \|DS\| < \Delta$$

(6-3)

, where $H$ is the Hessian matrix$^9$, $g$ is the gradient of $f$ of current point, $S$ is the step, $D$ is a diagonal scaling matrix and $\Delta$ is a positive scalar.

2. Solve Eq. (6-2) to determine $S$.

3. Set $x = x + S$ when $f(x + S) < f(x)$.

4. Adjust $\Delta$.

5. Decide whether the convergence condition is satisfied, if not, go back to step one for next iteration.

### 6.2 3-D positioning algorithm [63]

When the height information is not available, we presumed height $h^{(0)}$ based on previous estimate. The estimation on distance $d_i$ and the horizontal coordinates

$\mathbf{\hat{X}} = [\hat{x}, \hat{y}]^T$ is obtained as in Chapter 4. $\mathbf{X}$ is used for initialization which will be detailed later.

Figure 6-1 Flow diagram of 3-D positioning algorithm

Trust region reflective algorithm is a solver to find the solution of

$$\min \left\{ \tilde{S} = \sum_{i=1}^{4} \left( \sqrt{(x-x_i)^2 + (y-y_i)^2 + (z-z_i)^2} - d_i \right)^2 \right\}.$$  

First, an initial value $\mathbf{\tilde{X}}^{(0)} = [\tilde{x}^{(0)}, \tilde{y}^{(0)}, \tilde{z}^{(0)}]$ is provided and the corresponding $\tilde{S}^{(0)}$ is calculated. $\tilde{x}^{(0)}$ and $\tilde{y}^{(0)}$ are initialized with $\mathbf{\hat{X}}$ and $\tilde{z}^{(0)} = z_i - h^{(0)}$. Second, several points surrounding $\mathbf{\tilde{X}}^{(0)}$ are selected and their corresponding $\tilde{S}^{(1)}$ are calculated. $\mathbf{\tilde{X}}^{(1)}$ is updated with the point that minimizes $\tilde{S}^{(1)}$. After several iterative steps, $\mathbf{\tilde{X}}$ is finally obtained when $\tilde{S}$ converges. The obtained $\tilde{z}$ is used to presume $h^{(0)}$ at the next sampling. The flow diagram of this algorithm is shown in Fig. 6-1.
6.3 Simulation and Results

With the proposed nonlinear estimation algorithm, the 3-D positioning result is shown in Fig. 6-2, and the horizontal and vertical positioning performance are shown in Fig. 6-3. Large improvement of the vertical components is shown in Fig. 6-3 (b), even the estimates for the two ends follow the real path well. The uniformity of light distribution does not affect too much on the positioning performance. Fig 6-4 shows the CDF curve of the positioning errors, which further confirms the improvement. After the horizontal coordinates are estimated with the presumed vertical coordinates, all the $x$, $y$ and $z$ coordinates are fed back into the algorithm for further modification. While in the previous 3-D positioning algorithm mentioned in Chapter 4, only the $z$ coordinate is fed back into the system to be updated.
Figure 6-3 Positioning result of (a) horizontal components (b) vertical components.

Figure 6-4 CDF curve of the 3-D positioning results.

CDF of the overall, horizontal and vertical coordinates are shown in Fig. 6-4. The RMS errors and 95% confidence interval errors are summerized in Table 6-1. The entire error is just 0.0252 m and 95% of the errors are guaranteed within 0.0432 m. Vertical RMS error is just 0.0120 m and the 95% confidence interval error is just 0.0199 m.
Table 6-1 Positioning errors of the proposed algorithm (m).

<table>
<thead>
<tr>
<th></th>
<th>Horizontal</th>
<th>Vertical</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>RMS error</td>
<td>0.0222</td>
<td>0.0120</td>
<td>0.0252</td>
</tr>
<tr>
<td>95% confidence interval</td>
<td>0.0421</td>
<td>0.0199</td>
<td>0.0432</td>
</tr>
</tbody>
</table>
Chapter 7

Impact of multipath reflections

In the previous chapters, all the research are based on LOS link, which is impossible to be satisfied for the complex indoor environment. As shown in Fig. 7-1, multipath propagation phenomenon exist in the indoor wireless communications, i.e., the signals reaching the receiver through more than one path. Multipath reflections induce the degradation of communication quality as well as positioning accuracy. In this chapter, we will analyze the impact of multipath reflections on the positioning accuracy.

Figure 7-1 Geometry used to describe the multiple-reflections propagation.

7.1 Impulse response

Impulse response which usually characterizes the linear time-invariant (LTI) system, is used to describe the multipath reflections. When the input is a single, ideal
Dirac pulse of electromagnetic power, its output is named as impulse response to describe
the system with a function of time. Assume the transmitted signal is $x(t)$, with the
knowledge of impulse response $h(t)$, the received signal can be expressed as:

$$y(t) = h(t) * x(t).$$  \hspace{1cm} (7-1)

![Figure 7-2 Example of impulse response in (a) frequency domain (b) time domain.](image)

Fig. 7-2 is an example of impulse response in frequency and time domain. Both
experiment and simulation methods are proposed to analyze the multipath reflections in
the indoor optical wireless communication system. Experimentally, the frequency
response is measured first and then time domain response is obtained by applying inverse
Fourier transform [64]. Simulation methods are proposed with different algorithms, and
in the following part, deterministic methods and modified Monte Carol methods (MMC)
will be explained before our method is finally introduced.
7.2 Deterministic approach

A deterministic approach is proposed by Barry et al. where the surfaces of the entire room such as the walls, ceiling, floor, furniture are divided into small reflecting elements [65]. The LOS signal is calculated directly with the channel DC gain as mentioned in Chapter 3. In order to calculate the first reflections, each reflecting element is considered as a receiver, and the received power from the LOS link are calculated. The travelling time to the receivers are also recorded. These elements are then considered as separate transmitters, and their transmitted power is the received power degraded by the reflection coefficient. The power to the primary receiver, i.e., PD, from these elements through LOS link is calculated, and the traveling time is computed. The impulse response...
for the first reflections are calculated which includes the entire traveling time and received power.

To calculate the second reflections, each small reflector is considered as a receiver and then all the other reflectors are considered as the transmitter. The same with the calculation of first reflections, the received power of the PD is calculated when these small reflectors are considered as transmitters again. The entire travelling time is recorded. In this recursive way, subsequent contribution of reflections can be calculated. The smaller the reflecting elements are, the higher the approximation accuracy is. However, the computing time will increase considerably when the reflecting elements are smaller. Computing time increases tremendously after three orders of reflections with Barry’s algorithm, therefore modification is needed to reduce the computational cost, especially in the high data rate communication systems where higher order of reflections should be considered. The flow diagram of Barry’s method is shown in Fig. 7-3.

7.3 MMC approach

In order to decrease the computation time, an iterative approach named as Monte Carlo ray-tracking is proposed [66]. The Lambertian pattern of the LED emission is treated as the PDF. Rays are generated with equal optical power from the source and their directions follow the PDF. When each ray hits the surface of the room, the hit point is considered as a new source. New rays are generated from these new sources where their directions are generated randomly with the PDF and the power is reduced considering the reflectivity of the surface. The number of reflections is not limited as that of deterministic
method. However, the number of rays that finally hit the receiver is not large enough, which makes it necessary to generate a large amount of rays resulting in high computational cost.

As a solution, MMC approach is proposed [67]. One ray to the receiver is generated from each source so that the number of rays from the source is reduced. This approach is fast but the calculated impulse response is not accurate enough considering variances are induced by the randomness of the directions of the rays. The variance can be reduced by increasing the number of rays, which in return brings up computation time. As MMC algorithm can be executed parallel, the total computation time can be further reduced. The flow diagram of MMC approach is shown as in Fig. 7-4.
7.4 CDMMC methods.

In the two main branches of algorithms as mentioned above, the Barry’s method is much accurate while suffers from extensive computation. MMC algorithm speeds up the computation while the variances will influence the estimation accuracy. We present a new approach named as combined deterministic and modified Monte Carlo (CDMMC) method, which has the advantages of the two proposed algorithms [68]. The contribution of first reflections to the total impulse response is significant, which is calculated by Barry’s method to ensure the accuracy. The contributions of the subsequent reflections are estimated by MMC method, where the computation time is decreased. Although MMC is not accurate enough, less power is remained after the first reflections so that the variance is acceptable. As there are a lot of small reflection elements, the rays generated from each element do not need to be large in energy.

The first step is to divide the room surfaces into many small square elements, each of which has an area of $1 \times 10^{-4}$ m$^2$, equals to the PD’s receiving area.

Second, the received power of the PD from the LED is calculated and the travelling time is recorded. The vector including power and time is considered as the LOS contribution to the total impulse response.

Third, the small elements act as the receivers, and the received power is:

$$P_{\text{received}}^{(0)} = H(0) * P_{\text{source}}^{(0)}, \quad (7-2)$$

where $P_{\text{source}}^{(0)}$ is the power emitted from the LED transmitter. In Eq. (7-2), $H(0)$ is the channel DC gain and $P_{\text{received}}^{(0)}$ is the received power of each small element. The travelling time is tracked for each link.
Fourth, each of these small elements is considered as a point source again:

\[
\mathbf{P}_{\text{source}}^{(1)} = \mathbf{P}_{\text{received}}^{(0)} * \rho_{\text{surface}}. \tag{7-3}
\]

where \(\rho_{\text{surface}}\) is the reflection coefficient of the surfaces such as ceiling, floor and walls.

In the fifth step, the received power of PD from each small element transmitter is calculated and the travelling time is recorded. These vectors including power and time are treated as the contribution of first reflections to the total impulse response.

In the sixth step, MMC method is employed and \(N\) rays are generated from each small element transmitter sharing the equal power \(P_{\text{ray}} = \frac{P_{\text{source}}^{(1)}}{N}\). The PDF of the rays’ directions follows:

\[
f(\alpha, \beta) = \frac{m + 1}{2\pi} \cos^m(\alpha). \tag{7-4}
\]

In Eq. (7-4), \(\alpha\) is the angle between z-axis and the ray vector, \(\beta\) is the angle between projection of the ray vector on the X-Y plane and x-axis, and \(m\) is the Lambertion order. In Fig. 7-5, the origin point is each ray’s point source and the X-Y plane represents the surface plane of the source. Note that Eq. (7-4) is independent of \(\beta\).

These rays hit the surface of the room with power \(P_{\text{received}}^{(1)} = H(0) * P_{\text{source}}^{(1)}\). The travelling time is tracked. The impact points are considered as new transmitters, the power of these transmitters is:

\[
P_{\text{source}}^{(2)} = P_{\text{received}}^{(1)} * \rho_{\text{surface}} / N. \tag{7-5}
\]
One of the rays hits the PD and the received power as well as the entire travelling time is recorded. In this way, the contributions of the second reflections are calculated. The other $N-I$ rays have the directions following the same PDF and the subsequent reflections can be calculated iteratively.

Fig. 7-6 shows the flow diagram of the CDMMC method. The impulse response of the channel is computed by adding up all the contributions from LOS and each order of reflections [41][69].
7.5 Analysis on the impulse response

Consider that an entire room should be simulated including the corner and edge, in this section, we use a new model instead of just a cell. As shown in Fig. 7-7(a), sixteen LEDs are installed on the ceiling of the room. Fig. 7-7(b) shows a bird’s-eye view of the system model. The circles show the locations of all the LED bulbs, and the three selected locations are marked with squares representing corner, edge and center. The area within the dashed line is the inside region while the rest area is considered as the outside region.
Figure 7-7 (a) System configuration (b) Bird’s eye view.

Table 7-1 Parameters of the model

<table>
<thead>
<tr>
<th>Room dimensions</th>
<th>Reflection coefficients</th>
<th>Transmitter</th>
</tr>
</thead>
<tbody>
<tr>
<td>length: 8 m</td>
<td>$\rho_{walls}$: 0.66</td>
<td>Wavelength: 420nm</td>
</tr>
<tr>
<td>width: 8 m</td>
<td>$\rho_{Ceiling}$: 0.35</td>
<td>Height: 3.3 m</td>
</tr>
<tr>
<td>height: 3.5 m</td>
<td>$\rho_{Floor}$: 0.60</td>
<td>Lambertian mode: 1</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Elevation: -90°</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Azimuth: 0°</td>
</tr>
</tbody>
</table>

Horizontal coordinates of LED bulbs

<table>
<thead>
<tr>
<th>Area A: $1\times10^{-4}$ m²</th>
</tr>
</thead>
<tbody>
<tr>
<td>Receiver</td>
</tr>
<tr>
<td>Height: 1.2 m</td>
</tr>
<tr>
<td>Elevation: +90°</td>
</tr>
<tr>
<td>Azimuth: 0°</td>
</tr>
</tbody>
</table>
There are six reflection surfaces of the room, i.e., four walls, one ceiling and one floor, and they are assumed to be perpendicular to each other. The parameters of the model are shown in Table 7-1, and the reflection coefficients are assumed to be fixed considering the material of the room surface and the 420 nm light source. The transmitters in the algorithm are treated as point sources and located at the height of 3.3 m considering the practical installation. The distance between the transmitters is 2 m. As the transmitters are facing downwards, the azimuth angle is $0^\circ$ and the elevation angle is $-90^\circ$. The receiver is facing upwards, thus the azimuth angle is $0^\circ$ and the elevation angle is $+90^\circ$. The receiving area of the PD is $1\times10^{-4} \text{ m}^2$, with $70^\circ$ FOV.

Figure 7-8 Impulse response of each reflection order at location A
Three typical locations are selected to analyze the effect of multipath reflections. Considering that the positioning system is low data rate, three orders of reflections are calculated. A (0, 0, 1.2) represents a point at the corner of the room, where the scatterings and reflections are severe; B (4, 0, 1.2) represents a point at the edge of the room, right beside the wall, where reflections are medium; C (4, 4, 1.2) represents central point where the effect of multipath reflections becomes weak. Considering the symmetrical property of the room, the impulse responses from the transmitter located at (3, 3, 3.3) are investigated at the three selected locations. The contribution of the LOS and the first three reflections are shown from Fig. 7-8 to Fig. 7-10.

![Impulse response of each order of reflections at location B](image)

**Figure 7-9** Impulse response of each reflection order at location B

Particularly, Fig. 7-8 demonstrates the impulse response of each reflection order at Location A. The impulse response amplitude of reflections is comparable to that of LOS incurring large positioning errors. Fig. 7-9 shows the impulse response of each
reflection order at Location B. The amplitude of the reflections significantly decreases compared to Location A, and thus positioning accuracy is expected to be improved. As can be seen from Fig. 7-10, the LOS component almost dominates the total impulse response, and the amplitude of the reflections is negligible at Location C. Therefore, the positioning performance is expected to be less affected by multipath reflections.

![Impulse Response of Each Order of Reflections at Location C](image)

Figure 7-10 Impulse response of each reflection order at Location C.

7.6 Power intensity distribution analysis

As RSS information is applied to estimate the distance between a transmitter and receiver, the received power from each transmitter directly affects positioning performance. In this subsection, we investigated received power from different LED transmitters at each reflection order for the three selected locations. Fig. 7-11 to Fig. 7-13
present the highest six received power values for the selected locations inside the room in descending order. The received power of each reflection order at the corner point is shown in Fig. 7-11. As can be seen clearly, only for the first LED signal, the LOS power value is much greater than that of the reflections. However, for the other five LED signals, the reflection components are comparable to the LOS component. The reflection components affect positioning accuracy since only direct power attenuation from the transmitter is considered in the distance estimation.

Figure 7-11 Received power from each LED bulb at Location A.
Figure 7-12 Received power from each LED bulb at Location B.

Figure 7-13 Received power from each LED at Location C.
Fig. 7-12 shows the received power of each reflection order at Location B. It is apparent that the received LOS power value is much greater than the received reflection power values from the first two LED transmitters. For the other four LED signals, the LOS power value significantly decreases but is still more than the reflection components. Therefore, the positioning error is expected to be smaller than Location A.

Fig. 7-13 shows the received power of each reflection order at Location C. For the first four strongest LED signals, the reflection components are negligible comparing to the LOS component. Although for the other two LED signals, the LOS power value remarkably decreases, it is still much more than the reflection components. Therefore, the central point is expected to be less affected by multipath reflections.

7.7 Analysis of positioning accuracy

As a benchmark and in order to show the effect of multipath reflections on the positioning accuracy, positioning error neglecting the reflected power is also calculated and shown in Fig. 7-14. As can be seen, the positioning error is low all over the room, and only a little higher in the corner area. Fig. 7-15, on the other hand, shows the positioning performance considering the multipath reflections. It can be noted that each location of the room is affected by multipath reflections, especially the corner and edge area. However, the positioning accuracy is satisfactory at the central point of the room as reflections are weak there.
Figure 7-14 Positioning error considering no reflections.

Figure 7-15 Positioning error considering reflections.
Figure 7-16 Histogram of positioning error (a) without (b) with reflections.

Fig. 7-16 presents the histograms of positioning errors when neglecting and considering multipath reflections, respectively. When no reflections are considered, the errors only come from the thermal noise and shot noise. In this case most of the errors are within 0.005 m as an ideal scenario. However, reflections cannot be practically avoided, and they are a major concern in the positioning system impairing dramatically the system performance as shown in Fig. 7-16 (b). In this case, most of the positioning errors are below 1 m while at some locations, the error climbs up to 1.7 m.
Figure 7-17 CDF of positioning errors (a) without (b) with reflections.

Fig.7-17 shows the CDF of positioning errors of inner region, outer region and entire room. If only LOS link is considered, 95% of the errors are guaranteed within 0.0085 m and the reflections raise the errors up to 1.41 m. Table 7-2 compares the positioning error quantitatively when neglecting and considering the reflections. At Location A, the error is 1.6544 m since the reflections are strong there. The effect of multipath reflections is medium at Location B while the positioning performance is the best at Location C. The RMS error of the outside region is 0.8173 m due to severe reflections while the RMS error of the inside region is 0.2024 m. The RMS error of the entire room is 0.5589 m, while it is only 0.0040 m when no reflections are considered.
Table 7-2 Positioning error neglecting/considering reflections.

<table>
<thead>
<tr>
<th></th>
<th>Neglecting reflections (m)</th>
<th>Considering reflections (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Location A</td>
<td>0.0098</td>
<td>1.6544</td>
</tr>
<tr>
<td>Location B</td>
<td>0.0019</td>
<td>0.9966</td>
</tr>
<tr>
<td>Location C</td>
<td>0.0012</td>
<td>0.1674</td>
</tr>
<tr>
<td>Outside (RMS)</td>
<td>0.0059</td>
<td>0.8173</td>
</tr>
<tr>
<td>Outside (95% confidence interval)</td>
<td>0.0100</td>
<td>1.285</td>
</tr>
<tr>
<td>Inside (RMS)</td>
<td>0.0016</td>
<td>0.2024</td>
</tr>
<tr>
<td>Inside (95% confidence interval)</td>
<td>0.0032</td>
<td>0.382</td>
</tr>
<tr>
<td>Total (RMS)</td>
<td>0.0040</td>
<td>0.5589</td>
</tr>
<tr>
<td>Total (95% confidence interval)</td>
<td>0.0085</td>
<td>1.141</td>
</tr>
</tbody>
</table>

7.8 Modification approaches

Since multipath reflections considerably affect the positioning accuracy, especially on the outer region, three calibration approaches are proposed in this subsection to improve the system performance.

7.8.1 Nonlinear estimation

In this section, we use nonlinear estimation on the 2-D scenario. After we obtain

\[ \hat{X} = [\hat{x}, \hat{y}]^T \]

from Eq. (4-11) as the initial value, in order to find an appropriate

\[ \tilde{\hat{X}} = [\tilde{\hat{x}}, \tilde{\hat{y}}]^T \],

the following equation should be minimized:

\[
\tilde{S} = \sum_{i} \left( \sqrt{(x - x_i)^2 + (y - y_i)^2} - r_i \right)^2
\]  

(7-6)
Trust region reflective algorithm is applied to estimate $\hat{X}$. With initial value $\hat{X}_0$, several points surrounding $\hat{X}_0$ are substituted to Eq. (7-6). The one minimizes $\hat{S}_1$ is selected as $\hat{X}_1$. After several iterative steps, receiver coordinates $\hat{X}$ will finally be obtained when $\hat{S}$ converges.

![Positioning error with reflections by nonlinear estimation](image)

Figure 7-18 Positioning error with nonlinear estimation.

Fig. 7-18 demonstrates the positioning error distribution with the non-linear estimation approach. At Location A, the error decreases from 1.6544 m with LLSE to 1.1334 m with nonlinear estimation. At Location B, the error decreases from 0.9966 m to 0.8311 m. While only slight improvement can be found at center point, the error decreases from 0.1674 m to 0.1427 m. The histogram of the positioning errors is shown in Fig. 7-19 (a). In this case, most of the errors are within 0.8 m, and only a few of them
are over 1 m. The worst positioning error is just around 1.5 m. In Fig. 7-19 (b), the CDF distributions of inner region, outer region and entire room are shown respectively.

Figure 7-19 (a) Histogram (b) CDF of positioning error of nonlinear estimation.

Table 7-3 shows the positioning performance of non-linear estimation method in RMS and 95% confidence interval error. The nonlinear estimation outperforms original algorithm, especially for the outside region where the reflections are severe and the RMS error decreases from 0.8173 m to 0.6871 m. RMS error decreases from 0.2024 m to 0.1401 m at the inner region and from 0.5589 m to 0.4642 m for the entire room. The
95% confidence interval error corresponding to inner region, outer and entire room also decreases, respectively.

In LLSE, we use Eq. (4-6) to approximate Eq. (4-5), but the mathematical deduction from Eq. (4-5) to Eq. (4-6) is not reversible. In other words, the optimum solution for Eq. (4-5) is applicable for Eq. (4-6), but the reverse is not always true. Therefore, previous estimation may induce approximation error. To avoid this error, the nonlinear estimation is applied by avoiding the approximation from Eq. (4-6) to Eq. (4-5), solution of Eq. (4-5) is directly estimated through trust region algorithm.

<table>
<thead>
<tr>
<th>Table 7-3 Positioning error by nonlinear estimation (m).</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
</tr>
<tr>
<td>RMS</td>
</tr>
<tr>
<td>95% confidence interval</td>
</tr>
</tbody>
</table>

7.8.2 Selection of LED signals

The received power decreases when the distance between the transmitter and receiver increases. As shown in Fig. 7-11 to Fig. 7-13, the reflections contribute more to the total received power when the signal is from a further LED transmitter and brings larger errors in the distance estimation. In this subsection, a signal selection approach is proposed, i.e., the receiver only selects strong signals for the coordinate estimation. In the numerical analysis, the six, five, four and three strongest LED signals are selected, and the results are shown in Table 7-4. By removing the signals affected considerably by
multipath reflections, the positioning accuracy is improved. The total RMS error decreases to 0.4046 m, 0.3527 m, 0.3240 m and 0.3169 m respectively for the cases when the six, five, four and three strongest LED signals are selected. Note that, for the scenario with three LED bulbs, the strongest three ones which are not in a row must be selected to avoid singularity in matrix $A$ of Eq. (4-7). As can be noted from Table 7-4, the outer region is improved more than the inner region.

Table 7-4 RMS error with transmitter selection approach (m).

<table>
<thead>
<tr>
<th>RMS error</th>
<th>Outer Region</th>
<th>Inner Region</th>
<th>Entire Room</th>
</tr>
</thead>
<tbody>
<tr>
<td>6 LEDs (linear)</td>
<td>0.6760</td>
<td>0.1640</td>
<td>0.4616</td>
</tr>
<tr>
<td>6 LEDs (nonlinear)</td>
<td>0.6016</td>
<td>0.1112</td>
<td>0.4046</td>
</tr>
<tr>
<td>5 LEDs (linear)</td>
<td>0.5472</td>
<td>0.1251</td>
<td>0.3722</td>
</tr>
<tr>
<td>5 LEDs (nonlinear)</td>
<td>0.5272</td>
<td>0.0851</td>
<td>0.3527</td>
</tr>
<tr>
<td>4 LEDs (linear)</td>
<td>0.4838</td>
<td>0.0933</td>
<td>0.3259</td>
</tr>
<tr>
<td>4 LEDs (nonlinear)</td>
<td>0.4828</td>
<td>0.0849</td>
<td>0.3240</td>
</tr>
<tr>
<td>3 LEDs (linear)</td>
<td>0.4726</td>
<td>0.0917</td>
<td>0.3185</td>
</tr>
<tr>
<td>3 LEDs (nonlinear)</td>
<td>0.4714</td>
<td>0.0863</td>
<td>0.3169</td>
</tr>
</tbody>
</table>

For the sake of conciseness, only the best results are presented. Fig. 7-20 shows the positioning error distribution when the three strongest LED signals are selected for distance calculation and the nonlinear estimation is applied to obtain the receiver coordinates. Fig. 7-21(a) presents the corresponding histogram of positioning errors. It can be seen from Fig. 7-21(a) that many of the locations have positioning errors which are less than 0.4 m, and only a few locations have positioning error that is larger than 0.8
m. Fig. 7-21(b) is the CDF of the positioning errors where 95% confidence interval error decreases from 0.2941 m to 0.1698 m for the inner region, from 0.9681 m to 0.7039 m for the outer region, from 1.119 m to 0.7366 m for the entire room.

![Positioning error (m) with 3 LEDs by nonlinear estimation](image)

**Figure 7-20** Positioning error with 3 LED signals by nonlinear estimation.
Figure 7-21  (a) Histogram (b) CDF of positioning error of nonlinear estimation with 3 LED selected.

7.8.3 Decreasing the distance between LED bulbs

When LED bulbs are installed in a denser layout (i.e., the distance between LED bulbs is reduced, and a greater number of LED bulbs are used), the light intensity distribution becomes more uniform for the entire room, and therefore, the positioning accuracy is improved. Table 7-5 shows the RMS error where distance between the LED bulbs decreases to 1.5 m, and 25 LED bulbs are installed in total. With no LED signal selection, the entire RMS error is 0.3121 for the nonlinear estimation. The RMS error
decreases to 0.2922 m, 0.2699 m, 0.2554 m and 0.2458 m when six, five, four, three LED signals are selected, respectively. The positioning errors are summarized in Table 7-5.

The linear model, i.e., Eq. (4-6), is a simplified version of Eq. (4-5). Therefore, in most of the cases, the nonlinear estimation provides a better performance than the linear estimation. There are some cases that Eq. (4-6) approximates Eq. (4-5) much more accurate and provides optimized solution. Meanwhile, the nonlinear estimation based on the trust region algorithm may not provide the optimized solution because of some convergence conditions. Therefore, the linear estimation outperforms its nonlinear counterpart in some cases of Table 7-5.

Table 7-5 RMS error with 1.5 m distance between the LED bulbs (m).

<table>
<thead>
<tr>
<th>RMS error</th>
<th>Outer Region</th>
<th>Inner Region</th>
<th>Entire Room</th>
</tr>
</thead>
<tbody>
<tr>
<td>All LEDs (linear)</td>
<td>0.4703</td>
<td>0.1052</td>
<td>0.3194</td>
</tr>
<tr>
<td>All LEDs (nonlinear)</td>
<td>0.4672</td>
<td>0.0718</td>
<td>0.3121</td>
</tr>
<tr>
<td>6 LEDs (linear)</td>
<td>0.4400</td>
<td>0.0916</td>
<td>0.2976</td>
</tr>
<tr>
<td>6 LEDs (nonlinear)</td>
<td>0.4362</td>
<td>0.0729</td>
<td>0.2922</td>
</tr>
<tr>
<td>5 LEDs (linear)</td>
<td>0.4106</td>
<td>0.0691</td>
<td>0.2751</td>
</tr>
<tr>
<td>5 LEDs (nonlinear)</td>
<td>0.4014</td>
<td>0.0742</td>
<td>0.2699</td>
</tr>
<tr>
<td>4 LEDs (linear)</td>
<td>0.4002</td>
<td>0.0571</td>
<td>0.2668</td>
</tr>
<tr>
<td>4 LEDs (nonlinear)</td>
<td>0.3791</td>
<td>0.0729</td>
<td>0.2554</td>
</tr>
<tr>
<td>3 LEDs (linear)</td>
<td>0.3916</td>
<td>0.0554</td>
<td>0.2610</td>
</tr>
<tr>
<td>3 LEDs (nonlinear)</td>
<td>0.3644</td>
<td>0.0718</td>
<td>0.2458</td>
</tr>
</tbody>
</table>
Figure 7-22 Positioning error with 3 LED signals by nonlinear estimation and 1.5 m distance between the LEDs.

Fig. 7-22 shows the positioning performance for the best scenario, i.e., 3 LED signals selected for the nonlinear estimation. As can be seen from Fig. 7-22, for the most of the inner area, the positioning performance is satisfactory while at the edges and corners of the room, there are some locations with large positioning errors. Fig. 7-23 (a) is the histogram of the positioning errors where most of the errors are within 0.4 m and only few outliers which can be removed with the filtering techniques mentioned in Chapter 5. Fig. 7-23 (b) is the CDF of positioning errors where 95% confidence interval error decreased from 0.1695 m to 0.1379 m for inner region, from 0.7366 m to 0.6165 m for outer region, and from 0.7039 m to 0.5613 m for the entire room.
Figure 7-23 (a) Histogram (b) CDF of positioning error with 3 LED signals by nonlinear estimation and 1.5 m distance between the LEDs.

The CDF comparison presented in Fig. 7-24 better demonstrates improvement in the positioning performance and usefulness of the proposed methods. For linear estimation, the 95% confidence interval error is at 1.14 m while the nonlinear estimation reduces it to 0.9681 m. Furthermore, by applying LED signal selection and decreasing the distance between LED bulbs, it can be improved to 0.7039 m and 0.5613 m, respectively.
Figure 7-24 Comparison of the CDF of positioning errors
Chapter 8

OFDM based positioning algorithm

8.1 OFDM in communication

OFDM is an effective modulation scheme by encoding the digital data on multiple orthogonal subcarriers. OFDM technique has been widely applied in wireless communication system since it performs well in reducing the intersymbol-interference (ISI) when data rate is high [70]. As shown in Fig. 8-1, compared with traditional frequency-division multiplexing (FDM) scheme, the sub-carrier signals used by OFDM are orthogonal with each other to save the bandwidth. The modulation of these subcarriers follows the traditional scheme such as quadrature amplitude modulation (QAM) and phase-shift keying (PSK). As each subcarrier is transmitted in low data rate, equalization process is simplified and the channel requirement is decreased.

There are several advantages of OFDM. First of all, OFDM can achieve high spectral efficiency. Second, it is robust against narrow-band and severe channel conditions, which contributes to less requirement on the equalization process. Third, it performs well with the help of guard intervals (GI) when there is severe fading caused by multipath propagation and ISI. However, OFDM also suffers from several shortcomings such as sensitive to Doppler shift and frequency synchronization and high peak-to-average-power ratio (PAPR). The cyclic prefix, guard interval and even training sequence also induce low transmission efficiency.
Figure 8-1 OFDM modulation scheme compared with traditional FDM.

The orthogonality of OFDM signal is usually implemented with fast Fourier transform (FFT) algorithm. Inverse FFT is applied on the sender side to generate orthogonal subcarriers and FFT is applied on the receiver side for the demodulation. GI is inserted between OFDM symbols to alleviate the ISI caused by multipath reflections, eliminates the requirement on the pulse-shaping filter and reduces the sensitivity to time synchronization problems.

Considering so many advantages of OFDM, it is wildly proposed in various wireless communication standard such as digital audio broadcasting, digital video broadcasting, WLAN (802.11, HIPERLAN), and so forth.
8.2 OFDM for VLC

Considering the complex indoor environment with lots of obstacles, multipath reflections are considered as one of the major factors that degrade the communication performance. OFDM is proposed as a modulation scheme to combat the ISI incurred by the multipath reflections. As IM/DD is applied in the VLC system, the transmitted signal shown is positive and real. Hermitian symmetry is always required for the input data to ensure the data to be real, while several methods are proposed to ensure the positivity. There are also specific drawbacks in the OFDM base VLC system. High PAPR requires a wide dynamic range for the linear power amplifier. As a result, some non-linear characteristics of the LED transmitter will largely impair the communication quality.

Several OFDM techniques have been proposed including pulse-amplitude-modulated discrete multitone (PAM-DMT) OFDM, DC-clipped optical OFDM (DCO-OFDM) as well as asymmetrically clipped optical OFDM (ACO-OFDM). PAM-DMT only modulates the imaginary parts of the subcarriers, and then the entire negative parts of the waveform are clipped off. The clipping noise only falls on the real part of each subcarrier and is orthogonal to the desired signal [71]. DCO-OFDM works by adding a DC bias to the signal and then a hard clipping is carried out on the negative signal pulses. In ACO-OFDM, only odd subcarriers are modulated and the impairment from clipping noise is avoided [72][73].
8.2.1 PAM-DMT [71]

\[ N \text{ complex symbols as } \mathbf{I} = [I_0, I_1, \ldots, I_{N-1}] \text{ represent the input bits, where } \mathbf{I}^T \]
denotes the transpose of a vector. \( I_0 \) and \( I_{N-1} \) are not modulated. Considering the
requirement of Hermitian symmetry, the modulated symbol is written as
\[ \mathbf{\tilde{I}} = [0, I_0, I_1, \ldots, I_{N-1}, 0, I_{N-1}^*, \ldots, I_1^*, I_0^*] \]. \( I_m \) is represented as \( j^m a_m \) where \( a_m \) is real symbol
mapped from a PAM constellation as shown in Fig. 8-2.

![Figure 8-2 PAM constellation.](image)

With IFFT operation, the output signals can be obtained as:
\[ x_k = \frac{1}{2N} \sum_{m=0}^{2N-1} I_m e^{j2\pi \frac{m}{2N} k} \]
\[ = \frac{1}{2N} \left[ \sum_{m=0}^{N-1} I_m e^{j2\pi \frac{m}{2N} k} + \sum_{m=0}^{N-1} I_{2N-m} e^{j2\pi \frac{(2N-m)}{2N} k} \right] \]
\[ = \frac{1}{2N} \sum_{m=0}^{N-1} i \left( a_m e^{j2\pi \frac{m}{2N} k} - a_m e^{-j2\pi \frac{m}{2N} k} \right) \]
\[ = -\frac{1}{N} \sum_{m=0}^{N-1} a_m \sin \left( 2\pi \frac{m}{2N} k \right) \quad k = 0, 1, \ldots, 2N - 1 \]

The symbols have the following property:

\[ x_{2N-k} = -\frac{1}{N} \sum_{m=0}^{N-1} a_m \sin \left( 2\pi \frac{m}{2N} (2N - k) \right) \]
\[ = \frac{1}{N} \sum_{m=0}^{N-1} a_m \sin \left( 2\pi \frac{m}{2N} k \right) = -x_k \quad (8-2) \]

As shown in Eq. (8-1) and Eq. (8-2), the entire symbol can be written as:

\[ \mathbf{x} = [0, x_0, x_1, \ldots, x_{N-1}, 0, -x_{N-1}, \ldots, -x_1, -x_0] \quad (8-3) \]

Considering that it includes both positive parts and negative parts equally, all the negative parts can be clipped out without losing any information. After inverse FFT (IFFT) process, CP is added and then the negative part is clipped and expressed as \( \mathbf{x}_c \).

At the receiver side, the reverse operation is performed with FFT operation:
As shown in Eq. (8-4), the clipping noise mainly influence the real part of the subcarriers, and the symbols can be recovered with the imaginary part of the first half subcarriers.

### 8.2.2 DCO-OFDM

DCO-OFDM works in a straight-forward way where the DC bias is added to the symbols to make them positive. The same symbol \( \hat{I} = [0, I_0, I_1, \ldots, I_{N-1}, 0, \ldots, I_1', I_0'] \) is generated but not constrained to PAM modulation. After IFFT operation, \( x \) becomes real but not always positive:

\[
x_k = \frac{1}{2N} \sum_{m=0}^{2N-1} I_m \exp\left(\frac{j2\pi km}{2N}\right).
\]  

(8-5)

After parallel to serial (P/S) converter, CP is added and then the analog signal \( x(t) \) passes through a low pass filter. An appropriate DC bias \( B_{dc} \) is added:

\[
B_{dc} = \mu \sqrt{E\{x(t)^2\}}.
\]

(8-6)
\( \mu \) is a proportionality constant and \( x(t) \) is assumed to follow a Gaussian model whose mean is zero and variance is \( E\{x_k^2\} \). As OFDM signals have a high PAPR, negative peaks still exist and the clipping process induces noise. The noise can be reduced by a relatively larger bias, which in turn brings up the optical energy/bit to noise power spectral density ratio \( E_b / N_0 \). As a result, DCO-OFDM scheme has the disadvantage that the optical power efficiency is low. The flow diagram of DCO-OFDM is shown in Fig. 8-3.

8.2.3 ACO-OFDM

Only odd subcarriers are used to carry data symbols in the ACO-OFDM scheme, biased signals are formed on the even subcarriers so the non-negative requirement is satisfied.
In the time duration of $T$ sec, $N/4$ complex symbols are transmitted after a $M$-QAM mapping ($M=4, 16, 64...$). A set of $N$ complex data symbols as $\mathbf{I} = [0, I_0, 0, I_1, ..., 0, I_{N/4-1}, 0, I_{N/4-1}, 0, ..., I_1, 0, I_0]^T$ are used to represent the input bits. The requirement of Hermitian symmetry is satisfied so that the symbols after IFFT are real:

$$x_k = \frac{1}{N} \sum_{m=0}^{N-1} I_m \exp \left( \frac{j2\pi km}{N} \right).$$  

(8-7)

The resulted time domain signal $x$ has the following property [73] as:

$$x_k = -x_{N/2+k}, \quad k = 0,1,\ldots,N/2-1$$  

(8-8)

$x$ is serialized and then after adding CP, the clipped subcarriers become $\lfloor x_k \rfloor_c$ so that the transmitted signal is unipolar. After passing through DAC and an ideal low pass filter, an analog signal $x_c(t)$ is generated to modulate the intensity of the optical transmitter. As clipping noise only falls on the even subcarriers, the transmitted symbols will not be affected and no information is lost.
After the signals pass through the optical channel, at the receiver side, PD is applied to convert optical signal to electrical signal. After passing through ADC, the discrete time domain signal is:

\[ \hat{x}_k = \left[ x_k \right]_c + w_k \]  

(8-9)

CP-removed signal is obtained and N-point FFT operation is carried out, useful information is extracted and then de-mapped to obtain the final output bits.

8.3 OFDM in VLC positioning

8.3.1 System configuration

The positioning system model is shown in Fig. 7-7, where the LEDs are modulated in the OFDM scheme. ACO-OFDM is applied considering that in the positioning system, optical power should be more efficiently utilized. The block diagram of the ACO-OFDM positioning system is depicted in Fig. 8-5. The LED-IDs are encoded as the input bits and mapped to the M-QAM constellation as \( I = \left[ I_0, I_1, \ldots, I_{N-1} \right] \), the real and non-negative signals are generated to modulate the light intensity.

These modulated signals passing through the optical channel, taken the multipath reflections as well as shot noise and thermal noise into consideration. The channel impulse response is estimated by CDMMC method, where the first three reflections are considered.
At the receiver end, PD is applied to detect the optical signal and then electrical domain signal is generated afterwards. Signals are obtained as $\hat{I} = [\hat{I}_0, \hat{I}_1, \ldots, \hat{I}_{N-1}]$ and after de-mapping, LED-ID are decoded so that the transmitter coordinates can be obtained for the positioning block. Training sequence is used to estimate the signal attenuation, so $I$ at transmitter side and $\hat{I}$ at receiver side are the input of the positioning block and the receiver coordinates are finally estimated.

![ACO-OFDM positioning system configuration](image)

Figure 8-5 ACO-OFDM positioning system configuration.

### 8.3.2 Positioning algorithm

For each subcarrier, the signal attenuation is expressed as [74][75]:

$$\text{Attenu}^k_i = \left| \frac{\hat{I}^k_i}{I^k_i} \right|^2 \quad k = 1\ldots l .$$

(8-10)

Considering FOV of the receiver, $l$ in Eq. (8-10) is the number of LED signals received by the PD, $k$ is the index of LED signal, and $i$ is the index of subcarriers. $\hat{I}^k_i$ is
the $k$-th received signal from the $i$-th subcarrier of the training sequence, while $\text{Atten}_i^k$ is the signal attenuation of the $i$-th subcarrier of $k$-th signal. By averaging the attenuation from all the subcarriers, the estimated attenuation value of $i$-th signal is expressed as:

$$\text{Atten}_i^k = \frac{1}{N} \sum_{i=1}^{N} \text{Atten}_i^k.$$ (8-11)

In light communication system, the distance between the $k$-th transmitter and the receiver is estimated as:

$$d_k = \sqrt{\frac{(m+1)A\cos^m(\phi_k)T_i(\psi_k)g(\psi_k)\cos(\psi_k)}{2\pi \text{Atten}_i^k}}.$$ (8-12)

Nonlinear estimation algorithm is applied and the flow diagram is shown in Fig. 8-6.

![Flow diagram of positioning algorithm with nonlinear estimation.](image)

Figure 8-6 Flow diagram of positioning algorithm with nonlinear estimation.

### 8.4 Simulation and discussion

The performance of the proposed OFDM-VLC system is detailed in this section where 512 subcarriers are used and symbols are drawn from 4-QAM constellations.
Sixty-four out of 512 subcarriers are used as the CP. Nineteen of 20 frames are used to transmit data while one is used as the training frame used to estimate the signal attenuation. With 20 MHz bandwidth, the data rate is around 8 Mbps.

Table 8-1 Optical and electrical characteristics of OPTEK, OV SPxBCR4 1-Watt White LED

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Parameter</th>
<th>MIN</th>
<th>TYP</th>
<th>MAX</th>
<th>Units</th>
</tr>
</thead>
<tbody>
<tr>
<td>$V_F$</td>
<td>Forward Voltage</td>
<td>3.0</td>
<td>3.5</td>
<td>4</td>
<td>V</td>
</tr>
<tr>
<td>$\Phi$</td>
<td>Luminous Flux</td>
<td>67</td>
<td>90</td>
<td>113</td>
<td>lm</td>
</tr>
<tr>
<td>$\Theta^{1/2}$</td>
<td>50% Power Angle</td>
<td>-</td>
<td>120</td>
<td>-</td>
<td>deg</td>
</tr>
</tbody>
</table>

Figure 8-7 Transfer characteristics of OPTEK, OVSPxBCR4 1-Watt white LED. (a) Fifth-order polynomial fit to the data. (b) The curve from the data sheet.

OPTEK, OVSPxBCR4 1-Watt white LED is considered as the model and its optical and electrical characteristics are given in Table 8-1. The nonlinearity of LED is taken into account where a polynomial order of five is applied to model the real measured
transfer function. Fig. 8-7 demonstrates the non-linear transfer characteristics of the LED and the polynomial function for simulation. The four OPTEK LEDs are biased at 3.2 V.

8.4.1 Positioning Results

![Positioning error (m) with OFDM modulation](image)

Figure 8-8 Positioning error (m) with OFDM modulation.

Based on nonlinear estimation algorithm, positioning performance with OFDM are estimated as in Fig. 8-8. The positioning error decreases a lot, although the error is still high at the outer region because of the multipath reflections. Fig. 8-9 compares the error distribution of OOK and OFDM modulation at the same data rate. Most of the positioning errors are within 1 m, and the highest error is around 1.7 m. With OFDM modulation, most of the errors are within 0.1 m and the highest error is just 0.5223 m.
Figure 8-9 Histogram of positioning error (m) with OOK and OFDM modulation.

CDF of positioning errors is calculated as shown in Fig. 8-10 where the 95% confidence interval line is marked out. For the inner, outer as well as entire region, the OFDM largely improves the positioning performance than OOK modulation. Table 8-2 numerically compares the positioning performance for OOK and OFDM in RMS and 95% confidence interval errors. OFDM scheme largely improves the positioning performance especially for the outer region where the multipath reflections are severe. For the OOK modulation, the system is able to deliver an accuracy of 1.183 m positioning services with 95% confidence and the RMS error is 0.5678 m. OFDM improves the positioning performance of the outer region to 0.1506 m, and the RMS error of the entire room is just 0.1387 m, 95 % of the positioning errors are within 0.2220 m.
Figure 8-10 CDF of positioning errors for OOK and OFDM.

Table 8-2 Positioning error for OOK/OFDM modulation (m).

<table>
<thead>
<tr>
<th></th>
<th>Inner region</th>
<th>Outer region</th>
<th>Entire room</th>
</tr>
</thead>
<tbody>
<tr>
<td>OOK RMS</td>
<td>0.2457</td>
<td>0.8159</td>
<td>0.5678</td>
</tr>
<tr>
<td>OOK 95% confidence interval</td>
<td>0.4908</td>
<td>1.249</td>
<td>1.118</td>
</tr>
<tr>
<td>OFDM RMS</td>
<td>0.0540</td>
<td>0.1501</td>
<td>0.1068</td>
</tr>
<tr>
<td>OFDM 95% confidence interval</td>
<td>0.0794</td>
<td>0.3638</td>
<td>0.2220</td>
</tr>
</tbody>
</table>

8.4.2 Improvement with Signal Selection Approach

Signal selection is also applied in the OFDM VLC system to improve the positioning performance. In Table 8-3, it is obvious that the positioning accuracy
increases when some weak signals are removed, especially for the outer region. The performance of the inner region is not improved largely, since the received signal are less affected by the multipath reflections.

Table 8-3 RMS error for LED selection (m).

<table>
<thead>
<tr>
<th></th>
<th>All</th>
<th>6 LED</th>
<th>5 LED</th>
<th>4 LED</th>
</tr>
</thead>
<tbody>
<tr>
<td>Inner</td>
<td>0.0540</td>
<td>0.0537</td>
<td>0.0531</td>
<td>0.0528</td>
</tr>
<tr>
<td>Outer</td>
<td>0.1501</td>
<td>0.1371</td>
<td>0.1118</td>
<td>0.1004</td>
</tr>
<tr>
<td>Entire</td>
<td>0.1068</td>
<td>0.0989</td>
<td>0.0837</td>
<td>0.0771</td>
</tr>
</tbody>
</table>

Figure 8-11 Positioning errors with 4 LED signal selected.
8.5 Parameter analysis

In this section, positioning performance is analyzed on three system parameters: modulation order, carrier number and signal to noise ratio (SNR).
8.5.1 Modulation order

Table 8-4 RMS error for different OFDM modulation order (m).

<table>
<thead>
<tr>
<th></th>
<th>All LEDs</th>
<th>6 LEDs</th>
<th>5 LEDs</th>
<th>4 LEDs</th>
</tr>
</thead>
<tbody>
<tr>
<td>4 QAM</td>
<td>0.1068</td>
<td>0.0989</td>
<td>0.0837</td>
<td>0.0771</td>
</tr>
<tr>
<td>16 QAM</td>
<td>0.1079</td>
<td>0.0997</td>
<td>0.0844</td>
<td>0.0796</td>
</tr>
<tr>
<td>64 QAM</td>
<td>0.1033</td>
<td>0.0963</td>
<td>0.0852</td>
<td>0.0750</td>
</tr>
<tr>
<td>128 QAM</td>
<td>0.1103</td>
<td>0.0986</td>
<td>0.0831</td>
<td>0.0745</td>
</tr>
<tr>
<td>256 QAM</td>
<td>0.1107</td>
<td>0.0950</td>
<td>0.0859</td>
<td>0.0776</td>
</tr>
</tbody>
</table>

Figure 8-14 Positioning error when M=256, Carrier Number=512 and SNR= 15dB.

The RMS errors are summarized shown in Table 8-4, which are not affected too much by the modulation order. The variance of RMS errors is around $10^{-6}$, which can be
considered as almost not affect the positioning performance. As increasing the
modulation order will increase the data rate, the proposed OFDM modulation system can
realize indoor positioning and high data rate communication at the same time.

Figure 8-15 Histogram of positioning error when M=256, Carrier Number=512 and
SNR= 15 dB.

Figure 8-16 CDF of different modulation order.

In order to make this paper concise, the results of 256 modulation order is shown
in Fig. 8-14 and Fig. 8-15. Fig. 8-16 depicts the CDF distribution of positioning errors,
which further shows the modulation order does not influence too much on the positioning
performance.
8.5.2 Subcarrier number

The positioning performance of different subcarrier numbers (i.e., the FFT size) are analyzed in this section. The positioning error decreases slightly as the number of subcarriers increases. The larger the size of FFT is, the narrower the band of sub-channels is. As a result, the estimation of the channel is less affected by the multipath reflections. Fig. 8-17 and Fig. 8-18 shows the positioning error with 256 and 1024 subcarriers, respectively. The corresponding histogram is shown in Fig. 8-19.

Table 8-5 RMS error for different OFDM subcarriers (m).

<table>
<thead>
<tr>
<th></th>
<th>All LEDs</th>
<th>6 LEDs</th>
<th>5 LEDs</th>
<th>4 LEDs</th>
</tr>
</thead>
<tbody>
<tr>
<td>256 subcarriers</td>
<td>0.1085</td>
<td>0.0101</td>
<td>0.0849</td>
<td>0.0797</td>
</tr>
<tr>
<td>512 subcarriers</td>
<td>0.1068</td>
<td>0.0989</td>
<td>0.0837</td>
<td>0.0771</td>
</tr>
<tr>
<td>1024 subcarriers</td>
<td>0.1059</td>
<td>0.0974</td>
<td>0.0832</td>
<td>0.0735</td>
</tr>
</tbody>
</table>
Figure 8-17 Positioning error when M=4, Carrier Number=256 and SNR= 15 dB.

Figure 8-18 Positioning error when M=4, Subcarrier Number=1024 and SNR= 15 dB.
Figure 8-19 Histogram of positioning error when M=4, SNR= 15 dB (a) 256 subcarriers (b) 1024 subcarriers.

Fig. 8-20 estimates the CDF distribution of positioning errors, where only slight improvement is observed with the increasing of subcarrier number.

Figure 8-20 CDF of positioning errors with 256, 512 and 1024 subcarriers.
8.5.3 Effect of SNR

In this subsection, we analyze the effect of SNR on the positioning accuracy. As shown in Table 8-6, when SNR decreases to 0 dB, the positioning accuracy decreases, which follows the common sense. However, when the SNR increases to 30 dB, the improvement on the positioning accuracy is not large. The reason is that although the effect from the noise decreases, the effect from multipath reflections still remains. Fig. 8-21 and Fig. 8-22 show the positioning errors for the 0 dB and 30 dB SNR, respectively. The histogram is shown in Fig. 8-23.

Figure 8-21 Positioning error when M=4, Subcarrier Number=512 and SNR= 0 dB.
Figure 8-22 Positioning error when M=4, Subcarrier Number=512 and SNR= 30 dB.

Table 8-6 RMS error for different SNR (m)

<table>
<thead>
<tr>
<th>SNR</th>
<th>All LEDs</th>
<th>6 LEDs</th>
<th>5 LEDs</th>
<th>4 LEDs</th>
</tr>
</thead>
<tbody>
<tr>
<td>SNR=0 dB</td>
<td>0.1366</td>
<td>0.1229</td>
<td>0.1117</td>
<td>0.1011</td>
</tr>
<tr>
<td>SNR=15 dB</td>
<td>0.1068</td>
<td>0.0989</td>
<td>0.0837</td>
<td>0.0771</td>
</tr>
<tr>
<td>SNR=30 dB</td>
<td>0.1008</td>
<td>0.0973</td>
<td>0.0773</td>
<td>0.0719</td>
</tr>
</tbody>
</table>
Figure 8-23 Histogram of positioning error when M=4, subcarriers=512 (a) SNR=0 dB (b) SNR= 30 dB.

Figure 8-24 CDF of positioning errors when SNR = 0 dB, 15 dB and 30 dB.
Chapter 9

Conclusion and Future Work

9.1 Conclusion

This dissertation focuses on indoor localization with VLC technology, which overcomes some problems currently existing in RF based technology such as multipath reflections, shortage of radio frequency spectrum and electromagnetic radiation.

This dissertation demonstrates the research in three main aspects: first, it constructs the concept and the model of the system; second, positioning algorithms, as the main issue in indoor localization, are detailed; third, many approaches are proposed to further improve the positioning performance.

First section includes Chapter 2 and 3. In Chapter 2, the current positioning algorithms as triangulation, scene analysis and proximity are detailed, and the positive and negative aspects of these algorithms are analyzed. Different techniques as the candidates of indoor localization are addressed such as Assisted-GPS, UWB, Zigbee, WLAN and Bluetooth. Finally, the advantages of the positioning system based on VLC are detailed. In Chapter 3, the VLC technology is introduced in detail. As the LED acts as the transmitter, the radiation pattern is detailed. Receiver is usually a PD to detect the received signal strength and its FOV decides how many signals it can detect. If the channel is the LOS link, the channel DC gain is the main factor that determines the received power. Channel DC gain is related to the transmitter and receiver property and
the distance. The noise in the channel induce positioning errors, which is mainly compose of shot noise and thermal noise and follows Gaussian distribution.

The second section is Chapter 4, where the positioning system is detailed. Channel access methods are addressed. TDMA has the synchronization requirement but the bandwidth usage is efficient. With BFSA, deployment cost is decreased with no synchronization requirement but bandwidth is wasted. The positioning algorithm is based on the RSS information detected from PD. Signal attenuation is calculated so that the distance between the transmitters and receiver is estimated. The transmitter’s coordinates are obtained by decoding the ID signals. These transmitters act as the center of several different circles and the calculated distances are the radius of these circles. The receiver position is finally estimated as in the intersection of these circles. For the 3-D scenario, positioning is realized by firstly making an assumption on the vertical coordinates and then feed the initial estimates back to the original equation for final estimate.

The third section focuses on the improvement of positioning performance which includes Chapter 5 to Chapter 8. In Chapter 5, three filtering techniques are applied to remove the large deviations and achieve high accuracy. Kalman filter includes two phases which only can be used for linear and Gaussian model. Particle filter, as a Monte Carlo approach uses a set of particles to approximate the posterior distribution. GM-SPPF uses a set of Gaussian model to represent the particles. In Chapter 6, a nonlinear model is built up for the 3-D scenario, which better approximates the real situation when the height of the receiver is unknown. The trust region reflective algorithm acts as the solver.

Chapter 7 analyzes the impact of multipath reflections on the positioning accuracy in the complex indoor environment, and the impulse response is analyzed by employing
CDMMC algorithms. Impulse response and received signal power for three specific regions as corner, edge and center are addressed. The positioning error, histogram as well as CDF are demonstrated. To alleviate the influence of multipath reflections, three modification approaches are proposed. First, nonlinear estimation is proposed to better approximate the model. Second, signal selection is conducted so that the largely influenced signals can be removed. Finally, the distance between the LED bulbs is adjusted to make the light distributed more uniformly.

OFDM is used in the positioning system to achieve high positioning accuracy in Chapter 8. The previous studies on indoor VLC positioning are built on a low speed modulation, while high data rate transmission can be realized with OFDM. Both communication and positioning can be realized at the same time, so service data can be transmitted.

9.2 Future Work

For the channel access method, the author proposes to use carrier sense multiple access with collision detection (CSMA/CD) approach as in Fig. 9-1. Before each LED sends the signal, it firstly detects whether other LEDs are sending signals. If the channel is occupied, it will wait for a random time and then send it again. When the LED is transmitting its signal, it will keeps detecting whether there is any collision, if not, it continues to transmit. If collision happens, it will stop and then send the signal after a random time. The collision possibility during the transmission is low since the positioning information is short.
Figure 9-1 Block diagram of CSMA/CD

Figure 9-2 Sensor fusion with centralized Kalman filter
Considering there may be some blockage exists, inertial navigation system (INS) is proposed to work together with the light positioning system to realized robust positioning. INS usually includes the estimation from accelerometer, gyroscope and e-campus. Fig. 9-2 shows the sensor fusion system combines the INS and the light positioning system with Kalman filter. Data from INS are used in the time update phase while the data from VLC are used in the correction phase.

Finally, as shown in Fig. 9-3, VLC is proposed to combine with current WiFi system for both communication and positioning purposes. VLC is used for downlink with CSMA/CD protocol to transmitter data and positioning information, while WiFi is used as the uplink to send the data request and report current position to the hub. In this way, LBS can be realized without using a lot of WiFi band as the uplink always has a low data load.

Figure 9-3 LBS realized by combining VLC and Wi-Fi


2009.


Wenjun Gu; Mohsen Kavehrad; Mohammadreza Aminikashani, “Three-
dimensional indoor light positioning algorithm based on nonlinear estimation,”


VITA

Wenjun Gu

Wenjun Gu is now a Ph.D. candidate in the Department of Electrical Engineering at the Pennsylvania State University under the supervision of Prof. Mohsen Kavehrad. She obtained her B.S. degree from the Department of Opt-electronic Engineering at Tianjin University, Tianjin, China in 2011. She joined the Center for Information and Communications Technology Research (CICTR) at Penn State in 2012 as a research assistant pursuing her Ph.D degree in Electrical Engineering. She has performed research on optical wireless communication and related applications, especially indoor optical positioning and related techniques, funded by Boeing, Airbus and other industry members through NSF Award no. IIP-1169024, IUCRC on optical wireless applications. Her work has been presented and published in prestigious conferences and journals.