Performance of positioning and lighting services for smart buildings : a wireless sensor network approach

Chan, Edwin Yiu Wing

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**NANYANG
TECHNOLOGICAL
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**PERFORMANCE OF POSITIONING AND LIGHTING
SERVICES FOR SMART BUILDINGS:
A WIRELESS SENSOR NETWORK APPROACH**

**CHAN YIU WING EDWIN
SCHOOL OF ELECTRICAL & ELECTRONIC ENGINEERING
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**Performance of Positioning and Lighting
Services for Smart Buildings:
A Wireless Sensor Network Approach**

CHAN Yiu Wing Edwin

School of Electrical & Electronic Engineering

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Abstract

Continuous population growth and global urbanization is forcing us to review the current usage of resources, such as energy and water, in cities. In response, researchers and practitioners are leveraging the latest information and communication technologies (ICT) to make our cities smarter. Smart buildings in particular, as a building block of smart cities, will play a critical role in utilizing the resources in a more efficient and sustainable manner.

A smart building, enabled by technologies, is able to monitor and control its sub-systems effectively and efficiently, while at the same time, provide a comfortable and productive environment to its occupants. With the extensive use of wireless sensors networks (WSN) and Internet of Things (IoT) technologies within a building, real-time environment data are collected by sensors and relayed to the building automation system (BAS), which then holistically manages the services, e.g. lighting, HVAC and security, of the building.

In this thesis, we focus on two important services, namely lighting and positioning, which are commonly found in smart buildings and can potentially benefit from the use of WSN technology. For the former, a WSN-based light management system, which involves sensing, control and wireless communications, is first studied. The issues of energy efficiency and occupant comfort are considered when a new model of daylight-responsive lighting and shading control problem is formulated. As a consequence of the preliminary evaluation, a survey of available illuminance sensing technologies is conducted. Subsequently, a wireless sensing platform consisting of high accuracy

analog illuminance sensors is developed, and its performance is assessed in a high-tech life-sized test facility.

Positioning service is another important asset to a smart building. The occupancy data, including positions and identities, that it obtains are critical to the effectiveness of other services, such as lighting and HVAC, in a smart building. Taking advantage of the envisaged large scale deployment of WSNs in smart buildings, the Discrete Weighted Centroid Localization algorithm (dWCL) is proposed as a potential solution for a WSN-based indoor positioning system (IPS). Under this architecture, a wireless device can estimate its own position within the building with the aid of the underlying WSN infrastructure. Considering the current state of digital electronics, dWCL is a more practical alternative to other WCL-based algorithms and is flexible to accommodate different performance requirements. Based on the presented analytical framework, two optimizing approaches are introduced to further elevate its performance.

Finally, the thesis examines the fundamental limit of the class of range-free localization algorithms in WSN. Mathematical framework to analyze the resolution of this class of algorithms is proposed. In addition, the analytical expression for the localization error distribution is presented. Unlike the prior work based on the circular coverage model, a more realistic scenario is considered, where the radio propagation is subject to the log-normal shadow fading and the correlation of shadow fading is also taken into account in the analysis of the problem.

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List of Abbreviations

AOA	Angle of arrival
BAS	Building automation system
CDF	Cumulative distribution function
CRB	Cramér-Rao Bound
DALI	Digital Addressable Lighting Interface
dWCL	Discrete Weighted Centroid Localization
HVAC	Heating, ventilation, and air conditioning
ICT	Information and communication technologies
IEEE	Institute of Electrical and Electronics Engineers
IETF	Internet Engineering Task Force
i.i.d.	Independent and identically distributed
IoT	Internet of Things
IP	Internet Protocol
IPS	Indoor positioning system
PDF	Probability density function
RF	Radio frequency
RV	Random variable
RSS	Received signal strength
TOA	Time of arrival
TDOA	Time difference of arrival
WCL	Weighted Centroid Localization
WSN	Wireless sensor network

Chapter 1

Introduction

1.1 Background

Currently the world is witnessing rapid urbanization at a global scale. Only in 2007 did the urban population surpass the rural population for the first time in history. In 2014, about 54 % of the world's population is residing in urban areas. This upward trend is expected to continue, and by 2050, it is estimated that the figure will reach 66 %. To put this into perspective, the urban population is going to increase by another 2.5 billion people [2]. With this influx of people comes the escalating demand for resources such as energy and water, as well as services such as housing, education, transportation and health care. If this is left unchecked, it may stress the existing infrastructures and systems in the cities, and pose numerous challenges on both the city governance and the quality of life for residents.

In response to these needs, researchers and practitioners all over the world are leveraging the latest development in information and communication technologies (ICT) to manage the resources and infrastructures more efficiently or in a “smarter” way. Take buildings for example, applying wireless sensor network (WSN) and Internet of Things (IoT) technologies greatly enhances the sensing and actuation capability and also connects subsystems which otherwise operate separately, thereby converting

them into more energy-efficient and smarter buildings [3, 4]. Similarly, the conventional transport system, health care system and power grid are also being upgraded and transformed into intelligent transport system [5], smart health care system [6, 7] and smart grid [8] respectively. By combining these subsystems, there are currently a number of research efforts (e.g. [9, 10]) endeavoring to pave the way to the realization of smart cities [11]. Evidently, the notion of smart city is well-received by governments throughout the world. Numerous programs and initiatives have been proposed, some of which are already well underway in a number of cities. Notable examples include Smart Nation of Singapore [12], Amsterdam Smart City of Amsterdam [13], iBarcelona of Barcelona [14], MK:Smart of Milton Keynes [15] and Smart Cities Mission of India [16].

1.2 Smart Buildings

Evolving from primitive shelters made from stones, animal skins and other natural materials, buildings nowadays are much more complex in design, and their structures are much stronger as they are normally built with steels and glasses. Yet they all serve the same purpose—to provide shelter and comfort for the people inside. In fact, buildings are an integral part of people’s lives, as they, on average, spend 87 % of their time inside buildings [17]. It perhaps comes as no surprise that the buildings sector is consuming a lion share of energy globally. In the U.S., for instance, buildings account for over 40 % of total energy consumption or 73 % of electricity generated in 2015 [18]. In Singapore, buildings use about half of the nation’s electricity [19]. In light of these, many researchers are developing smart building technologies to reduce energy consumption in buildings. It is also in line with the fact that many countries are rolling out policies to curb energy consumption in the buildings sector, with added benefits of lowering CO₂ emission and improving sustainability. The “Better Buildings Initiative” in the U.S. aims to improve energy efficiency in commercial buildings by

20 % by 2020 [20]. In Singapore, several “Green Building Masterplans” have been launched to achieve the target of “greening” at least 80 % of buildings by 2030 [21].

In addition to academia, there are also a lot of interests in the industry. International corporations, such as Siemens and Johnson Controls, are providing a plethora of commercial solutions to make buildings “smarter”. A recent retrofitting project sees the Empire State Building in the U.S. saving nearly 40 % of its energy consumption [22]. This successful business case will spur other building owners and operators to adopt energy saving strategies more readily. As such, the global market for smart building solutions is forecast to grow from \$7.0 billion in 2015 to \$17.4 billion in 2019 [23].

A smart building, enabled by technologies, is able to monitor and control its subsystems effectively and efficiently, while at the same time, provide a comfortable and productive environment to its occupants. Sensors, like the skin of a building, sense and measure the environmental conditions, e.g. temperature, humidity, illuminance and occupancy, within the building. Not limited to the indoor environment, sensors can also be deployed outside a building such as rooftop in order to measure the parameters of the external environment, e.g. solar irradiance and sky conditions. Rapid development of WSN technology has made large scale deployment of sensors affordable. Moreover, low-power wireless communications also allows these sensors to be deployed virtually anywhere to sense and relay environmental data for a long period of time on batteries, without being tethered to the power mains.

With the real-time data gathered by the sensors, the building automation system (BAS), as the brain of the building, can holistically manage and control different physical systems (e.g. HVAC system, lighting and shading system and security system) in the building in an intelligent and coordinated manner. For example, the BAS can control the air conditioning and lighting services according to the occupancy data and their preferences. In doing so, energy waste is reduced and the building energy efficiency is greatly improved. In addition to cutting operation cost, it also brings a

wealth of benefits to the occupants. A well-designed visual environment, for instance, can maximize the occupants' comfort and thereby their productivity [24].

Furthermore, IoT defines the networking framework and mechanism to interconnect all devices and subsystems within the building to the Internet. Information beyond the building can be made available and exploited to further enhance the operation of the building. Based on the price signal from the utilities, for example, the BAS can turn off non-critical loads within the building in order to reduce the demand at peak time. Fig. 1.1 summarizes the interactions of these components in a smart building. The remaining of this section further elaborates on two core components of a smart building, namely the BAS and the WSN.

Fig. 1.1: Data flow in a smart building.

1.2.1 Building Automation System

Given the complexity and scale of a smart building, building automation system (BAS) is often employed for better management and operation. BAS is essentially a computer-based control system linked to different subsystems, e.g. the HVAC system, the lighting and shading system and the security system. The integrated system allows data to be consolidated on a single platform, which eases the information management

effort tremendously and reduces the manpower required. Maintenance cost for the building is also lowered due to early fault detection in equipment, which avoids long downtime and major repair.

Energy management is one of the major functions of BAS. This feature is enabled by real-time monitoring, and energy saving is realized by controlling and coordinating all the subsystems within a building intelligently in response to the external environment. Facilitated by the installed sensors, a BAS is able to monitor the conditions of the building constantly. Any deviation from the desired operating point is feededback to the BAS, which will automatically adjust the corresponding subsystems accordingly. A BAS, for example, normally schedules the air-conditioning system based on the time of day schedules. But in one warm afternoon, when it detects the space near the window is getting too warm, it decides to lower the temperature setting of the air-conditioning system for that particular zone. In case of lighting, the BAS can raise the window blinds to admit daylight into the building such that it can dim the electrical lighting to save electricity. In addition, if occupancy sensing is available, BAS can activate lighting when and where needed.

BAS's nowadays are often implemented using IP and a few open standards, e.g. BACnet, KNX, LonWorks [25]. Hence interoperability issues between products from different vendors are eliminated. Moreover, the usage of buildings may change over time, and the construct of a BAS offers the flexibility to reconfigure and adapt to the new requirements with ease.

1.2.2 Wireless Sensor Network

Recent technological advances in low-power electronics and wireless communications have made available efficient, low-cost, low-power and multifunctional devices for use in sensing applications. These devices are typically small, limited in memory and computational capacity. Battery is usually the main source of power, while a sec-

ondary power supply such as solar panel may be available depending on the deployed location. These miniature devices are often just referred to as sensor nodes when they are equipped with sensors for some specific parameters, e.g. temperature, illuminance, humidity, etc.

In general, a WSN is a network of wireless sensor nodes formed in order to monitor or sense the environmental conditions cooperatively. In a typical monitoring application, a number of sensor nodes are deployed either inside of or near a monitoring area (sensor field). Using the on-board sensors, the sensor nodes sense and measure the properties of the environment. Under the prescribed mechanisms, the collected data are transmitted along other sensor nodes hop by hop to the gateway node, which forwards to the client afterwards.

WSNs are suitable for performing the sensing and monitoring functions in smart buildings for a multitude of reasons. Firstly, the IEEE 802.15.4 standard is created specifically for low power and low data rate wireless communication between devices, and the transmission distance is assumed to be short (about tens of meter). This is quite adequate for a typical deployment of sensor nodes within a building. Secondly, the sensor nodes are able to connect and organize themselves into a network. This greatly improves the robustness of the network. Even when some nodes are added or removed, the network is able to adapt to changes. In addition, mesh networking techniques allow data transmission along different paths, hence increasing the reliability of the network dramatically. Furthermore, WSNs feature much easier deployment and better flexibility when compared with wired solutions, whose cost for extra cabling and maintenance is high. This superiority is especially critical in retrofitting projects for existing buildings. Fig. 1.2 illustrates a new WSN which can be easily integrated into the existing BAS of a building.

Fig. 1.2: System architecture of an existing BAS to be augmented with a new WSN.

1.2.2.1 Communications Standards for WSN

The IEEE 802.15.4 standard is maintained by the IEEE 802.15 working group [26]. It is widely adopted in WSNs, and it is the basis for a few higher layer specifications, e.g. ZigBee and 6LoWPAN. The standard defines only the physical layer (PHY) and media access control (MAC) in the OSI reference model. While the PHY defines frequency, power, modulation, and other wireless conditions of the link, the MAC defines the format of the data handling.

By building on the IEEE 802.15.4 standard, ZigBee is a mesh networking protocol from the network layer and up. A host of profiles has been defined to suit different applications. Over the years, it has gathered support from many industrial partners. Although the original specifications are not IP-ready, the ZigBee IP [27] specification is defined recently to support IPv6 applications. At the moment, a new ZigBee 3.0 standard is under development. An alternative is *IPv6 over Low power Wireless Personal Area Network* (6LoWPAN) [28] proposed by IETF. It provides an adaptation

layer that implements encapsulation and header compression between the link layer and IP layer. Essentially it defines the mechanism to connect a 802.15.4 device to the Internet.

1.3 Objectives and Contributions

As mentioned above, the buildings sector accounts for most of the electricity generation, and people tend to spend most of their time indoors. It is therefore imperative to make buildings smarter. With this in mind, smart buildings are designed to deliver their building services effectively and efficiently to the occupants, while at the same time, create a comfortable and productive environment by ensuring visual comfort, thermal comfort, etc. for them. This thesis focuses on two services—lighting and positioning—that are important components of smart buildings.

Lighting service plays an essential role in the operation of smart buildings. It continuously provides illumination for the occupants to carry out their tasks and activities. While doing this, it takes up a significant share of the total energy consumption of buildings. In order to address the effectiveness and efficiency of lighting services in smart buildings, the first objective of the thesis is to design and develop a WSN-based light management system, which involves sensing, control and wireless communications.

Among different proposed energy reduction strategies, daylighting is one of the popular approaches. Supplementing the lighting system with daylight allows the system to dim the electric lighting, thereby reducing the electricity consumption. However, admitting daylight into a building may also cause visual discomfort such as glare to occupants. As such, the issues of energy efficiency and occupant comfort are considered when a new model of daylight-responsive lighting and shading control problem is formulated. Its aim is to minimize energy consumption of the lighting system by utilizing daylight as much as possible, while at the same time ensuring

sufficient illumination and visual comfort to occupants.

Another aspect of the light management system to be investigated is the collection of high accuracy illuminance level within the building. As the skin of the building, sensors are responsible for collecting these data first-hand. The fidelity of the readings is therefore of paramount importance. However, sometimes due to budget constraint, low-cost sensors with dubious accuracy are in use. If the accuracy of the data is questionable, it will cause the “garbage in, garbage out” effect that negatively impacts the control system. Large amount of errors in the sensor readings will propagate to the control algorithm. Wasting energy at the very least, it may even cause discomfort to the occupants, so much so that they may override the system and take manual control. In view of this sensor accuracy issue, a survey of available illuminance sensing technologies are conducted in order to understand their limitations. As a result of the evaluation, a wireless sensing platform consisting of high accuracy analog illuminance sensors is developed. The adoption of wireless mesh networking technology grants further flexibility to the system, rendering it a suitable solution for retrofitting existing buildings. Finally, its performance is assessed in a high-tech life-sized test facility.

Positioning service is another important asset to a smart building. The occupancy data that it obtains are valuable to other subsystems. For example, knowing the positions and identities of the occupants, the lighting system only needs to adjust the lighting conditions in the relevant zones according to the occupants’ preferences, thereby reducing energy consumption and ensuring occupants’ satisfaction. Other building services, such as HVAC and security systems, would also benefit from the availability of accurate location information of occupants in a similar fashion.

Although GPS [29] is probably the most well-known and highly adopted system to acquire location information, it falls short in indoor environment. Consequently, a number of alternative technologies, such as Wi-Fi [30], camera [31], are proposed for indoor positioning system (IPS). Among them, we consider wireless sensor network (WSN) a promising candidate for enabling IPS. With the increasing need for

real-time sensing within buildings, it is safe to say that there will be a large number of wireless sensor nodes available in buildings. In addition to sensing, they may also serve a second purpose to offer positioning service, as numerous researchers have already demonstrated. It is therefore the second objective of the thesis to investigate the provisioning of an IPS with WSN in smart buildings. A new localization algorithm, dWCL, is proposed to make use of the existing WSN infrastructure. As dWCL is a discrete version of the Weighted Centroid Localization algorithm [32], it is a more practical alternative to its predecessors, considering the current state of digital electronics. Closed-form expression to characterize its performance is derived. Extensive simulations are conducted to validate the proposed model. Furthermore, two approaches to optimize its performance are suggested. A simple rule is also established to compute the optimal weighting factor if the boundaries of received signal strength levels are known.

As one of the main classes of localization algorithms, range-free algorithm has its merit of requiring simple, basic hardware and computation. The third and final objective of the thesis is to further examine the fundamental limit of the performance of localization algorithms of this type. Considering a more realistic radio model and correlated shadow fading, the theoretical bound on the resolution for the class of range-free localization algorithms is derived. Mathematical proof and simulation results are presented to support that the proposed scheme is able to generalize a highly-cited work [33], which is derived based on the more restrictive circular coverage model.

1.4 Organization of Thesis

The rest of the thesis is organized as follows. In Chapter 2, an overview of previous work on intelligent lighting systems, including sensing, control and user preferences, in buildings is presented. It is followed by an extensive literature review on localization, from the fundamental principles to some notable implementations. Furthermore, ex-

isting work on algorithms and error analyses for localization in WSN are surveyed. In addition, recent development on cooperative localization is covered. The development of a WSN-based light management system is discussed in Chapter 3. A new model of daylight-responsive lighting and shading control system is formulated. Additionally, a number of available illuminance sensing technologies are surveyed and evaluated. It is then followed by an assessment of the developed wireless platform for illuminance sensing. In Chapter 4, a new localization algorithm suitable for IPS is introduced. It takes advantage of the widespread use of wireless sensor nodes in smart buildings. Performance analysis and optimization regarding the proposed algorithm are also presented. Continuing on the investigation of localization, the theoretical bound on the resolution for the class of range-free localization algorithms is investigated in Chapter 5. Simulation results are provided to validate the analysis. Finally, the thesis is concluded in Chapter 6 with a discussion on the potential directions for future work.

Chapter 2

Literature Review

This chapter begins with a survey of existing works on intelligent lighting systems in buildings. This is certainly useful for enabling services, such as lighting, in future smart buildings that form a part of a smart city. It is then followed by an overview of indoor positioning systems, from the fundamental principles to some notable implementations. Since localization in WSN is one of the key aspects of the thesis, an extensive literature review, focusing on the algorithms and error analyses, is presented. Additionally, recent development on cooperative localization is covered in the final part.

2.1 Intelligent Lighting in Buildings

As lighting system is consuming a large portion of energy in buildings, researchers are motivated to look for techniques to reduce the energy consumption. Harvesting daylight is one of them. Daylighting is the practice of using natural sunlight effectively. In addition to saving energy, other benefits, e.g. promoting human health and increasing productivity [24], are well documented in the literature. A survey [34] also suggests that occupants prefer daylight to artificial light. In order to measure the amount of daylight, the authors in [35] describes a setup of monitoring system

incorporating illuminance sensors and digital single-lens reflex (DSLR) cameras.

On the other hand, admitting daylight also causes glare and solar heat gain, which in turn lead to occupant discomfort. Typically, motorized blinds or shades and electrochromic glass (i.e. smart windows) are used to control the amount of daylight entering a building [36]. A field study [37] shows that a carefully designed automatic shading system is able to save a significant amount of lighting energy and address occupant comfort requirements at the same time. In addition, a post-occupancy evaluation survey in a modern high-rise commercial building shows that some form of automatic lighting controls and automatic window shades are well received by the occupants [38]. In another study [39], the authors suggest that enabling tangible interaction in the lighting control system can improve its effectiveness and lead to high user satisfaction.

The key challenge for intelligent lighting systems in buildings is to strike the balance between energy saving and occupant comfort, especially in the presence of dynamic outdoor conditions and various indoor requirements. In response to the window orientation and the sky conditions, Lu *et al.* [40] propose schemes to control the window transparency (via motorized blind or electrochromic glass) and electric lighting in order to reduce the lighting energy and ensure the user comfort. The development of a lighting control system with daylight harvesting is described in [41]. By comparing the indoor and outdoor illuminance levels against the user preference, the system adjusts the opening angle of the venetian blinds and the intensity of artificial light accordingly.

Caicedo *et al.* [42] formulate the dimming control of a LED lighting system as a constrained linear program (LP). The objective is to minimize the power consumption by lighting system while maintaining the illuminance level around the occupants. An extension work [43] considers a networked LED-based lighting system with local sensing and control capability, and solves the problem as a distributed LP. A shading system combining split-pane electrochromic windows and blinds is studied in [44] using

simulation tools. Closed-loop proportional control algorithms are proposed in [45] to improve the performance of integrated system with automatic roller shade and dimmable light. A joint blind and light control problem is studied by Din and Kim [46]. It is solved sequentially by first finding the blind tilt angle that blocks the direct daylight and then adjusting intensity of the luminaires to meet the user requirement.

Recently, there are also a number of lighting control systems developed using WSN technology. For instance, a WSN-based intelligent lighting control system is proposed in [47] to satisfy each user's illumination requirement, defined as a combination of background and local lighting. Two user requirement models are proposed, and they lead to a LP and a NLP problem respectively. Assuming the local lighting has little effect on the background lighting, the problem can be solved by a two-stage heuristic to minimize the total power consumption. In [48], the authors employ a WSN to allow for personal control of a DC-grid powered and DALI-based LED system in a windowless office. In each personal workspace, a light sensor and a LED form a closed-loop system that controls the illuminance level in order to meet user preference in real-time. An intelligent LED lighting system is proposed in [49]. The system consists of multiple sensor nodes, each of which integrates a motion sensor, an illumination sensor and a ZigBee module. Users are required to input their feedback via smart phones such that the system parameter (i.e. minimum light intensity) is adjusted automatically. In [50], the authors integrate DALI devices into an IEEE 802.15.4-based WSN. A prototype has been implemented to control a light remotely.

A truly intelligent light management system should manage the occupant visual comfort as efficiently as possible. As such, various aspects of such system is discussed in Chapter 3. In particular, a daylight-responsive lighting and shading control problem is investigated. Its aim is to reduce energy consumption by utilizing daylight as much as possible, while at the same time not causing glare condition.

2.2 Indoor Positioning System

Over the past two decades, there are tremendous efforts in designing and implementing indoor positioning system (IPS). Various localization technologies have been applied. The most prevalent one is the use of radio frequency (RF) signals, including satellite, Wi-Fi, ZigBee, ultra-wideband, Bluetooth, cellular, etc. Others use non-RF techniques such as inertial measurements, earth's magnetic field, ultrasound signals, optical and so forth. This section highlights some fundamental principles of localization that form the basis of IPS, and then introduces a few prominent examples.

2.2.1 Principles of Localization

Localization is the process of determining an *unknown* position with reference to some known locations, which are usually referred to as *anchors* or *beacons*. In general, localization involves two steps [51]:

- (i) Determining the distance or angle between pairs of locations, or, in short, ranging (see details in Section 2.2.1.1)
- (ii) Inferring the *unknown* position from the range information (see details in Section 2.2.1.2)

2.2.1.1 Ranging Techniques

There are a number of ways to determine the distance and angle between a pair of locations. Distance can be inferred from received signal strength (RSS), time of arrival (TOA) and time difference of arrival (TDOA), whereas angle information is typically represented by angle of arrival (AOA).

Distance Estimation As radio signals attenuate during propagation, RSS is an obvious candidate for inferring the propagation distance. Ideally, RSS is inversely proportional to the squared distance, i.e. $RSS \propto 1/d^2$, where d is the distance between

the two transceivers. In reality, however, signal propagation is affected by reflection, diffraction and scattering. This leads to a large error in the distance estimation. Although it is susceptible to environmental effect, RSS remains a popular choice for distance estimation since it is readily available in most transceivers.

Another option is to use TOA. Since radio signals travel at constant speed, the propagation time is proportional to the distance travelled. In Fig. 2.1, the transmitter sends a signal at t_1 , and it arrives at the receiver at time t_2 . The distance in between is therefore $d = s(t_2 - t_1)$, where s is the propagation speed of the signal. However, this places a stringent requirement on clock synchronization between the two devices.

Fig. 2.1: Estimating distance using TOA.

To circumvent the clock synchronization problem, one can use a combination of RF and ultrasound hardware. As ultrasound signals propagate much slower than RF signals, the TDOA ($t_2 - t_1$ in Fig. 2.2) can be used to estimate the distance. However, ultrasound signals are unidirectional, hence suffering from the line-of-sight problem. Furthermore, due to high attenuation rate, ultrasound signals cannot propagate very far and hence have limited ranges [51]. An alternative definition of TDOA is the difference in time at which a single signal arrives at multiple receivers.

Recently, ultra-wideband (UWB) technology is gaining a lot of traction in localization systems, since it can offer accurate and robust TOA-based ranging capability even in indoor and harsh environments plagued with reflections and multipaths [30, 52, 53].

Fig. 2.2: Estimating distance using TDOA between two types of signals.

UWB is specified in the IEEE 802.15.4a standard as one of the two new physical layers. With two-way ranging, it is reported that commercially available UWB modules are able to achieve an accuracy below 10 cm [54]. In addition, the theoretical limits of UWB ranging are studied in [55].

Angle Estimation For angle estimation, there are two common approaches in measuring the AOA of a signal:

- (i) Directional antenna—a careful design of antenna can create a narrow beam in the radiation pattern. By rotating the receiver antenna, the direction corresponding to the maximum signal strength can be taken as the direction of the transmitter [56].
- (ii) Antenna array—three or more receivers are uniformly spaced, and the AOA can be inferred by the phase differences of the received signals [57].

An advantage of using AOA is that it does not require clock synchronization between measuring units.

2.2.1.2 Position Computation

Once the range information, i.e. distance or angle, is obtained, one can compute the *unknown* position using the following techniques.

Trilateration Trilateration is commonly used in surveying and navigation. If the distances between an *unknown* position and at least three *anchors* are known, then it is possible to calculate the *unknown* position based on the positions of the *anchors*. Assuming there are three *anchors* and the coordinates of the i th *anchor* is denoted by (x_i, y_i) , three circles can be drawn around the *anchors* as shown in Fig. 2.3. Each circle is represented by the formula $(x - x_i)^2 + (y - y_i)^2 = d_i^2$, where (x, y) is the *unknown* position and d_i is the distance between the *unknown* position and the i th *anchor*. If d_i 's and (x_i, y_i) 's are accurate, a unique solution for (x, y) can be obtained. A simple geometric interpretation is that the intersection point of the three circle is the *unknown* position.

Fig. 2.3: Trilateration with three *anchors*.

In reality, however, distance measurements are typically blended with errors. Moreover, if more than three *anchors* are available, the resulting system of equations becomes overdetermined. In either case, no analytical solution is available, but it can be solved by using techniques such as least squares approach [57].

Multilateration Multilateration, on the other hand, uses TDOA, which indicates the difference in time a signal reaching, and hence the difference in the distance from, the *anchors*. Each TDOA defines a hyperboloid on which the transmitter lies. If the measurements are perfect, the *unknown* position can be obtained as the single point that the hyperboloids intersect. This rarely happens in reality though, and often a least squares method is needed.

Triangulation In triangulation, angle information is used instead of distances. When AOA information from at least three *anchors* is available, the unknown position can be estimated using trigonometric relationships (Fig. 2.4).

Fig. 2.4: Triangulation with three *anchors*.

Fingerprinting Fingerprinting, also known as scene analysis, typically includes two phases—offline training phase and online query phase [58]. In the offline phase, a site survey is conducted to collect, in the case of Wi-Fi based systems, the vectors of RSS from different access points (APs). In the online phase, the current observed signal vector is compared against the stored fingerprinting map. The target position is estimated using some similarity metrics and pattern recognition techniques such as k-nearest neighbors algorithm.

2.2.2 Some Notable Implementations

The Active Badge system [59] is one of the early contributions to IPS. In this system, each wearable tag, or badge, emits a unique infrared (IR) signal periodically. A network of sensors placed within the building pick up the signals and relay them to a central server, which then determines the location of the particular person. The effectiveness of the system is limited by the range of IR and also the interference from sunlight for example.

The Global Positioning System (GPS) [29] is perhaps the most widely used location system in the world currently. With the aid of the satellite constellation, a device

estimates its distances from the satellites using TOA, and infers its own location using trilateration. However, it has a high setup cost. Furthermore, it targets primarily for outdoor uses. Accuracy drops significantly in densely built areas and it may even fail indoors.

SpotOn [60] is a RFID-based system. Using RSS measurements to infer distances, a hill-climbing algorithm is proposed to locate the position. RFID is also employed in the LANDMARC system [61], in which some tags are designated as reference tags. The location of a tracking tag is taken as a weighted average of the reference tags, where the weights are assigned according to the difference in the signal strengths measured by RFID readers.

A fingerprinting method on Wi-Fi signals is used in RADAR [62] to locate and track personnel. Taking advantage of different travel speeds of RF and sound in air, the Cricket system [63] infers the distance between a pair of transmitter and receiver by the time difference between RF and ultrasound beacon signals, before the position is determined by trilateration.

Only a sample of notable IPS implementations is cited here. For more examples, interested readers are referred to surveys on RF-based localization techniques and IPS, e.g. [30, 52, 64]. There are also survey papers specialized in certain types of IPS. For instance, [58] focuses on Wi-Fi fingerprint-based indoor positioning techniques and systems. Image-based techniques using cameras are studied in [31]. [65] reviews the works using visible LED lights for indoor positioning. Investigation of smart phone-based IPS are presented in [66]. A review on pedestrian dead reckoning systems based on inertial measurement for smart phones or wearable devices can be found in [67].

2.3 Localization in WSN

One key assumption of this thesis is that all wireless sensor nodes in a building are able to acquire their own positions beforehand. As such, this section is devoted to

reviewing the relevant localization strategies available for WSNs.

Typically, a subset of nodes in a WSN, known as *anchor* or *beacon* nodes, are assumed to have prior knowledge of their own physical positions, whereas the rest, who are unaware of their positions, are called *unknown* nodes. Depending on the usage of range information, localization algorithms can be broadly classified into two categories—range-free (Section 2.3.1) and range-based (Section 2.3.2).

2.3.1 Range-free Localization Algorithms

Range-free, also known as connectivity-based, schemes aim to avoid sophisticated ranging measurement and computation, and perform localization based on connectivity information, i.e. “who is within communications range of whom” [68], only and without using any distance or angle measurement. The underlying principle of this category is—if node A can receive node B’s message and subsequently connect with node B, then node A is in proximity to node B.

A distributed approach is proposed by Bulusu *et al.* [69] where a dense grid of *anchor* nodes is employed to beacon their positions continually. An *unknown* node then estimates its position as the centroid of the *anchors* from whom it can receive the beacons. This approach is straightforward but the estimate may be crude. Accuracy improves with a large number of *anchors* but it increases the cost as well.

Doherty *et al.* [70] propose a centralized approach in which the network-wide connectivity information is first translated into constraints. The localization problem is then formulated as a convex optimization problem in the form of semidefinite program (SDP). Existing algorithms for solving linear programs and semidefinite programs can be used to solve the localization problem and yield the estimates for the positions of the unknown nodes.

Another well-known algorithm is APIT [71], in which an *unknown* node randomly divides those *anchors* that it is aware of into groups of three. Based on the RSS’s, the

unknown node tests whether it is inside or outside the triangle formed by each trio. The node then assumes its position as the center of the intersection areas of those triangles it lies inside (see Fig. 2.5). Since multiple overlapping triangles usually result in a smaller overlapping area, APIT can achieve higher accuracy than the basic centroid approach [51].

Fig. 2.5: Overlapping triangles formed by APIT. The *unknown* node assumes its position to be the center of the shaded overlapping area.

In the DV-hop approach proposed by Niculescu and Nath [72], the *anchors* first flood the network with their positions. These messages are propagated hop by hop, with a hop-count incrementing accordingly. Once an *anchor* receives the location information of another *anchor*, it computes the average hop-distance based on the two *anchor* positions and the hop-count in between. Using this value as the correction factor, *unknown* nodes estimate their distances to the *anchors* and their positions by trilateration. A similar scheme is adopted by Nagpal *et al.* [33], except that the distances to the *anchors* are assumed simply the product of hop count and communications range.

Performance of algorithms based on the DV-hop approach relies on the accuracy in the hop-distance estimate. By introducing a hop progress analytical model, the authors in [73] obtain a better distance estimate. Combining with trilateration, they propose a Localization Algorithm using Expected hop Progress (LAEP) to estimate the position of the *unknown* node. On the other hand, in the presence of obstacles, the estimate of hop-distance can be significantly shortened when the shortest path is severely detoured. Hence in [74], the authors establish a minimum hop length as a

threshold to identify “unreliable” *anchors*. By using only the “reliable” *anchors*, the accuracy of location estimation is greatly improved.

Data analysis techniques can be applied in localization too. Shang *et al.* [68] first construct the distance matrix (in terms of hop-count) between every pair of nodes. Multidimensional scaling (MDS) is then used to build a relative map of the nodes, which is subsequently transformed into an absolute map by aligning with the coordinates of *anchors*.

In Sextant [75], both positive and negative information are used to infer the geographic constraints on the node positions. Compact representation of regions is possible with the use of Bézier curves. Motivated by this work, Wang *et al.* [76] propose a probabilistic region-based localization scheme to compute the likelihood of a node’s true position over its permissible region.

The above works assume that a certain number of *anchor* nodes are available to achieve a reasonable localization accuracy. In order to further reduce the number of *anchor* nodes and thus the cost, *anchor* nodes are made mobile and hence “reusing” becomes possible. Based on the geometric properties of circles and spheres, localization with a mobile *anchor* is proposed for 2-dimensional [77] and 3-dimensional [78] cases respectively.

By exploiting the mobility of sensor nodes, Hu and Evans [79] use sequential Monte Carlo Localization (MCL) method to perform localization. Each node keeps a set of sample locations and updates them recursively with new observations. However, MCL does not work when sensors move at low speeds, or worse, are static. By modifying the sampling procedure and using information from *unknown* nodes, Rudafshani and Datta [80] propose MSL (Mobile and Static sensor network Localization) and MSL* which are suitable for static networks. Simulation results show a performance improvement at the expense of more communications.

2.3.2 Range-based Localization Algorithms

Utilizing range information, range-based algorithms can outperform range-free algorithms, even by using similar computational techniques. For instance, Biswas and Ye [81] use a SDP relaxation based method to determine the node positions that minimizes deviation from the distance measurements. An MDS approach is employed by Ji and Zha [82] to incorporate distance measurements. In this work, the whole sensor network is divided into smaller groups of adjacent nodes. When the local maps for each group are completed, they are stitched together to reconstruct the global map.

For distributed schemes, Savarese *et al.* [83] present a two-phase algorithm. In the start-up phase, the *unknown* nodes obtain a rough estimate of their positions in a way similar to DV-hop [72]. The second phase refines the initial estimates using the distance measurements. The algorithm iteratively improves the position estimates by least square trilateration.

If the number of *anchors* is large, the “iterative multilateration” technique proposed by Savvides *et al.* [84] can be used. (Strictly speaking, it is a trilateration as absolute distance measurements are used.) With the help from three or more *anchors*, the algorithm computes the position of an *unknown* node by minimizing the squared error between the measured and approximated distances. This *unknown* node then assumes an *anchor* role and helps to localize other *unknown* nodes. In order to mitigate the effect of error propagation in iterative localization, an error control mechanism is introduced by Liu *et al.* [85]. Apart from location estimate, each node also holds an error value reflecting the level of uncertainty. The aim is to discard bad estimates at each iteration.

Ramadurai and Sichitiu [86] consider a probabilistic approach for localization. Given a known distribution of the RSS, an *unknown* node combines a series of measurements and deduces a distribution for its location. By the same token, the authors extend the techniques to mobile *anchors* [87].

A kernel-based approach is proposed by Nguyen *et al.* [88]. By posing the localization problem as a pattern recognition problem, RSS-based ranging error can be avoided. However, a large amount of RSS measurements between *anchors* are required to provide enough training data. In [89], Jia and Buehrer formulate the collaborative localization problem as a maximum likelihood estimation (MLE) problem. Due to its nonlinearity and non-convexity in general, they combine a branch and bound strategy with the reformulation linearization technique (RLT) to search for the globally optimal solution. In the presence of error in the *anchor* positions, Chiu *et al.* [90] formulate and solve the localization problem as a SDP.

Yedavalli and Krishnamachari propose a sequence-based localization technique in [91]. It is essentially a fingerprinting approach in which distinct sub-regions are defined and RSS vectors are encoded into sequences. Under the “convex hull constraint”, Zhu and Ding [92] propose a collaboration based localization scheme and iterative algorithms. In [93], Fang *et al.* suggest an ensemble approach to combine the location estimates from several localization algorithms. A recent work on indoor ranging and RSS-based localization algorithm is presented in [94]. The authors impose an *anchor* selection step based on an empirically-obtained threshold before localization. In essence, they are excluding those *anchor* with low RSS to improve the localization performance.

2.3.3 Weighted Centroid Localization Algorithms

Weighted centroid localization algorithms can be considered as the hybrid of both range-free and range-based algorithms. They make use of RSS measurements but do not attempt to estimate the distances.

The first weighted centroid localization (WCL) algorithm is proposed by Blumenthal *et al.* in [32]. The WCL algorithm generalizes the centroid localization algorithm [69] by introducing to each anchor a weight, which is a function of the

RSS. Instead of a static weighting function, [95] employs an extra step to identify subregions in which different weighting functions can be pre-determined. Behnke and Timmermann [96] also suggest normalizing the link quality indicator (LQI) value before applying WCL. Laurendeau and Barbeau [97] propose two different weighting scheme, linearly (RWL) or exponentially (REWL), based on the relative span of RSS in order to improve WCL. Furthermore, authors in [98] compare three different weighting strategies for WCL, and conclude that the choice of weighting function is a critical factor of localization accuracy.

All the WCL-based algorithms mentioned above and the corresponding analyses (Section 2.3.4.3) assume the weights are continuous variables. This is contrary to the fact that electronic devices nowadays, and thus the RSS measurements, are mostly digital, which may lead to unrealistic error predictions. Therefore, a discrete version of WCL is proposed and studied in Chapter 4 of the thesis.

2.3.4 Analysis of Localization Error

Since localization error is an important performance measure for localization algorithms, a better understanding of this error is highly desirable. A few influential factors, including range measurement accuracy, number of *anchors*, node density and geometry, have been identified in the literature. In this section, some major works on theoretical study of localization error are presented.

2.3.4.1 Estimation Theory

Cramér-Rao Bound (CRB) has been widely used in signal processing and parameter estimation problems. It provides a lower bound on the variance achievable by any unbiased estimator. As such, a number of works derive the CRBs for different situations, and use them as benchmarks to evaluate localization algorithms.

Considering the bias of each sensor's clock, Larsson [99] computes the CRB on

the position accuracy for a TOA-based localization system. In [100], Jia and Buehrer derive the CRB for TOA-based localization, assuming the ranging error model has a distance-dependent variance instead of Gaussian. Patwari and Hero [101] also present the CRBs for localization based on connectivity measurements and quantized RSS measurements. In [102], Patwari *et al.* give the outline of derivation of the CRBs on the location estimation when TOA, RSS and AOA measurements are used. Savvides *et al.* [103] derive the CRBs on localization accuracy when both distance and angular measurements are used. With these bounds, they also study the impact of error inducing parameters such as the measurement technology accuracy, network density, anchor node density, and anchor position uncertainty through simulations. In [104], Niculescu and Nath first derive the CRB for trilateration. Then they extend it to find the CRB for the DV-hop algorithm [72], where error arises from estimating the distance from an *unknown* node to an *anchor*. Yu [105] considers a 3D localization system using both distance and AOA measurements. CRBs for such system are derived for both cases where the *anchor* positions are with or without errors.

Moreover, CRB can be used for optimizing system design too. For example, Giorgetti *et al.* [106] select the optimal RSS threshold for connectivity-based localization algorithms in order to minimize the CRB value and thereby the localization error. In [107], they also show the existence of a critical connectivity value (number of neighbours), below which the CRB for range-free algorithms is lower than that for RSS-based ones. This implies a potential superiority of the former. The opposite is true if this critical value is exceeded.

In addition to CRB, Bayesian methods are also used to analyze the lower bound of localization uncertainty. For instance, Wang *et al.* [108] define the Bayesian Bound as the covariance of the minimum entropy target location distribution, and show that it is equal to the CRB when observation uncertainty is Gaussian.

2.3.4.2 Geometric Approach

Another approach, predominately for range-free localization algorithms, is to obtain the distribution of localization error from a geometric point of view. For instance, if a node travels or is displaced by a small distance without breaking or establishing any link, a range-free algorithm would return the same location estimate. The maximum distance a node can travel without changing the connectivity information therefore defines the lower bound on the localization error that *any* range-free algorithm can achieve.

Nagpal *et al.* [33] are the first to study this theoretical bound based on the circular coverage model. As illustrated in Fig. 2.6, if there is no other sensor node inside the shaded area $A(z)$, the center node will neither gain any new neighbor nor lose any existing neighbor when it travels a distance z . The connectivity information remains the same, and this distance z thus defines the bound. If Z is the continuous random

Fig. 2.6: Illustration of Nagpal's bound. Connectivity information remains the same if the center node travels a distance z and no other sensor node exists inside the shaded area.

variable representing this bound, then we can write

$$F(z) = \Pr(Z \leq z) = 1 - e^{-\rho A(z)} \quad (2.1)$$

where ρ is the average node density. Note that $F(z)$ is also the probability that there is at least one sensor in $A(z)$. When z is small compared to the communication range

r , $A(z)$ can be approximated as $4rz$. The expected value of Z is therefore

$$\begin{aligned}\mathbb{E}[Z] &= \int_0^\infty z \dot{F}(z) dz \\ &= \frac{1}{4\rho r}.\end{aligned}\tag{2.2}$$

Based on the same rationale, MacLean and Datta present another bound in [109]. Instead of a random direction, they “search” through all 360° for the smallest maximum distance z that a node can move. This is much more restrictive and therefore gives a bound smaller than Nagpal’s.

Following the analysis in [33], Hu and Evans present the resolution limit of MCL [79] by examining the two-hop neighbourhood. In [110], the authors derive the expected localization error of a random network by adjusting the error distribution of a regular network with a correction factor. For region-based localization algorithms—a subset of range-free algorithms—such as APIT [71], Zhang *et al.* present a bound on the localization error in [111]. However, the bound is not tight unless the localization algorithm is able to partition the deployment area into a large number of small subregions.

The theoretical bounds for range-free algorithms derived in [33] and [109] are based on the circular coverage model. This simple model is too ideal, and the analyses are, thus, too restrictive for practical use. In view of this, Chapter 5 investigates a new lower bound that is suitable for more realistic scenarios.

2.3.4.3 Statistical Study

Regarding WCL, Wang *et al.* [112] present an analytical framework for performance evaluation. The effect of a number of parameters, such as node density and shadowing variance, are studied. However, the derived closed-form expression is based on a known topology of the *anchor* nodes. In [113], Pivato *et al.* analyze the accuracy of WCL and REWL using measured data. The errors are broken down into two parts that are

caused by algorithm or by measurement respectively. The authors conclude that the former is usually negligible compared with the latter. However, when the number of *anchors* increases, the algorithmic error has been shown to become significant.

A few optimization algorithms that are commonly used for localization is reviewed in [114]. Based on the simulation results, the authors claim that the statistics of the localization errors can be well approximated by the family of Pearson distribution. In [115], Daneshgaran *et al.* present a framework to derive the probability that a randomly deployed WSN gets localized as a function of a variety of system parameters.

2.3.5 Cooperative Localization

The localization algorithms discussed so far are of the noncooperative type, in which *unknown* nodes do not communicate or cooperate with each other. Instead, they determine their own positions individually based on information gathered from *anchor* nodes only. On the contrary, communications and cooperation among *unknown* nodes are allowed in cooperative localization. This leads to more information available for localization, which in turn can increase the localization accuracy dramatically [116].

A number of published works addressing cooperative localization are available in the literature. For example, RSS-based cooperative localization in WSNs is investigated in [117], where an SDP relaxation approach is presented. Approximating the underlying ranging errors with Gaussian mixture model, Yin *et al.* [118] propose expectation-conditional maximization algorithms to estimate the unknown positions. Based on the framework developed in [119], cooperative localization for wideband wireless networks is studied in [120], and the performance bounds are derived based on the equivalent Fisher information matrix. By exploiting the temporal information, [121] extends the framework to tracking of mobile nodes. A nonparametric belief propagation method is proposed in [122] for cooperative localization in mobile networks.

Cooperation inevitably increases the power and communications overhead. In order to achieve a better tradeoff between localization accuracy and power consumption, power management strategies based on game theory are proposed in [123]. In addition to power, bandwidth is also considered in [124]. As the formulated joint optimization problems are nonconvex, iterative algorithms are proposed to find the near-optimal solutions.

Chapter 3

WSN-based Light Management System in Smart Buildings

3.1 Overview

Lighting, being the first service offered by electric utilities, continues to consume a significant portion of electricity production. IEA estimates that 19 % of the worldwide electricity production goes to lighting [125]. The number is slightly lower in developed countries. For instance, about 11 % of electricity consumed in the U.S. is used to power the lighting system in buildings in 2014 [126]. In Singapore, lighting takes up about 15 % of total electricity consumption by the building sector [127]. This can be partially attributed to a wider adoption of more energy-efficient lighting technologies.

Daylighting is one of the popular approaches to reduce the electricity usage. Supplementing the lighting system with daylight allows the system to dim the luminaires in the building. This is particularly effective in countries located in the equatorial belt (e.g. Singapore), where sunlight is plentiful with the sun being almost directly overhead throughout the year. On the flip side, sunlight can also cause glare, which is a major source of visual discomfort for the occupants. Blinds and shades are typical solutions to mitigate this problem. While lighting energy can be saved by adjusting

luminaires and blinds, it is also important to maintain the illuminance level within the recommended range, e.g. 300 lx to 500 lx for an office environment [128,129].

Although it is out of the scope of the thesis, introducing daylight into buildings may also increase the solar heat gain. For buildings in the Tropics, this requires additional cooling effort from the air-conditioning systems. Thus, compared to temperate climate, it has more potential and also challenges to achieve a sustainable built environment by utilizing the daylight to replace or supplement the electric lighting without affecting the overall energy efficiency of the building operations or causing visual discomfort to the occupants.

In [130], Pandharipandeg *et al.* present a mathematical framework to design an optimal daylight-responsive controller for the luminaires. On the other hand, Wen and Agogino [131] propose a framework to optimize the dimming levels of the luminaires in order to minimize energy usage and satisfy occupants' lighting preferences. However, both works fall short in certain aspects. [131] relies on a precise model of the space for computation. As a result, any deviation in the actual indoor configuration such as types of furniture can lead to error in the dimming control. In [130], illuminance sensor are mounted next to the luminaires on the ceiling instead of the workplane. This requires a tedious calibration step before the commissioning of the lighting system and after any reconfiguration of the space.

Hence, in this chapter, a new model of daylight-responsive lighting and shading control system is proposed. The goal of the proposed system is to reduce the electricity consumption in the lighting and shading domains by utilizing daylight intelligently, while at the same time ensuring the user satisfaction. As a consequence of the preliminary evaluation, a survey of available illuminance sensing technologies is conducted. Based on the study, a high accuracy analog illuminance sensor is selected and is integrated into a wireless platform for high accuracy illuminance sensing. Subsequently, the performance of the developed system is assessed in a high-tech life-sized test facility under different conditions. The major content of this chapter is based on the

works listed in [132–136].

The remainder of the chapter is organized as follows. Section 3.2 introduces the mathematical model of the proposed daylight-responsive lighting and shading control system, and the corresponding optimization framework. Performance evaluations and a survey of available illuminance sensing technologies are discussed in Section 3.3. In Section 3.4, the integration of high accuracy analog illuminance sensor into a wireless sensing platform and the subsequent assessments in a test bed are presented. Section 3.5 discusses the issues regarding the implementation framework of the proposed WSN-based light management system. Finally, Section 3.6 closes the chapter with some concluding remarks.

3.1.1 List of Symbols

N_x	Number of LED luminaires along the length of the room
N_y	Number of LED luminaires along the width of the room
N	Total Number of LED luminaires
P	Number of roller blinds
H_b	Height of roller blinds
h	Distance from workplane to ceiling
h_w	Height of workplane
$\mathbf{d}$	Dimming vector
$\mathbf{b}$	Blind height vector
T_i	Target illuminance level at location i
L_{min}	Minimum illuminance level
S_1	Set of locations with specified illuminance levels
S_2	Set of locations with minimum illuminance level
$E_{i,n}$	Illuminance at location i due to the n -th luminaire
E_i	Illuminance at location i due to all luminaires

s_i	Illuminance at location i due to daylight
s_i^{max}	Maximum illuminance at location i due to daylight and in the absence of the blinds
L_i	Total illuminance at location i on the workplane

3.2 Daylight-responsive Lighting and Shading Control System

3.2.1 System Description

Consider an indoor office where the light management system is installed. There are N LED luminaires mounted on the ceiling, forming a $N_x \times N_y$ ($N = N_x N_y$) grid along the length and width of the room respectively. Each of them is able to change the dimming levels independently of others. Furthermore, it is also assumed that they are able to deliver sufficient luminance to the space when they are on full power.

Parallel to the ceiling is the workplane where the spatial distribution of illuminance is of interest. The height of the workplane is denoted by h_w . For analytical purposes, the workplane is divided into a uniform spaced grid. Among the grid of points, there are some distinct locations where the illuminance levels are to be maintained at some particular values specified by users. These locations may represent an occupied desk, or a point of interest that needs to be illuminated. Furthermore, the set of these locations is labelled as S_1 . Similarly, the rest of the points on the workplane are then represented by the set S_2 .

In addition, there are P interior, top-down roller blinds installed on the window wall. The height of the blinds are adjusted in order to control the amount of daylight coming in through the windows.

3.2.2 Mathematical Model

Given the location of the n -th luminaire (x_n, y_n) , the illuminance at point i , located at (x_i, y_i) , can be estimated using the following model [42] :

$$E_{i,n} = \frac{(m+1)A_o}{2\pi h^2} \left[1 + \frac{\|(x_n, y_n) - (x_i, y_i)\|_2^2}{h^2} \right]^{-\frac{m+3}{2}}. \quad (3.1)$$

where A_o is the maximum luminous flux of the luminaire, h is the perpendicular distance between the ceiling and workplane, and m is the Lambertian mode ($m > 0$). This mode is related to the beam angle, Φ , of the luminaire as follows.

$$m = -\frac{\ln(2)}{\ln(\cos(\Phi/2))} \quad (3.2)$$

Following the notations in [130], the dimming vector for the N luminaires are denoted by $\mathbf{d} = [d_1, d_2, \dots, d_N]^T$, where d_n is the dimming level of the n -th luminaire. In our definition, $d_n = 1$ means that the luminaire is operating at the maximum output power level, while $d_n = 0$ represents that it is completely turned off. Thus, $0 \leq d_n \leq 1$.

Assuming the LED luminaires are dimmed using pulse width modulation, illuminance scales linearly with the dimming level. The total illuminance at location i due to all N luminaires is therefore

$$E_i = \sum_{n=1}^N d_n E_{i,n}. \quad (3.3)$$

In addition, let L_i denote the total illuminance level at location i . It is the summation of both artificial light and daylight, and hence is given by

$$L_i = E_i + s_i, \quad (3.4)$$

where s_i represents the illuminance at location i due to daylight. For simplicity's

sake, reflections off the wall or ceiling are assumed to be small and negligible in the following analysis. Fig. 3.1 shows how different components contribute to the total illuminance level at one of the locations on the workplane.

Fig. 3.1: The illuminance level at location i on the workplane is the combined effect of luminaires and daylight.

Among the locations in S_2 , the illuminance levels have to be at least L_{min} in order to provide adequate ambient lighting. For location i in S_1 , on the other hand, its illuminance level has to meet the preset requirements T_i ($T_i > L_{min}$). Furthermore, a study [137] shows that most people are insensitive to and are willing to accept a 20% discrepancy in the illuminance level. Consequently, in this work, some tolerance is allowed in the target illuminance level, which leads to the following constraint for location i :

$$T_i - \epsilon_{tol} \leq L_i \leq T_i + \epsilon_{tol}, \quad (3.5)$$

where ϵ_{tol} is the tolerance level a user can accept.

3.2.3 Daylight and Glare

While s_i in (3.4) is determined by a number of factors, such as the solar position, sky condition and fenestration condition, that the system cannot interfere, it can be

reduced by the roller blind heights, denoted by

$$\mathbf{b} = [b_1, b_2, \dots, b_P]^T. \quad (3.6)$$

In our notation, $b_j = 1$ represents that the j -th blind is fully drawn up whereas $b_j = 0$ refers to the blind being fully drawn down. Thus, $0 \leq b_j \leq 1$.

Glare arises when direct daylight enters an indoor space and shines into the eyes of occupants. Depending on its intensity, glare could be just a nuisance and cause discomfort. However, if the daylight is too brilliant, glare could reduce the visual performance and the visibility of the occupants [138].

In order to quantify and compare the glare conditions, there are a number of equations developed. Among those, two commonly adopted glare indices are:

- Unified Glare Rating (UGR) takes the following form:

$$\text{UGR} = 8 \log \frac{0.25}{L_b} \sum_n \frac{L_S^2 \omega}{p^2} \quad (3.7)$$

where L_b is the background luminance, L_S the luminance of the luminous area, ω the solid angle of source, p the Guth position index, and n the number of sources.

- Daylight Glare Index (DGI) is expressed as follows:

$$\text{DGI} = 10 \log 0.478 \sum_n \frac{L_S^{1.6} \Omega^{0.8}}{L_b + 0.07 \omega^{0.5} L_S} \quad (3.8)$$

where Ω is the solid angle of source modified for its position in the field of view.

Typically, a glare index larger than 22 (24) for UGR (DGI) is considered uncomfortable and unacceptable [138, 139].

These indices are location specific and depend on the whole scene model. Consequently, the computation is nontrivial, and simulation tools are often employed to

calculate the value of the index. For instance, lighting calculation and image rendering are performed using Radiance, a lighting simulation software, in [44]. In [140], images taken by cameras are analyzed with the same software. Furthermore, some limitations of these indices in the usage and reliability are reported in [139].

Due to the lack of suitable software tools, this work only limits to the glare situation where the sun is the brightest source of glare and is directly visible through the window. Consider a situation illustrated in Fig. 3.2. Assuming an occupant is sitting at her desk facing the window, her distance from the window is D_o and her eye level is H_o . Given the solar position, the incident angle of the direct daylight is θ . Neglecting the effect of diffraction, no glare occurs as long as the direct path between the sun and the eyes is blocked. In this example, given that the height of the roller blind is H_b , the critical height is defined as $b'_1 = (H_o + D_o \tan \theta) / H_b$, and when

$$b_1 \leq b'_1, \quad (3.9)$$

glare is prevented.

Fig. 3.2: Glare condition occurs if the blind remains clear of the direct path between the sun and the occupant's eyes.

It is further assumed that the blind blocks out the daylight completely in the

shadowed area. That is, for a location i on the workplane whose distance from the window is x_i , the illuminance due to daylight is

$$s_i = \begin{cases} s_i^{max} & \text{if } b_1 > \frac{h_w + x_i \tan \theta}{H_b}, \\ 0 & \text{otherwise,} \end{cases} \quad (3.10)$$

where s_i^{max} is the maximum illuminance at location i due to daylight in the absence of the blinds. Ideally, the values of s_i^{max} for all i on the workplane should be obtained by simulation tools or full scale measurements. However, due to the lack of available software or resources for a full scale measurement, a linear model for the spatial distribution of s_i^{max} is assumed in this thesis:

$$s_i^{max} = I_o \left(1 - \frac{\tan \theta}{H_b - h_w} x_i \right), \quad (3.11)$$

where I_o is the illuminance level due to daylight at the window.

3.2.4 Problem formulation

Mathematically, the lighting and shading control problem can be formulated as follows.

$$\min_{\mathbf{d}} \sum_{n=1}^N d_n \quad (3.12)$$

$$T_i - \epsilon_{tol} \leq L_i \leq T_i + \epsilon_{tol}, \quad \forall i \in S_1 \quad (3.13)$$

$$L_i \geq L_{min}, \quad \forall i \in S_2 \quad (3.14)$$

$$b_j \leq b'_j, \quad j = 1, \dots, P \quad (3.15)$$

$$0 \leq b_j \leq 1, \quad j = 1, \dots, P \quad (3.16)$$

$$0 \leq d_i \leq 1, \quad i = 1, \dots, N \quad (3.17)$$

The optimization problem aims to minimize the power consumption of the system, while at the same time meeting the illuminance requirements and preventing the glare condition. Note that the formulation describes a snapshot of the system at a particular time instant. In order to prevent instability such as system oscillation, the optimization problem is solved periodically, and thus the dimming levels of the luminaires and the heights of the blinds are adjusted once per period.

As the blinds only draw power when their heights are being adjusted, their average power consumption is negligible. Thus, the objective function (3.12) considers only the power consumption of the N luminaires. The constraint (3.15) ensures the blinds are able to block the direct daylight as described in Section 3.2.3. The illuminance requirements on the workplane are handled by (3.13) and (3.14). L_i in (3.4) consists of two components: E_i , a linear function of $\mathbf{d}$ (see (3.3)); s_i , a conditional function of $\mathbf{b}$ and x_i (see (3.10)). Now suppose that the direct daylight cuts across blind j when it shines on location i . For simplicity, effects of reflection and diffraction are ignored. In other words, blind j is solely responsible for controlling s_i . By introducing a new binary variable y_i and an arbitrarily large constant M , (3.4) can be rewritten as the following linear equations:

$$\begin{aligned} L_i &= E_i + y_i s_i^{max}, \\ b_j - h_i - M y_i &\leq 0, \\ h_i - b_j - M(1 - y_i) &\leq 0, \\ y_i &\in \{0, 1\}. \end{aligned} \tag{3.18}$$

where $h_i = (h_w + x_i \tan \theta) / H_b$.

Together with (3.18), (3.12)–(3.17) can be posed a mixed integer linear programming problem, which can readily be solved using standard optimization packages, e.g. MATLAB or CPLEX.

3.3 Performance Evaluation of Illuminance Sensors

As the “eyes and ears” of the light management system, the accuracy of illuminance sensor directly impacts the performance of the control. For instance, a sensor with 35 % error may detect an illuminance level between the recommended range of 300 lx to 500 lx [128, 129] but, in fact, the actual lux level can be anywhere between 222 lx and 769 lx. This wide range is unsuitable for any lighting control system with dimming features. Using such sensors may cause discomfort to the occupants and would lead them to manually override the settings of the system.

3.3.1 Comparison of Illuminance Sensors

A few typical sensing technologies for illuminance are selected for this study, and their pros and cons are highlighted. Photodiodes are simple to use but the output can be so low that it requires extra amplification circuits. On the other hand, phototransistors have a wider output range but the inconsistency requires additional effort in calibration.

Building on top of photodiodes, IC-based sensors can offer a better accuracy. The digital type has an advantage of direct interface to a microcontroller, but the output resolution depends on the in-built ADC. Its analog counterpart, on the other hand, provides extra freedom for designers to choose the ADC according to the needs and cost.

For those who can afford to pay more for an even better performance, high accuracy illuminance sensors are available. For instance, analog sensors from EKO Instruments [141] have an accuracy as low as 3 %. Table 3.2 summarizes the characteristics of these illuminance sensor technologies. Handheld lux meter is also included as a benchmark. Despite the superior accuracy, they tend to be bulky and expensive. Interfacing to

microcontroller usually requires a serial interface or USB to a computer, hence making it difficult for system integration and mass deployment.

Table 3.2: Comparison of Different Types of Illuminance Sensors

Type	Operation	Advantages	Disadvantages
Photodiode [142]	ADC required	Low cost Small size	Low accuracy of > 30 %
Phototransistor [142]	ADC required	Low cost Small size	Low accuracy of > 30 %
Analog IC sensor [143]	ADC required	Low cost Small size	Low accuracy of > 15 %
Digital IC sensor [143]	I ² C or SPI interface	Easy to integrate Low cost Small size	Low accuracy of > 15 %
EKO analog sensor [141]	ADC required	High accuracy of < 3 %	High cost Bigger size
Handheld lux meter [144]	Standalone	High accuracy of < 3 %	Difficult to integrate Very high cost

In the following tests, the sensors are subject to different illuminance levels, from 10 lx to 1000 lx. A hand-held Gossen lux meter is placed next to the sensors to provide a reference illuminance level reading. The readings from the sensors and lux meter are recorded and shown below.

3.3.1.1 Phototransistors

A NPN phototransistor, TEPT5700 [145], is selected for evaluation. It has a spectral bandwidth ranging from 440 nm to 800 nm, well suited for visible light. In addition, it has a wide angle of half sensitivity of $\pm 50^\circ$.

As the light source in this test is LEDs, which are driven by pulse-width modulated signals, these illuminance sensors can pick up a series of fluctuating readings. Data processing techniques are required to mitigate the problem. It turns out that taking an average of 1000 readings is sufficient to smoothen the fluctuation.

The same procedures are repeated for four different sensors. The measurements are plotted in Fig. 3.3. Two observations are noticed from the results. First, the responses of all four sensors are reasonably linear. The responses, however, are not consistent with each other. Unless extensive calibration is carried out for each individual sensor, the accuracy of illuminance level measured by this type of sensors is questionable. Therefore it is not recommended to use this type of sensors for future implementation.

Fig. 3.3: Output currents of four different TEPT5700 sensors vs. illuminance level.

3.3.1.2 Digital IC sensors

BH 1750 [146] is chosen to represent digital IC sensors. It has a similar angle of half sensitivity of $\pm 50^\circ$, but the spectral bandwidth from 440 nm to 700 nm is slightly shorter than TEPT5700. It is factory-calibrated and its direct illuminance output in digital form lends it well to interfacing with microcontroller.

Two sensors are evaluated under LED luminaires, and the results are plotted in

Fig. 3.4. The responses for both sensors are generally linear. However, it seems the consistency in between different sensors is not maintained. Moreover, although claimed pre-calibrated, there is a $>10\%$ bias in the output illuminance values to the actual illuminance levels. Hence another calibration step is required before it can be used for accurate measurements.

Fig. 3.4: Sensor output of two different BH1750 sensors vs. illuminance level.

3.3.1.3 EKO analog sensors

For a comparison, one indoor sensor (ML-020S-I) and one outdoor sensor (ML-020S-O) from EKO Instruments [141] are subject to the same test. The former is designed for indoor environment while the latter for outdoor. Hence there is a big difference in the measurement range. Their detailed specifications are given in Table 3.3.

Table 3.3: Specifications of ML-020S-I and ML-020S-O sensors.

	ML-020S-I	ML-020S-O
Measurement Range	0 lx to 30 000 lx	0 lx to 150 000 lx
Output Voltage	0 mV to 30 mV	0 mV to 30 mV
Internal Resistance	1300 Ω	280 Ω
Error	2.3 %	2.3 %
Sensitivity	1000 lx/mV	5000 lx/mV

In order to realize the full potential of this high accuracy sensor, a high resolution

analog-to-digital converter (ADC) is used to interface the sensor to a microcontroller. With a 5 V reference voltage, the selected 24-bit ADC (LTC2493) can provide a sensitivity as high as $0.298 \mu\text{V}/\text{level}$. As the EKO sensor sensitivity is about $1 \mu\text{V}/\text{lx}$, the duo is able to deliver a resolution equivalent to $0.3 \text{ lx}/\text{level}$. The development kit for LTC2493 also includes a PC-based client software to read the digital output of the ADC via USB.

Fig. 3.5a shows the instantaneous reading from the setup corresponding to the illuminance level measured by a ML-020S-I sensor. The output reads 0.00092667 in V, which is equivalent to $926.67 \mu\text{V}$. Using the provided conversion factor for this sensor 0.964, the actual lux value is equal to $926.67/0.964 = 961.28 \text{ lx}$. At the same time, the lux meter reads 951 lx. The error is about 1 %. Similarly, for ML-020S-O sensor (see Fig. 3.5b), The output reads 0.00015348 in V, which is equivalent to $153.48 \mu\text{V}$. Using the provided conversion factor for this sensor 0.197, the actual lux value is equal to $153.48/0.197 = 779.09 \text{ lx}$. At the same time, the lux meter reads 750 lx. The error is about 3.8 %. Although the outdoor sensor has almost four times the error the indoor one has, the outdoor sensor may actually perform not as bad as it may seem if the range of measurement is also considered.

Fig. 3.5: Instantaneous sensor output of two EKO sensors vs. illuminance level: (a) ML-020S-I (b) ML-020S-O

3.3.1.4 Remarks

It is apparent from the study and measurements that the photodiodes and phototransistors lack the accuracy and consistency. With some improvement in the consistency, IC-based sensors still fall short in the accuracy. Unless extensive calibration is carried out for each individual sensor, the accuracy of the illuminance level measured by these types of sensors is questionable. Therefore it is not recommended to use these sensors for future implementation.

On the other hand, analog sensors such as those from EKO can deliver the best accuracy among the listed one. Between the two EKO sensors, the indoor one is preferred as its range is more than enough for normal indoor use.

3.4 Wireless Platform for High Accuracy Illuminance Sensing

3.4.1 Development and Implementation

Based on the study in the previous section, the EKO indoor sensor ML-020S-I are selected for future implementation due to its superior accuracy and sensitivity. Fig. 3.6 shows an EKO sensor with a leveling plate. The sensor itself is 33 mm in height with a 22 mm diameter. With the leveling plate, the size increases to 51 mm in height with a 80 mm diameter. This form factor allows the sensors to be deployed in a building or even integrated into furniture with ease. Moreover, each of the sensor comes with its own calibration certificate. Hence only a single conversion of the output voltage is required to obtain the reading of illuminance.

In order to evaluate the performance of the high accuracy illuminance sensor, an EKO sensor, an 24-bit ADC board, a microcontroller and a ZigBee module are integrated together into one “node”. Firmware is developed to sample the sensors, process the data and handle the wireless communications. The setup of a “node” is shown in

Fig. 3.6: EKO illuminance sensor (ML-020S-I) with leveling plate.

Fig. 3.7. Nine of these “nodes” are prepared for the assessment. They, together with a base station that collects all the sensor readings, form the high accuracy wireless sensing platform. Real-time measurements of illuminance level are then plotted in MATLAB on a personal computer.

Fig. 3.7: The setup of a “node” of the proposed wireless sensing platform. It consists of an EKO sensor, an ADC board, a microcontroller and an XBee module.

3.4.2 System Assessment

To assess the usability in an actual set up in built environment, the new wireless sensing platform is deployed and evaluated in the SinBerBEST test bed [147]. One of the four test chambers is chosen as the test site. The selected test chamber has

a setting of a typical office room and is equipped with modern lighting equipment such as suspended LED luminaires. As it is located inside a laboratory, there is no access to natural sunlight for experiment. As such, a Daylight Emulator (DE) is built and installed outside of the test bed to emulate different diffused light conditions of the sky. The DE can be programmed to provide different light intensities to the test chambers.

On the side of the chamber in front of the DE, there are three large window openings allowing the emulated sunlight to enter the test chamber. The chamber measures 5.6 m (L) $\times$ 4.25 m (W) $\times$ 2.6 m (H), similar to a medium size office. Nine nodes are deployed in a 3 $\times$ 3 grid structure as shown in Fig. 3.8.

Fig. 3.8: Grid deployment of sensors in the test bed, with the Daylight Emulator standing behind the three window openings in the background.

Four different scenes are defined for the experiment. The corresponding sky conditions emulated by the DE are listed in Table 3.4. The values are typical conditions encountered in the Tropics. The actual effect of the four scenes can be seen in Fig. 3.9. The black stripes appear in the photos are probably due to the switching of the LEDs on the DE when the photos were taken. Note that although scene 2 and scene 4 appear to have the same illuminance level, the colors, or the correlated color temperature (CCT) to be exact, are different. However, the discussion of CCT is beyond the

scope of this thesis and therefore omitted.

Table 3.4: Scene and sky conditions emulated by the Daylight Emulator

Scene	Sky condition	Illuminance level (lx)	CCT (K)
1	Sunset/Sunrise	580	2400
2	Blue Sky	40 000	10 000
3	Cloudy Day	20 000	7500
4	Midday	40 000	5500

(a)

(b)

(c)

(d)

Fig. 3.9: Effect of diffused daylight for the tested scenes: (a) sunset/sunrise (b) blue sky (c) cloudy day (d) midday.

The readings from the nine illuminance sensors are collected and plotted in Fig. 3.10. The data points are linked together to generate the illuminance profile using spline interpolation. Façade refers to the side of room with the window openings facing the DE.

A manual measurement using the professional grade handheld Gossen lux meter is also performed. The measurements are compared with results presented in Fig. 3.10.

Fig. 3.10: Illuminance profiles for the tested scenes: (a) sunset/sunrise (b) blue sky (c) cloudy day (d) midday.

The comparison can be found in Fig. 3.11. Among the four scenarios, it can be seen that, in all but one cases, the errors between the two instruments are within 3 %. The only exception is sensor 9 in Scene 1 where the error is about 3.3 %, slightly exceeding the rest.

3.5 System Implementation Framework

The modelling and optimization framework for control system (Section 3.2) and the development of wireless sensing platform (Sections 3.3 and 3.4) are parts of an ongoing effort to design and develop a WSN-based light management system in smart buildings. Such system would require elements of sensing, control and wireless communications. The architecture of the proposed system is portrayed in Fig. 3.12.

In the sensing domain, two parameters are identified. The first and foremost is the illuminance level, or light intensity. It is the gauge whether user satisfaction is met. The second parameter is the presence of occupants. If human presence is detected, the system has to ensure the indoor condition meets the requirement. Otherwise it can enter an energy-saving mode. As a result, two different types of sensor nodes are developed to measure these two parameters. In our implementation, Type I sensor node is equipped with an illuminance sensor. Type I nodes are deployed over the workplane to measure illuminance level at different points of interest. Type II sensor node, on the other hand, consists of an occupancy sensor, and they are usually mounted on the ceiling to detect human presence.

According to the collected data and some preset preferences, the system controls the luminaires to maintain a desired illuminance level. At the same time, it also adjusts the heights of the window blinds in order to allow or stop daylight from entering through the windows. These two devices are also handled by two different types of control nodes respectively—Type I control nodes control the luminaires while Type II control nodes are responsible for the blinds.

(a)

(b)

(c)

(d)

Fig. 3.11: Error between data collected by the proposed wireless sensing platform and by manual measurement for the tested scenes: (a) sunset/sunrise (b) blue sky (c) cloudy day (d) midday.

Fig. 3.12: System architecture of the proposed WSN-based intelligent lighting system.

For ease of deployment, data communications between the sensor nodes and control nodes is completely wireless. Mesh network technology such as ZigBee is selected for its flexibility to expand the network and its ease to integrate with the BAS. Being able to self-organize, subsequent addition or removal of sensor nodes would not require manual network reconfiguration. Moreover, low power consumption by ZigBee modules also helps to prolong the battery life of the sensor nodes. Besides all the sensor nodes and control nodes, there is one base station which acts as the gateway between the devices and BAS.

Once the full system is implemented, a closed-loop model, as shown in Fig. 3.13, would be a better alternative for the daylight-responsive lighting and shading control system. As such, the optimization framework described in Section 3.2 is to be revisited. The new lighting optimizer will take the real-time illuminance measurement from the sensing network as one of the three inputs. Together with the user preferences toward illuminance levels and the occupancy of the indoor space, it can exercise control on the dimming level of luminaires and the heights of blinds. Daylight, as the external factor, provides the “free” energy for illumination that the system will capitalize.

Fig. 3.13: Model of the daylight-responsive lighting and shading control system.

The new model leads to a networked control system over WSN. In this case, system stability is an important consideration during the design of the controller. Especially for IEEE 802.15.4-based WSNs, variable time delays and packet drops over the wireless links between sensors and controller can cause oscillations in the system. Choice of the sampling rate can also affect the transient responses at the expense of network capacity. Therefore, the controller must be designed to cope with or compensate for these factors.

3.6 Concluding Remarks

This chapter addresses some of the issues regarding the design and development of a WSN-based light management system in smart buildings. Such system would be beneficial to the operation of buildings. After all, lighting takes up a significant portion of electricity consumption. Different measures have been proposed to reduce the electricity usage. Daylighting, one of the popular approaches, can supplement the electric lighting and reduce the energy consumption. Admitting daylight, however, can cause visual discomfort such as glare to the occupants. Although it is out of the scope of the thesis, daylighting can also cause solar heat gain.

As such, a new model of daylight-responsive lighting and shading control system

is proposed. The goal of the system is to reduce the energy consumption by the lighting system by utilizing daylight intelligently, while at the same time ensuring user satisfaction in terms of illuminance requirements and glare prevention. The problem formulation results in a mixed integer linear programming problem, which can readily be solved using standard optimization packages.

As the “eyes and ears” of the light management system, the quality of illuminance sensors is of paramount importance to the system performance. As a consequence of preliminary evaluation, a survey of all available illuminance sensing technology is conducted. Based on the findings, a high accuracy analog sensor is chosen and is subsequently integrated into a wireless sensing platform. The new platform is assessed in a high-tech life-size test facilities. Compared against a professional grade handheld lux meter, all the readings are within 3 % except in 1 case where the deviation is about 3.3 %. The result is promising. The improved system is able to collect high accuracy illuminance data automatically and continuously. Furthermore the adoption of ZigBee protocol allows the system to expand and reconfigure with little manual intervention.

Finally, the implementation framework of the WSN-based light management system and relating issues are discussed. The works described in this chapter are only parts of an ongoing effort to design and develop the proposed system. More effort is needed before a full system can be implemented. For instance, system stability is an important aspect for further investigation, and will require coordination and interaction between elements of sensing, control and wireless communications.

Chapter 4

Discrete Weighted Centroid Localization Algorithm

4.1 Overview

Large scale WSNs are being deployed in smart buildings to enhance the real-time sensing capability. In addition to sensing, WSN may also assist in indoor positioning service. As such, in this chapter, an underlying WSN infrastructure that supports indoor positioning system is envisaged, and its localization capability is investigated.

In the literature, a number of localization algorithms have been proposed and applied in such setting. A well-known one, Weighted Centroid Localization algorithm (WCL), proposed by Blumenthal *et al.* [32], calculates the position of a device by taking the weighted average of the positions of all the *anchors* it can *connect* to. WCL and its subsequent variants such as [97] either use RSS directly or RSS-inferred distance as the weights in computing the position. In addition, the RSS or the inferred distances, and hence the weights, are assumed to be continuous numbers. However, electronic devices nowadays are mainly digital, and the RSS measurements are typically discrete and finite. For instance, a popular WSN transceiver such as CC2430 represents the RSS with an 8-bit number [148]. This mismatch may jeopardize the

location estimation.

In view of these, Discrete Weighted Centroid Localization algorithm (dWCL), a discrete version of WCL, for the location computation is proposed and presented in this chapter. Compared with its predecessor, dWCL is more advantageous as its weighting function is more compliant with the current state of digital electronics. Furthermore, by decoupling the definition of weight from range, dWCL is flexible enough to adapt to different performance requirements.

Each localization algorithm or system has its own merits, limitations, and trade-offs. In order to compare the effectiveness of them, a few criteria to measure their performances are introduced in [52, 64]. Some important ones are listed below.

- **Accuracy** indicates the error in the location estimate.
- **Precision** is the probability of attaining a desired accuracy.
- **Complexity** depends on the hardware, software and operation factors.
- **Robustness** refers the continuity of operation even in the presence of faults.
- **Cost** relates to factors such as money, time, space, weight and energy.

This work focuses on the first two performance metrics, namely *accuracy* (ϵ) and *precision* (α). ϵ denotes the magnitude of the error in the location estimate while α indicates the probability of achieving such *accuracy*. The pairs are used together to characterize the performance of dWCL in the form of the error distribution. The major content of this chapter is based on the works listed in [149, 150].

The remainder of the chapter is organized as follows. Section 4.2 introduces the model of the proposed dWCL. Section 4.3 presents the analytical framework to characterize the performance of dWCL. In order to further improve the performance of dWCL, two approaches to optimize the system parameters are described in Section 4.4. The relation between dWCL and other existing centroid-based localization algorithms is highlighted in Section 4.5. Numerical evaluations and simulation results

to validate the proposed model are shown in Section 4.6. Finally, Section 4.7 closes the chapter with some concluding remarks.

4.1.1 List of Symbols

n	Path loss exponent
σ_s	Standard deviation of shadow fading
σ_ξ	Standard deviation of error in the sensor node location information
P_T	Transmitting power
P_r	Receiving power
P_{th}	Receiving power threshold
d_o	Reference distance
ρ	Sensor node density
R_o	Nominal range of sensor node
R	Effective range of sensor node
M	Number of RSS levels
w_i	Weight associated with RSS levels
γ_i	Lower boundary of RSS level i
S_i	Set of sensor nodes of RSS level i
ϵ	Accuracy
α	Precision
$\overline{D_c}$	Average distance to the closest <i>connected</i> sensor
$\mathbf{H} [.]$	Hessian matrix

4.2 System Model

Under the envisaged architecture of an underlying WSN infrastructure, a network of wireless sensor devices, or simply sensor nodes, are deployed in some operational area. By leveraging the recent development of IoT technology, widespread wireless

connectivity among wireless devices is becoming a reality. As such, it is unlikely that their locations would fall into a grid-like or any other well-defined regular structures. Instead, a random distribution would be a more reasonable description for their deployed locations. Furthermore, the sensor nodes are assumed to have previously acquired their own location information with some self-localization techniques as stated in [56, 151].

When a wireless device (hereinafter referred to as the Target node), whose position is unknown, enters the sensor field, it sends out a location request to the WSN. Those sensor nodes within range and receiving the request then reply with their location information to the Target node. Based on the location information, the Target node estimates its own position using the dWCL algorithm. Fig. 4.1 illustrates a typical scenario where only a subset of sensor nodes in the WSN are aware of the Target node and response to the request.

Fig. 4.1: A typical deployment of WSN in a $40\text{ m} \times 40\text{ m}$ area. The blue asterisk in the center represents the Target node. The red circles are the *connected* sensor nodes while the green triangles represent those not *connected*.

The rest of the section states the underlying assumptions and settings, and the model of the proposed dWCL algorithm is also presented.

4.2.1 Indoor Radio Model

Indoor path loss can be predicted using log-normal shadowing model [152]. The receiving power, $P_r(d)$, at a distance d from a transmitter can be expressed as

$$\begin{aligned} P_r(d) &= \overline{P_r}(d) + s \\ \overline{P_r}(d) &= P_o - 10n \log_{10}(d/d_o) \end{aligned} \quad (4.1)$$

where s is the shadow fading loss and characterized by $s \sim \mathcal{N}(0, \sigma_s^2)$. The reference power, P_o , is the average received power measured at a reference distance, d_o , from the transmitter. The parameters, n and σ_s , are the path loss exponent and the location variability respectively, and are environment-dependent.

For two wireless nodes to communicate successfully, the receiving power must exceed some threshold, P_{th} , as prescribed by the transceivers on the sensor nodes. For instance, when one node is transmitting at distance d from another node, the two are said to be *connected* if $P_r(d) \geq P_{th}$. In other words, the probability of having a successful connection between the two is given by

$$\begin{aligned} \Pr[2 \text{ sensor nodes are } connected] &= \Pr[P_r(d) \geq P_{th}] \\ &= Q\left(\frac{P_{th} - \overline{P_r}(d)}{\sigma_s}\right) \\ &= \frac{1}{2} - \frac{1}{2} \operatorname{erf}\left(\frac{P_{th} - \overline{P_r}(d)}{\sigma_s \sqrt{2}}\right). \end{aligned} \quad (4.2)$$

Furthermore, it is assumed that all sensor nodes are equipped with identical receivers and are transmitting at the same power level P_T . As mentioned earlier, in practice, the receiving power, also known as RSS in RF hardware specifications, is often expressed in the form of integer values. Since there is usually a linear mapping between receiving power and RSS [148], P_r and RSS will be used interchangeably in the following text.

4.2.2 RSS Levels

One important difference between the proposed dWCL and the original WCL [32] is that in dWCL, the span of RSS from the sensor nodes is divided into a number of levels, each of which is assigned with a weight taken from a finite set of discrete values.

More specifically, of the overall span of RSS, i.e. from the threshold, P_{th} , to the transmitting power, P_T , it is divided into M non-overlapping levels as illustrated in Fig. 4.2. The boundaries of these RSS levels are defined by the variables γ_i for $i = 1, \dots, M$. As a result, the ranges of the M levels are:

$$\begin{aligned} \text{Level } i: & [\gamma_i, \gamma_{i+1}) \\ \text{Level } M: & [\gamma_M, P_T) \end{aligned} \tag{4.3}$$

Without loss of generality, by default, $\gamma_1 = P_{th}$.

Fig. 4.2: M non-overlapping RSS levels defined over the overall span of RSS.

4.2.3 Location Estimation

In this thesis, the sensor nodes of the underlying WSN are assumed to be deployed on a 2-dimensional x, y -plane, although the proposed dWCL can easily be extended to a 3-dimensional space. As such, let the position of the j th node be represented by a 2-dimensional coordinates (x_j, y_j) . Furthermore, although the sensor nodes can

acquire their positions with some self-localization techniques [56, 151], the location information may not be always perfect. That is, there may exist an error between one node's apparent position and its actual position. For this, one can write

$$x'_j = x_j + \xi_{j,x} \quad (4.4)$$

for node j , where x'_j is the apparent x-coordinate, x_j the real x-coordinate and $\xi_{j,x}$ the error. This error is often modelled with a Gaussian distribution, i.e. $\xi_{j,x} \sim \mathcal{N}(0, \sigma_\xi^2)$, where σ_ξ is the standard deviation of error in the sensor node location information.

Let us consider the Target node which is able to establish communications with a number of sensor nodes. The receiving power, or the RSS, corresponding to these transmissions can be predicted using (4.1). Furthermore, RSS_k is used to denote the RSS from sensor node k . According to the value of RSS_k , sensor node k falls into one of the M RSS levels as defined in (4.3).

Let us further define S_i as the set of sensor nodes of RSS level i , and $|S_i|$ as the cardinality of set S_i . All sensor nodes in set S_i are associated with a weight w_i . Generally, one would assign a larger weight to sensor nodes with higher RSS, as they should have bigger influence on the position estimation. Therefore, a reasonable weighting scheme would have to satisfy the inequality $w_i \leq w_{i+1}$.

Based on the location information of all *connected* sensor nodes, the Target node can estimate its own x-coordinate using

$$\hat{x} = \frac{\sum_i \sum_{j \in S_i} w_i x'_j}{\sum_i w_i |S_i|}. \quad (4.5)$$

The y-coordinate of the Target node can also be obtained in a similar fashion.

4.3 Performance Analysis

Since dWCL estimates the position of the Target node using (4.5), the distribution of $\hat{x}$ thus completely characterizes the localization error distribution of dWCL in terms of *accuracy* (ϵ) and *precision* (α). This section presents the analytical framework with which one can evaluate the performance of dWCL.

4.3.1 Coverage Area

Let R_o be the *nominal range* that satisfies the equality $\overline{P}_r(R_o) = P_{th}$. In other words, from a distance R_o , there is a 50 % chance that the Target node and a sensor node are *connected*. Let us further define a circular region $\mathcal{D}$ of radius R around the Target node. When R is large enough, the probability of the Target node being able to *connect* with any sensor node outside of $\mathcal{D}$ is virtually 0, i.e.

$$\Pr [P_r(R) \geq P_{th}] \approx 0 \text{ as } R \rightarrow \infty.$$

Ideally, R should go to ∞ . However, due to practicality and computational consideration, a large but finite value for R has to be selected. For a Gaussian distribution, the probability of exceeding 4 standard deviations from the mean is effectively 0 (< 0.00003). The value of R hence can be computed using

$$\frac{P_{th} - \overline{P}_r(R)}{\sigma_s} = 4 \tag{4.6}$$

Let R denote the *effective range*, and it is related to the *nominal range* as follows.

$$R = R_o 10^{0.4\sigma_s/n} \tag{4.7}$$

In a related work [152], $U(\gamma)$ represents the percentage of area within $\mathcal{D}$ that has a RSS equal to or greater than a threshold γ . In a similar fashion and based on the

author's previous work [150], U_i is defined as the percentage of area within $\mathcal{D}$ that has a RSS equal to or greater than a threshold γ_i , and it is expressed as

$$\begin{aligned} U_i &= \frac{1}{\pi R^2} \iint_{\mathcal{D}} \Pr [P_r(r) \geq \gamma_i] dA \\ &= \frac{1}{2} \left\{ 1 - \operatorname{erf}(a_i) + \exp \left(\frac{1 - 2a_i b}{b^2} \right) \left[1 - \operatorname{erf} \left(\frac{1 - a_i b}{b} \right) \right] \right\} \end{aligned} \quad (4.8)$$

where

$$a_i = (\gamma_i - P_r(R)) / \sqrt{2}\sigma_s,$$

$$b = 10n \log_{10} e / \sqrt{2}\sigma_s,$$

and dA in (4.8) is an incremental area for integration.

4.3.2 Accuracy and Precision

The justification of describing the deployed locations of the wireless sensor nodes with random distribution is given in Section 4.2. Let us discuss the statistical properties of their locations relative to that of the Target node. Without loss of generality, the Target node is assumed to be placed at the center of the area and hence its coordinates are $(0, 0)$. In the following, the analysis shows the x-coordinates only, as that for the y-coordinates is independent and identical.

Following [150], the expectation of x-coordinates of sensor nodes of RSS level i can be shown to be equal to

$$\mathbb{E}[X_i] = \frac{1}{\mathcal{A}_i} \iint_{\mathcal{D}} x \Pr [\gamma_{i+1} \geq P_r(r) \geq \gamma_i] dA = 0 \quad (4.9)$$

where $\mathcal{A}_i$ is the area in $\mathcal{D}$ that has a RSS within the range of RSS level i , and

$$\mathcal{A}_i = \begin{cases} \pi R^2 (U_i - U_{i+1}) & \text{if } i < M, \\ \pi R^2 U_M & \text{if } i = M. \end{cases} \quad (4.10)$$

Furthermore, the variance of x-coordinates of sensor nodes in RSS level i , σ_i^2 can be computed as follows. For $i = 1, \dots, M-1$,

$$\begin{aligned} \text{Var}[X_i] &= \mathbb{E}[X_i^2] \\ &= \frac{1}{\mathcal{A}_i} \iint_{\mathcal{D}} x^2 \Pr[\gamma_{i+1} \geq P_r(r) \geq \gamma_i] dA \\ &= \frac{R^2}{8(U_i - U_{i+1})} \left\{ \text{erf}(a_{i+1}) - \text{erf}(a_i) + \exp\left(\frac{4 - 4a_i b}{b^2}\right) \left[1 - \text{erf}\left(\frac{2 - a_i b}{b}\right)\right] \right. \\ &\quad \left. - \exp\left(\frac{4 - 4a_{i+1} b}{b^2}\right) \left[1 - \text{erf}\left(\frac{2 - a_{i+1} b}{b}\right)\right] \right\}. \end{aligned} \quad (4.11)$$

The variance for level M is given by

$$\begin{aligned} \text{Var}[X_M] &= \mathbb{E}[X_M^2] \\ &= \frac{1}{\mathcal{A}_i} \iint_{\mathcal{D}} x^2 \Pr[P_r(r) \geq \gamma_M] dA, \\ &= \frac{R^2}{8U_M} \left\{ 1 - \text{erf}(a_M) + \exp\left(\frac{4 - 4a_M b}{b^2}\right) \left[1 - \text{erf}\left(\frac{2 - a_M b}{b}\right)\right] \right\}. \end{aligned} \quad (4.12)$$

For detailed derivations, the reader can refer to Appendix A.1.

The number of sensor nodes of RSS level i is equal to $|S_i|$, which is in fact a Poisson random variable (RV), i.e. $|S_i| \sim Po(\lambda_i)$, where

$$\lambda_i = \begin{cases} \rho \pi R^2 (U_i - U_{i+1}) & \text{if } i < M, \\ \rho \pi R^2 U_M & \text{if } i = M, \end{cases} \quad (4.13)$$

and ρ is the sensor node density.

4.3.2.1 Gaussian Approximations

With the variables defined above, the dWCL estimation equation (4.5) can be rewritten as follows.

$$\hat{x} = \frac{\sum_i \sum_{j \in S_i} w_i(x_j + \xi_{j,x})}{\sum_i w_i |S_i|} \triangleq \frac{N}{D}. \quad (4.14)$$

By this definition, $\hat{x}$ is a ratio of two RVs, N and D , and they can be approximated as Gaussian RVs with the following properties:

$$\begin{aligned} \mathbb{E}[N] &= \mu_N = 0 \\ \text{Var}[N] &= \sigma_N^2 = \sum_{i=1}^M w_i^2 \lambda_i (\sigma_i^2 + \sigma_\xi^2) \\ \mathbb{E}[D] &= \mu_D = \sum_{i=1}^M w_i \lambda_i \\ \text{Var}[D] &= \sigma_D^2 = \sum_{i=1}^M w_i^2 \lambda_i \end{aligned} \quad (4.15)$$

The following simulation aims to verify that Gaussian distribution is sufficient to approximate the distributions of N and D . Three tests are set up and their parameter values are listed in Table 4.2.

Table 4.2: Parameter values used in the simulation

Test	n	σ (dB)	R_o (m)	ρ (m ⁻²)	M
1	2.3	3.92	30	0.10	2
2	2.3	3.92	30	0.10	5
3	2.3	3.92	30	0.10	10

Anderson–Darling test is used to test the null hypotheses that N and D follow the Gaussian distributions described in (4.15) respectively. A sample size of 10 000 N s and D s are simulated, and their corresponding p -values are calculated and shown in Table 4.3. At the 5 % significance level, both hypotheses cannot be rejected.

Moreover, histograms and normal probability plots of another 100 000 simulated samples of N and D are presented in the top and middle subplots in Fig. 4.3, Fig. 4.4,

Table 4.3: p -values of Anderson–Darling test

Test	N	D
1	0.9437	0.0535
2	0.7346	0.0767
3	0.8150	0.0828

and Fig. 4.5. The bottom subplots of the three figures superimpose the histograms with the corresponding fitted Gaussian distributions.

Fig. 4.3: (top) Histogram (middle) normal probability plot (bottom) superimposition of histogram and fitted Gaussian distribution of (a) numerators and (b) denominators for Test 1.

The results show that, in all three tests, the numerators N can be fitted very well with Gaussian distribution. The denominators D , on the other hand, are somewhat problematic. Due to the fact that the D s are sums of discrete values, the resultant distribution is not entirely smooth, and series of spikes appear in the histograms. Nevertheless, its general shape still resembles a Gaussian distribution, and the fitted Gaussian distribution is able to capture the essence of the distribution of the denominators.

Fig. 4.4: (top) Histogram (middle) normal probability plot (bottom) superimposition of histogram and fitted Gaussian distribution of (a) numerators and (b) denominators for Test 2.

In addition, based on these Gaussian approximations, the mean and variance of the samples are compared with their theoretical counterparts obtained from (4.15). The results are tabulated in Table 4.4, Table 4.5 and Table 4.6. Close agreements between the two are observed in all three test cases. These justify the adoption of Gaussian distribution as the model for both the numerator N and denominator D in (4.14).

Table 4.4: Comparison of sample and theoretical means and variances for Test 1

	Numerator	Denominator
Sample Mean	1.163	397.569
Theoretical Mean	0	397.517
Sample Variance	219064.052	423.113
Theoretical Variance	218257.752	423.166

Fig. 4.5: (top) Histogram (middle) normal probability plot (bottom) superimposition of histogram and fitted Gaussian distribution of (a) numerators and (b) denominators for Test 3.

Table 4.5: Comparison of sample and theoretical means and variances for Test 2

	Numerator	Denominator
Sample Mean	0.809	516.895
Theoretical Mean	0	516.874
Sample Variance	265900.027	862.514
Theoretical Variance	265786.685	867.858

Table 4.6: Comparison of sample and theoretical means and variances for Test 3

	Numerator	Denominator
Sample Mean	-0.288	778.593
Theoretical Mean	0	778.690
Sample Variance	498537.349	2333.261
Theoretical Variance	495208.548	2359.834

Furthermore, by definition, the correlation between N and D is

$$\rho_{N,D} = \text{corr}(N, D)$$

$$\begin{aligned}
 &= \frac{\text{cov}(N, D)}{\sigma_N \sigma_D} \\
 &= \frac{\mathbb{E}[ND] - \mathbb{E}[N]\mathbb{E}[D]}{\sigma_N \sigma_D}.
 \end{aligned} \tag{4.16}$$

Since $\mathbb{E}[N] = 0$, $\sigma_N \neq 0$ and $\sigma_D \neq 0$, it is sufficient to show that N and D are uncorrelated by proving $\mathbb{E}[ND] = 0$.

$$\begin{aligned}
 \mathbb{E}[ND] &= \mathbb{E}\left[\sum_{i=1}^M \sum_{j=1}^{|S_i|} \sum_{k=1}^M w_i x_{ij} w_k |S_k|\right] \\
 &= \mathbb{E}\left[\sum_{i=1}^M \sum_{k=1}^M w_i w_k |S_k| \sum_{j=1}^{|S_i|} x_{ij}\right]
 \end{aligned} \tag{4.17}$$

where x_{ij} represents x'_j of RSS level i . Since w_i and w_k are constants, and x_{ij} and $|S_k|$ are independent, $\mathbb{E}[ND] = 0$. In addition, a scatterplot between the corresponding numerators and denominators is presented in Fig. 4.6. It further confirms that the numerator and denominator are uncorrelated.

Fig. 4.6: Scatterplot of numerators N and denominators D .

There are a few approximation methods for the ratio distribution of two Gaussian RVs readily available (more information is presented in Appendix A.2). The method

proposed by Hayya *et al.* [153] allows us to simplify (4.14) into

$$\hat{x} \sim \mathcal{N}(0, \sigma_N^2 / \mu_D^2). \quad (4.18)$$

4.3.2.2 Error Distributions

The distribution of localization error in terms of ϵ and α of dWCL can be derived using the Gaussian approximation mentioned above (4.18). The 1-dimensional error is in fact $|\hat{x}|$, and it follows a half-normal distribution¹:

$$|\hat{x}| \sim \mathcal{HN}(\sigma_N / \mu_D). \quad (4.19)$$

Moreover, since the sensor nodes are assumed to be randomly deployed, their x- and y-coordinates are i.i.d. As a result, the distribution of total (2-dimensional) error, $\hat{r}$, follows the corresponding Rayleigh distribution:

$$\hat{r} \sim \text{Rayleigh}(\sigma_N / \mu_D). \quad (4.20)$$

4.4 Optimization of dWCL

While the previous section describes the general framework to analyze the proposed dWCL, it also shows that the localization error of dWCL is determined by the variance in (4.18). Let us denote it by σ_{dWCL}^2 , and

$$\sigma_{dWCL}^2 = \frac{\sum_{i=1}^M w_i^2 \lambda_i (\sigma_i^2 + \sigma_\xi^2)}{\left(\sum_{i=1}^M w_i \lambda_i\right)^2}. \quad (4.21)$$

In here, dWCL is optimized by minimizing σ_{dWCL}^2 . In fact, there are two different optimizing approaches to take. For the sake of brevity, the subscript *dWCL* of σ_{dWCL}^2

¹Let $X \sim \mathcal{N}(0, \sigma^2)$, then $Y = |X|$ follows a half-normal distribution $\mathcal{HN}(\sigma)$, whose CDF is given by $F_Y(y) = \text{erf}\left(\frac{y}{\sqrt{2}\sigma}\right)$.

is dropped in the following derivations when possible.

4.4.1 Optimizing by Weights

The first and most intuitive way to optimize dWCL is by setting the best weighting factors for each RSS level. In other words, given the range of the M RSS levels, or the RSS level boundary vector $\boldsymbol{\gamma}$, one is seeking the optimal weight vector $\mathbf{w}$ such that (4.21) is minimized. With the construction of (4.21), one can assume $w_M = 1$ and iterate on $w_1, \dots, w_{M-1}$ without affecting the solution.

Using calculus, it can be shown that the gradient with respect to each weight w_i is

$$\begin{aligned} \frac{\partial \sigma^2}{\partial w_i} &= \frac{1}{(\sum_m w_m \lambda_m)^4} \left\{ \left(\sum_k w_k \lambda_k \right)^2 (2w_i \lambda_i) (\sigma_i^2 + \sigma_\xi^2) \right. \\ &\quad \left. - \left[\sum_\ell w_\ell^2 \lambda_\ell (\sigma_\ell^2 + \sigma_\xi^2) \right] \left(2\lambda_i \sum_k w_k \lambda_k \right) \right\} \\ &= \frac{2\lambda_i \sum_k w_k \lambda_k}{(\sum_m w_m \lambda_m)^4} \left[\left(\sum_k w_k \lambda_k \right) w_i (\sigma_i^2 + \sigma_\xi^2) - \sum_\ell w_\ell^2 \lambda_\ell (\sigma_\ell^2 + \sigma_\xi^2) \right] \\ &= \frac{2\lambda_i}{(\sum_m w_m \lambda_m)^3} \left[\left(\sum_k w_k \lambda_k \right) w_i (\sigma_i^2 + \sigma_\xi^2) - \sum_\ell w_\ell^2 \lambda_\ell (\sigma_\ell^2 + \sigma_\xi^2) \right]. \end{aligned} \quad (4.22)$$

For $\frac{\partial \sigma^2}{\partial w_i} = 0$, it requires that

$$\left(\sum_k w_k \lambda_k \right) w_i (\sigma_i^2 + \sigma_\xi^2) - \sum_\ell w_\ell^2 \lambda_\ell (\sigma_\ell^2 + \sigma_\xi^2) = 0. \quad (4.23)$$

Rearranging, this gives

$$w_i (\sigma_i^2 + \sigma_\xi^2) = \frac{\sum_\ell w_\ell^2 \lambda_\ell (\sigma_\ell^2 + \sigma_\xi^2)}{\sum_k w_k \lambda_k}. \quad (4.24)$$

In other words, one solution exists when all $w_i (\sigma_i^2 + \sigma_\xi^2)$ are equal. Denoting the

solution by $\mathbf{w}^*$, one can also establish the following condition

$$\frac{w_i^*}{w_M} = \frac{\sigma_M^2 + \sigma_\xi^2}{\sigma_i^2 + \sigma_\xi^2} \quad (4.25)$$

for the component w_i^* at the critical point.

To identify the nature of the critical point, the Hessian matrix $\mathbf{H}[\boldsymbol{\sigma}^2]$ of (4.21) is investigated, and its diagonal elements are

$$\begin{aligned} \mathbf{H}[\boldsymbol{\sigma}^2]_{i,i} &= \frac{\partial^2 \sigma^2}{\partial w_i^2} \\ &= \frac{2\lambda_i}{(\sum_m w_m \lambda_m)^6} \left\{ \left(\sum_m w_m \lambda_m \right)^3 \right. \\ &\quad \times \left[\left(\sum_k w_k \lambda_k + w_i \lambda_i \right) (\sigma_i^2 + \sigma_\xi^2) - 2w_i \lambda_i (\sigma_i^2 + \sigma_\xi^2) \right] \\ &\quad \left. - 3\lambda_i \left(\sum_m w_m \lambda_m \right)^2 \left[\left(\sum_k w_k \lambda_k \right) w_i (\sigma_i^2 + \sigma_\xi^2) - \sum_\ell w_\ell^2 \lambda_\ell (\sigma_i^2 + \sigma_\xi^2) \right] \right\}. \end{aligned} \quad (4.26)$$

Since $\mathbf{w}^*$ is chosen according to (4.23), (4.26) can be further simplified into

$$\begin{aligned} \frac{\partial^2 \sigma^2}{\partial w_i^2} &= \frac{2\lambda_i}{(\sum_m w_m \lambda_m)^6} \left(\sum_m w_m \lambda_m \right)^3 (\sigma_i^2 + \sigma_\xi^2) \left(\sum_k w_k \lambda_k + w_i \lambda_i - 2w_i \lambda_i \right) \\ &= \frac{2\lambda_i (\sigma_i^2 + \sigma_\xi^2) (\sum_k w_k \lambda_k - w_i \lambda_i)}{(\sum_m w_m \lambda_m)^3}. \end{aligned} \quad (4.27)$$

Letting $C = w_i(\sigma_i^2 + \sigma_\xi^2)$, (4.27) can be rewritten as

$$\frac{\partial^2 \sigma^2}{\partial w_i^2} = \frac{2\lambda_i}{(\sum_m w_m \lambda_m)^3} \left[(\sigma_i^2 + \sigma_\xi^2) \sum_k w_k \lambda_k - \lambda_i C \right]. \quad (4.28)$$

On the other hand, the off-diagonal elements of the Hessian matrix are

$$\mathbf{H}[\boldsymbol{\sigma}^2]_{i,j} = \frac{\partial^2 \sigma^2}{\partial w_i \partial w_j}$$

$$\begin{aligned}
 &= \frac{2\lambda_i}{(\sum_m w_m \lambda_m)^6} \left\{ \left(\sum_m w_m \lambda_m \right)^3 [w_i \lambda_j (\sigma_i^2 + \sigma_\xi^2) - 2w_j \lambda_j (\sigma_j^2 + \sigma_\xi^2)] \right. \\
 &\quad \left. - 3\lambda_j \left(\sum_m w_m \lambda_m \right)^2 \left[\left(\sum_k w_k \lambda_k \right) w_i (\sigma_i^2 + \sigma_\xi^2) - \sum_\ell w_\ell^2 \lambda_\ell (\sigma_i^2 + \sigma_\xi^2) \right] \right\}.
 \end{aligned} \tag{4.29}$$

Similarly, it can be further simplified into

$$\begin{aligned}
 \frac{\partial^2 \sigma^2}{\partial w_i \partial w_j} &= \frac{2\lambda_i}{(\sum_m w_m \lambda_m)^6} \left(\sum_m w_m \lambda_m \right)^3 [w_i \lambda_j (\sigma_i^2 + \sigma_\xi^2) - 2w_j \lambda_j (\sigma_j^2 + \sigma_\xi^2)] \\
 &= \frac{-2\lambda_i \lambda_j C}{(\sum_m w_m \lambda_m)^3}.
 \end{aligned} \tag{4.30}$$

For the cases of $M = 2$ and 3 , it has been shown that the Hessian matrices are positive-definite at $\mathbf{w}^*$ (detailed derivations are presented in Appendix A.3). Hence $\mathbf{w}^*$, with its components being

$$w_i^* = \frac{\sigma_M^2 + \sigma_\xi^2}{\sigma_i^2 + \sigma_\xi^2} w_M = \frac{\sigma_M^2 + \sigma_\xi^2}{\sigma_i^2 + \sigma_\xi^2}, \tag{4.31}$$

is the local minimum for (4.21).

For larger M , however, analytical proof is unavailable, but one can easily verify the positive-definiteness of the corresponding Hessian matrix numerically. Alternatively, one can formulate the problem as a unconstrained minimization problem (P1):

$$(\text{P1}) \quad \min_{\mathbf{w}} \sigma_{dWCL}^2 \tag{4.32}$$

and solve it with optimization packages, e.g. MATLAB or CPLEX.

4.4.2 Optimizing by Level Boundaries

The second approach tries to optimize the performance of dWCL by finding the optimal boundaries of the RSS levels, i.e. γ 's or the vector $\boldsymbol{\gamma}$. Assuming the weight vector $\mathbf{w}$ is given, it can be formulated as a constrained minimization problem.

$$\begin{aligned} \text{(P2)} \quad & \min_{\boldsymbol{\gamma}} \sigma_{dWCL}^2 \\ \text{s.t.} \quad & \gamma_1 < \gamma_2 < \dots < \gamma_M \end{aligned} \tag{4.33}$$

Note that, by default, $\gamma_1 = P_{th}$ is assumed in the system model. Hence one needs to iterate on $\gamma_2, \dots, \gamma_M$ only. The inequality constraints in (4.33) can be converted into the following canonical form:

$$\begin{bmatrix} \gamma_2 & \gamma_3 & 0 & 0 & \dots & 0 \\ 0 & \gamma_3 & \gamma_4 & 0 & \dots & 0 \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \dots & \gamma_{M-1} & \gamma_M \end{bmatrix} < 0.$$

4.5 Relation to Other WCL Algorithms

The proposed dWCL generalizes weighted centroid localization algorithms. It should be highlighted that the original Centroid Localization algorithm (CL) [69] is in fact a special case of dWCL with $M = 1$. The analytical work on the performance of CL algorithm can be found in the author's earlier work [150].

With regard to other WCL-based algorithms, it can be shown that dWCL is able to approximate the Relative Span Weighted Localization (RWL) [97] by choosing the parameter values judiciously. Assuming a linear mapping between the weights and the RSS values relative to the overall RSS span, RWL estimates the position as the weighted centroid of all *connected* sensors. One can easily see that if $v_{min} = \gamma_1$ is assumed and the weights are assigned with the equality $w_i = \gamma_i - \gamma_1$, the dWCL

converges to RWL in the limiting case, i.e. when $M \rightarrow \infty$.

4.6 Numerical Results and Simulations

In this section, the performance of the proposed dWCL algorithm is evaluated using the analytical framework described in Section 4.3. In particular, the effects of the number of RSS levels M , node density ρ , shadow fading σ_s and sensor node location information error σ_ξ on the error distribution of dWCL are investigated. The results are validated with corresponding simulations. Moreover, the average distance to the closest *connected* sensor, $\overline{D_c}$, is also given in each case for comparison. In later parts, it is demonstrated that dWCL can converge to other WCL algorithms, and the results for optimizing dWCL are also shown.

Table 4.7 lists the values of the parameters used across all analyses and simulations. The values of n and σ_s are adopted from a measurement study in an office environment [154]. d_o is the close-in reference distance. R_o and P_{th} are set according to typical IEEE 802.15.4 transceivers. Furthermore, the size of simulation area is chosen to be large enough ($\gg 2R$) such that border area effect [155] is not affecting the results. Within the simulation area, the sensor nodes are randomly deployed, and their quantities are determined by the node density ρ . Unless stated otherwise, the simulation results presented here are evaluated based on the average of 10 000 runs.

In this study, the following weighting scheme is adopted.

$$w_i = i \tag{4.34}$$

where i is the index of RSS level. In addition, for convenience, evenly-spaced γ_i 's are chosen. Hence their values can be computed according to the equation

$$\gamma_i = \frac{P_o - P_{th}}{M}(i - 1) + P_{th}. \tag{4.35}$$

Note that the choices of w_i 's and γ_i 's shown here are arbitrary. Our analytical framework can in fact take any values for both parameters.

Table 4.7: Simulation Parameters

Parameters	Values
n	2.3
σ_s	3.92 dB
d_o	1 m
R_o	30 m
P_{th}	-90 dBm
Simulation Area	1000 m $\times$ 1000 m

4.6.1 Distributions of Localization Errors

The investigation starts with the verification that both the 1-dimensional and 2-dimensional localization errors computed by dWCL follow the half-normal and Rayleigh distributions as stated in (4.19) and (4.20) respectively.

In this experiment, the node density ρ is 0.05 m^{-2} and the number of RSS levels M is assumed to be 5. Samples of 1-dimensional and 2-dimensional localization errors are generated and collected from simulations. The normal probability plot and histogram of $\hat{x}$ of (4.18) are shown in Fig. 4.7. It is clear from the simulation results that $\hat{x}$ follows a normal distribution. The 1-dimensional localization error, $|\hat{x}|$, is therefore half-normally distributed. Similarly, the 2-dimensional localization error, $\hat{r}$, follows a Rayleigh distribution as indicated in Fig. 4.8a and Fig. 4.8b. Further experiments using different parameter values give the same observation.

4.6.2 Effect of Number of RSS Levels

The effect of the number of RSS levels M on the performance of dWCL is investigated in this section. The results for M equal to 1, 5, 10 and 256 when $\rho = 0.02 \text{ m}^{-2}$ and $\sigma_\xi = 0 \text{ m}$ are plotted in Fig. 4.9. It is clear from the figures that the predicted error

Fig. 4.7: (a) Probability plot and (b) Histogram of 1-dimensional localization errors computed by dWCL.

Fig. 4.8: (a) Probability plot and (b) Histogram of 2-dimensional localization errors computed by dWCL.

distribution from our model matches closely with the simulation results in both 1-dimensional and 2-dimensional cases. In this setting, $\overline{D_c}$ is 3.542 m. As shown in Fig. 4.9b, in nearly 60 % of the time the localization errors are less than $\overline{D_c}$ when M is as low as 1. When $M \geq 10$, in more than 80 % of the time dWCL performs better than $\overline{D_c}$.

One also observes that an increasing M reduces the error in all cases. For instance, in the 1-dimensional case, the median error when $M = 1$ is about 1.8 m whereas, when $M = 256$, it is reduced to 1.3 m. Almost all errors are within 6 m when $M = 256$ but they are up to 9 m in the case of $M = 1$ for the 2-dimensional scenario. This general trend is expected, as a larger M allows for a finer distinction between sensor nodes with different RSS, which in turn improves the quality of estimation of dWCL.

On the other hand, a rapid diminishing returns of improvement occurs as M increases. For example, increasing M from 1 to 5 results in a sizeable improvement in the error distribution. By comparing $M = 10$ with $M = 256$, the improvement becomes very insignificant. It is therefore not economical to keep increasing the number of RSS levels M in the hope of improving the performance of dWCL.

4.6.3 Effect of Node Density

In this section, the node density ρ is varied to see what effect it brings to the error distribution of dWCL. Fig. 4.10 shows a good agreement between the theoretical and simulation results in all test cases for both 1-dimensional and 2-dimensional scenarios. When ρ are 0.02 m^{-2} , 0.05 m^{-2} and 0.10 m^{-2} , $\overline{D_c}$ are 3.542 m, 2.209 m and 1.582 m respectively. The results also show that the errors reduce quite rapidly as more sensor nodes are deployed, i.e. ρ increases. Note that although ρ determines how many sensor nodes are present within the whole simulation area, the number of sensor nodes that can *connect* with the target node ($\sum_{i=1}^M |S_i|$) is actually a RV, owing to random node deployment and random shadow fading. As a result, the number of sensor nodes

Fig. 4.9: Effect of number of RSS levels M when $\rho = 0.02 \text{ m}^{-2}$ and $\sigma_\xi = 0 \text{ m}$. (a) 1-dimensional error distribution (b) 2-dimensional error distribution

contributing to the estimation of position in each simulation instance is also a RV.

Fig. 4.10: Effect of node density ρ when $M = 10$ and $\sigma_\xi = 0 \text{ m}$. (a) 1-dimensional error distribution (b) 2-dimensional error distribution

4.6.4 Effect of Shadow Fading

Unlike M or ρ , the level of shadow fading is not controllable by the system or users. Instead, it is intrinsic to the environment that the system is deployed in. Hence it is important to study the effect of shadow fading on the dWCL. In here, the level of shadowing σ_s is varied, and 10 RSS levels (i.e. $M = 10$) are assumed for the dWCL. Node density ρ is set at 0.02 m^{-2} and σ_ξ is fixed at 0 m. In this experiment, $\overline{D_c}$ are 3.511 m, 3.542 m and 3.544 m when σ_s are 2.00 dB, 3.92 dB and 7.50 dB respectively. The simulation results are shown in Fig. 4.11. When the level of shadowing σ_s increases, the error distribution, and hence the performance of dWCL, worsens. Also note that our theoretical framework is still able to predict precisely when it is compared with the simulation results.

Fig. 4.11: Effect of level of shadow fading σ_s when $\rho = 0.02 \text{ m}^{-2}$, $M = 10$ and $\sigma_\xi = 0$ m. (a) 1-dimensional error distribution (b) 2-dimensional error distribution

4.6.5 Effect of Sensor Node Location Information Error

As explained in Section 4.2.3, sensor nodes in the underlying WSN may possess imperfect information about their own locations. These errors in turn affect the prediction

of dWCL. This section gives an account of such situation.

In the following simulations, one assumes that the level of sensor node location information error σ_ξ takes the following values: 0 m, 5 m and 10 m. As σ_ξ does not affect the actual sensor position or RSS, $\overline{D_c}$ remains 3.542 m. The results are plotted in Fig. 4.12. It is evident that dWCL is not very susceptible to sensor node location information error. As seen in Fig. 4.12, increasing σ_ξ only slightly degrades the performance of dWCL. For instance, there is a small increment in the 50-percentile error (from 2.3 m to 2.5 m) in the 2-dimensional case when σ_ξ increases from 0 m to 5 m. Increasing σ_ξ further to 10 m, the median error merely rises to 2.9 m. Referring to Fig. 4.11, a raise in σ_s from 2 dB to 7.5 dB inflates the 50-percentile error almost threefold from 1.9 m to 5.2 m. Thus, comparing with the effect of shadow fading σ_s , the impact of σ_ξ is marginal.

Fig. 4.12: Effect of sensor node location information error σ_ξ when $\rho = 0.02 \text{ m}^{-2}$ and $M = 10$. (a) 1-dimensional error distribution (b) 2-dimensional error distribution

4.6.6 Optimizing dWCL

4.6.6.1 By Weights

It has been shown in Section 4.4.1 that the performance of dWCL can be optimized by selecting the best weight (in the the weight vector $\mathbf{w}$) for each RSS level. By varying $\mathbf{w}$, the changes of σ_{dWCL}^2 of (4.21) for $M = 2$ and $M = 3$ are plotted in Fig. 4.13 and Fig. 4.14 respectively. Without loss of generality, one assumes $w_M = 1$ and iterates on $w_1, \dots, w_{M-1}$ only. Furthermore, the γ 's are assumed to be evenly-spaced in this experiment.

Fig. 4.13: σ_{dWCL}^2 with different weight vector $\mathbf{w}$ when $M = 2$ and w_M is assumed to be 1.

As shown, there is an optimum point, $\mathbf{w}^*$, which yields the smallest σ_{dWCL}^2 in each case. Using (4.31), one can compute that $\mathbf{w}^* = [0.0323, 1]$ for $M = 2$, and $\sigma_{dWCL}^2 = 3.8020 \text{ m}^2$. When $M = 3$, $\mathbf{w}^* = [0.0097, 0.0939, 1]$ and $\sigma_{dWCL}^2 = 2.8050 \text{ m}^2$. Both $\mathbf{w}^*$'s for $M = 2$ and 3 match the optimal points indicated in Fig. 4.13 and Fig. 4.14.

Alternatively, one can also use the optimization formulation (P1) in (4.32) to ob-

Fig. 4.14: σ_{dWCL}^2 with different weight vector $\mathbf{w}$ when $M = 3$ and w_M is assumed to be 1.

tain the $\mathbf{w}^*$. Since the objective function of (P1) is nonlinear and nonconvex in general (as indicated in Fig. 4.13), one may resort to heuristic techniques. For instance, the Nelder-Mead simplex algorithm in MATLAB is used, and the same $\mathbf{w}^*$'s are obtained.

4.6.6.2 By Level Boundaries

The evenly-spaced RSS level boundaries used in the previous experiments are arbitrary, and are not required in the analytical framework. In fact, the second approach to optimize the performance of dWCL tries to find the optimal vector of the level boundaries, i.e. $\boldsymbol{\gamma}$. Fig. 4.15 and Fig. 4.16 show the resulting variance by varying $\boldsymbol{\gamma}$. Note that in Fig. 4.16, only the part above the diagonal line is feasible, as $\gamma_2 < \gamma_3$ is assumed. As $\gamma_1 = P_{th}$ is specified in the system, one iterates on $\gamma_2, \dots, \gamma_M$ only. Similar to the previous section where the weights are optimized, a clear minimum point exists in either case.

The minimization problem (P2) in (4.33) is also readily solved by existing optimization tools. With MATLAB, one can easily compute the $\boldsymbol{\gamma}^*$. For instance,

Fig. 4.15: σ_{dWCL}^2 with different RSS level boundaries γ when $M = 2$ and γ_1 is assumed to be P_{th} .

Fig. 4.16: σ_{dWCL}^2 with different RSS level boundaries γ when $M = 3$ and γ_1 is assumed to be P_{th} .

when $M = 2$, $\gamma^* = [-90, -84.5010]$ dBm and $\sigma_{dWCL}^2 = 5.5155 \text{ m}^2$. When $M = 3$, $\gamma^* = [-90, -84.5010, -81.9494]$ dBm and $\sigma_{dWCL}^2 = 4.7972 \text{ m}^2$. Both γ^* match the optimal points indicated in Fig. 4.15 and Fig. 4.16.

4.6.6.3 Optimized Values

The two aforementioned approaches are able to find either the optimal weight vector $\mathbf{w}^*$ or level boundary vector γ^* respectively that minimizes the variance σ_{dWCL}^2 . While the system parameters such as M, n, σ_s, P_{th} can influence the optimal solution, the node density ρ does not affect $\mathbf{w}^*$ or γ^* . Instead, it only affects the resulting variance as follows.

$$\sigma_{dWCL}^2 \propto \frac{1}{\rho} \quad (4.36)$$

This in turn affects the error distribution of dWCL as indicated in Section 4.6.3.

4.6.7 Converging to Other WCL Algorithms

Based on the approximation described in Section 4.5, the performance comparison between dWCL and RWL is illustrated in Fig. 4.17. It clearly shows that when increasing the number of RSS levels M from 5 to 10 and subsequently 50, the error distribution of dWCL improves and approaches that of RWL. It is also worth noting that, although $M \rightarrow \infty$ is assumed for convergence, dWCL is already able to give an excellent approximation to RWL for a moderate value of M , say 50.

4.7 Concluding Remarks

This chapter investigates the possibility of utilizing the WSN infrastructure to provide positioning service in smart buildings. To this end, Discrete Weighted Centroid Localization algorithm (dWCL), a new and discrete version of WCL, for WSN-based IPS is proposed. dWCL allows a wireless device, or the Target node, to estimate its

Fig. 4.17: Comparison between dWCL and RWL when $\rho = 0.02 \text{ m}^{-2}$ and $\sigma_{\xi} = 0 \text{ dB}$. (a) 1-dimensional error distribution (b) 2-dimensional error distribution

own position with the aid of an underlying WSN infrastructure. Comparing with the original Weighted Centroid Localization algorithm [32] and its subsequent variants, one can claim that dWCL is superior for two reasons. First, it is more compliant with the current state of digital electronics. The weighting function is discrete in nature, rendering it suitable for the RSS values available in any typical transceivers. Yet at the same time, the model is flexible to accommodate different performance requirements. In addition to generalizing the author's earlier work [150] on the original Centroid Localization algorithm [69], it is also shown that dWCL can be easily adapted to approximate some existing WCL-based algorithms, e.g. RWL [97].

The analytical framework to characterize the performance of dWCL in terms of two important metrics, namely *accuracy* (ϵ) and *precision* (α), is fully described. More specifically, it is shown that the 1-dimensional localization error follows a half-normal distribution whereas the 2-dimensional localization error follows a Rayleigh distribution. The work also demonstrates how erroneous sensor location information can be incorporated in the model. Using the framework, one is able to investigate

the effect of a few system parameters, including number of RSS levels, node density and level of shadow fading. One important observation from the investigation is the diminishing returns of performance improvement by increasing the number of RSS levels. In other words, increasing the resolution of RSS measurements after certain point may not be as effective as deploying extra sensor nodes in the sensor field.

In order to further elevate the performance of dWCL, two optimization approaches are presented. The first one optimizes dWCL by assigning the best weight to each RSS level whereas the second one determines the best RSS level boundaries. Regarding the first approach, a simple rule is established to compute the optimal weights $\mathbf{w}^*$ when the RSS level boundaries γ_i 's are known. Extensive simulation results are presented to validate the theoretical analysis. In all test cases, the theoretical model is able predict the distributions of localization error with remarkable accuracy.

Chapter 5

Theoretical Resolution for Range-free Localization Algorithms

5.1 Overview

As discussed in the previous chapter, *accuracy* and *precision* are two important performance metrics for localization algorithms. In this chapter, we endeavor to look further into the fundamental limit of *accuracy* and establish theoretical bounds for the class of range-free localization algorithms for WSN.

One of the key advantages of range-free localization algorithms are their relatively simple hardware specifications, since no additional ranging hardware is required. Instead, the localization process relies only on the *connectivity* information, i.e. “who is within communications range of whom” [68]. This information is readily available to any transceivers—if one device can communicate with another, then they are within the communications range of each other.

A number of research works on the theoretical bound on localization error has been highlighted in Section 2.3.4. For example, Patwari *et al.* present the Cramér-Rao Bound (CRB) for connectivity-based scheme in [101]. However, by definition, CRB only bounds the variance of the location estimator rather than the mean error

values [156].

Another approach is to bound the localization error from a geometric point of view. Consider a scenario where a node travels from one location to another without breaking or establishing any link. Since there is no change in the *connectivity* information, a range-free localization algorithm is oblivious to such movement, thus giving the same location estimate. The average distance that a sensor node can move without changing the *connectivity* information hence defines the theoretical resolution for this class of algorithms.

Based on a circular coverage model, both Nagpal *et al.* [33] and MacLean and Datta [109] study the lower bound on localization error. The former takes the average distance a sensor node can travel in a *random* direction before changing the *connectivity* as the theoretical resolution. In contrast, the latter considers *all* directions. This overly-strict condition allows them to achieve a smaller bound. In the circular coverage model, *connectivity* depends solely on the inter-node distance. Two nodes are *connected* as long as the distance is less than the constant communications range. This assumption allows significant simplification in the analysis of the bound, but at the same time, restricts the use of this model in reality.

Motivated by this, this work examines the theoretical resolution for *all* range-free localization algorithms while adopting a more realistic radio propagation model. In addition, the effect of correlated shadow fading is taken into account. Assuming the sensor nodes are randomly distributed, the analytical expression is derived for the distribution of the bound. The proposed scheme allows a rapid evaluation of the resolution without resort to expensive simulations. In addition, the result can be used as a lower bound to evaluate the probabilistic error bounds achieved by some range-free localization algorithms (e.g. [150]). The major content of this chapter is based on the works listed in [157–159].

The rest of the chapter is organized as follows. Section 5.2 first overviews the concept of correlated shadow fading and some well-known correlation models. The

system model for derivation of the theoretical limit on the resolution for the class of range-free algorithms is introduced in Section 5.3. Next, Section 5.4 demonstrates how the proposed approach can generalize the well-studied circular coverage model. Numerical evaluations and simulation results are presented in Section 5.5 to validate the proposed model. Finally, Section 5.6 closes the chapter with some concluding remarks.

5.1.1 List of Symbols

n	Path loss exponent
σ_s	Standard deviation of shadow fading
P_T	Transmitting power
P_r	Receiving power
P_{th}	Receiving power threshold
d_o	Reference distance
λ	Sensor node density
R_o	Nominal range of sensor node
R_e	Effective range of sensor node
d_{cor}	Decorrelation distance
θ_T	Threshold angle
ρ	Correlation coefficient
$P_i(.)$	Probability of “no <i>connectivity</i> change” due to node i
$P(.)$	Probability of “no <i>connectivity</i> change” due to all nodes

5.2 Correlation of Shadow Fading

Research on correlation of shadow fading has been going on for decades, and they are predominantly focusing on mobile radio systems. Numerous studies, e.g. [160–162], have demonstrated that when two wireless links are in close proximity, the two shadow fading losses exhibit certain amount of correlation. The phenomenon can be explained

like this. When two nearby wireless signals propagating in a similar environment, they are affected in a similar fashion. The more they overlap, the more similar their shadow fading losses are. In here, two well-known and highly cited correlation models for shadow fading are introduced. Interested readers are referred to Appendix B for a more thorough discussion.

Gudmundson's Model

When two wireless links are in proximity, or a mobile radio travels a small distance d from one location x_1 to another location x_2 , as illustrated in Fig. 5.1, a sizeable portion of the two links overlap and are subject to similar terrain conditions. Hence, the shadow fading losses associated with the two links are expected to be similar in magnitude.

Fig. 5.1: Two mobile radios are *connected* to the base station. The distance between the radios is d whereas the distances from the base station to location x_1 and x_2 are r_1 and r_2 respectively. When a mobile radio travels from x_1 to x_2 , the wireless links at the two instants can be considered as two separate links.

Based on empirical studies, Gudmundson proposes a simple exponential model in [161] to estimate the correlation of the shadowing losses as

$$\rho_{gud}(d) = \exp\left(-\frac{d}{d_{cor}} \ln 2\right) \quad (5.1)$$

where d (in m) is the distance between x_1 and x_2 , and d_{cor} (in m) is the decorrelation

distance where the correlation drops to 0.5. It depends on the environment. For instance, it is typically between dozens and hundreds of meters for outdoor environments [163]. On the other hand, several indoor measurements report that d_{cor} is a few meters and, in some cases, can be less than a meter [164, 165]. Furthermore, in Gudmundson's model, the correlation is assumed to be a function of d only, and is independent of r_1 and r_2 . The result of an indoor scenario based on (5.1) is illustrated in Fig. 5.2.

Fig. 5.2: Correlation coefficient by Gudmundson's model (5.1) with d_{cor} as the parameter. In this example, r_1 is 9 m and r_2 is 10 m.

Saunders' Model

In contrast, when the two links are widely separated or very different in length, Saunders *et al.* [163] provide another prediction model for the correlation coefficient:

$$\rho_{sau}(d) = \begin{cases} \sqrt{\frac{r_1}{r_2}} & \text{if } 0 \leq \theta < \theta_T \\ \left(\frac{\theta_T}{\theta}\right)^\gamma \sqrt{\frac{r_1}{r_2}} & \text{if } \theta_T \leq \theta \leq \pi \end{cases} \quad (5.2)$$

where r_1 and r_2 are the lengths of the links, and r_1 is taken to be the smaller of the two. θ is the angle between the two links as shown in Fig. 5.1. θ_T is the threshold angle between the two regimes in (5.2) and is defined by

$$\theta_T = 2 \sin^{-1} \frac{d_{cor}}{2r_1}. \quad (5.3)$$

The distance constant d_{cor} is the same as the one specified in (5.1). γ is an exponent constant and its value depends on the surroundings such as terrain, obstacle arrangements, height of antenna, etc. The results from (5.2) are illustrated in Fig. 5.3.

Fig. 5.3: Correlation coefficient by Saunders' model (5.2) with d_{cor} and γ as parameters. In this example, r_1 is 9 m and r_2 is 10 m.

Remarks

It is evident from Fig. 5.2 and Fig. 5.3 that the two correlation models produce quite distinctive results, for they are proposed for rather different scenarios. Actually, in Gudmundson's model, the travelling distance d is assumed to be small compared to the lengths of both links, i.e. $\min\{r_1, r_2\} \gg d$. The angle θ is hence also very small. In Saunders' model, on the other hand, d_{cor} is typically small relative to r_1 , hence θ_T

is very small. As a result, the second part of (5.2) is usually dominating. When d_{cor} is comparable to r_1 , however, the first part is dominating. It is therefore important to choose a correlation model most suitable for the situation at hand. The choice of the adopted model and its impact on the resolution of range-free localization algorithms will become apparent in the subsequent sections.

5.3 System Model

5.3.1 Indoor Radio Model

This chapter and the previous chapter have a lot in common regarding the underlying assumptions and models. For instance, the same radio model described in Section 4.2.1, i.e. the log-normal shadowing model, is adopted to predict the indoor path loss. As a result, the probability of having a successful connection between a pair of wireless sensor nodes is given by (4.2).

5.3.2 Pairwise Connectivity due to a Small Movement

This section studies the effect of a small movement on the connection status, or the *connectivity*, between a pair of nodes. As illustrated in Fig. 5.4, node j travels a small distance z to a new position j' at an angle θ with node i . Considering that the link between node i and node j at the two time instances—before and after the movement—are two distinct links, they are labelled as *link 1* and *link 2* respectively. If the distance between node i and node j is initially r_{ij} , then the length of *link 2* is

$$r'_{ij} = \sqrt{r_{ij}^2 + z^2 - 2r_{ij}z \cos \theta}. \quad (5.4)$$

Next, the *connectivities* of *link 1* and *link 2* are compared. If *link 1* and *link 2* are both *connected* or *disconnected* at the same time, it is considered that there is “no *connectivity* change”. If, otherwise, they are different, then there is a “*connectivity* change”.

Fig. 5.4: Node j travels a small distance z to a new position labelled as j' . As a result, the length of the link with node i changes from r_{ij} to r'_{ij} .

change". Let us define P_{ij} as the pairwise probability of "no *connectivity* change" due to the movement z :

$$\begin{aligned}
 & P_{ij}(z, r_{ij}, \theta) \\
 &= \Pr[\text{disconnected before movement} \cap \text{disconnected after movement}] \\
 &\quad + \Pr[\text{connected before movement} \cap \text{connected after movement}] \\
 &= \Pr[\text{link 1 disconnected} \cap \text{link 2 disconnected}] \\
 &\quad + \Pr[\text{link 1 connected} \cap \text{link 2 connected}]. \\
 &= \Pr \left[\{P_r(r_{ij}) \leq P_{th}\} \cap \{P_r(r'_{ij}) \leq P_{th}\} \right] \\
 &\quad + \Pr \left[\{P_r(r_{ij}) \geq P_{th}\} \cap \{P_r(r'_{ij}) \geq P_{th}\} \right]. \tag{5.5}
 \end{aligned}$$

Associated with *link 1* and *link 2*, there are shadowing fading losses s_1 and s_2 respectively. As discussed in Section 5.2, s_1 and s_2 are correlated when *link 1* and *link 2* are in close proximity. Since z is expected to be small compared to r_{ij} or r'_{ij} , the Gudmundson's model [161] is adopted here. The correlation function of s_1 and s_2 is therefore

$$\rho(z) = \exp \left(-\frac{z}{d_{cor}} \ln 2 \right) \tag{5.6}$$

where d_{cor} is the decorrelation distance at which correlation drops to 0.5. Expressing it as a joint distribution function, one can use a bivariate normal distribution to model

s_1 and s_2 , and the PDF is

$$f(s_1, s_2) = \frac{1}{2\pi\sigma_s^2\sqrt{1-\rho^2}} \exp\left(-\frac{s_1^2 + s_2^2 - 2\rho s_1 s_2}{2\sigma_s^2(1-\rho^2)}\right). \quad (5.7)$$

With (5.7), (5.5) can be rewritten as

$$\begin{aligned} & P_{ij}(z, r_{ij}, \theta) \\ &= \Pr\left(\left\{s_1 \leq \frac{P_{th} - \overline{P}_r(r_{ij})}{\sigma_s}\right\} \cap \left\{s_2 \leq \frac{P_{th} - \overline{P}_r(r'_{ij})}{\sigma_s}\right\}\right) \\ &+ \Pr\left(\left\{s_1 \geq \frac{P_{th} - \overline{P}_r(r_{ij})}{\sigma_s}\right\} \cap \left\{s_2 \geq \frac{P_{th} - \overline{P}_r(r'_{ij})}{\sigma_s}\right\}\right) \\ &= 1 - \Pr\left(s_1 \leq \frac{P_{th} - \overline{P}_r(r_{ij})}{\sigma_s}\right) - \Pr\left(s_2 \leq \frac{P_{th} - \overline{P}_r(r'_{ij})}{\sigma_s}\right) \\ &+ 2 \Pr\left(\left\{s_1 \leq \frac{P_{th} - \overline{P}_r(r_{ij})}{\sigma_s}\right\} \cap \left\{s_2 \leq \frac{P_{th} - \overline{P}_r(r'_{ij})}{\sigma_s}\right\}\right). \end{aligned} \quad (5.8)$$

Similar to the previous chapter, the wireless sensor nodes are assumed to be randomly distributed. Hence, one can compute the expected value of probability of “no *connectivity* change” due to a small movement of node i by integrating $P_{ij}(z, r_{ij}, \theta)$ over r_{ij} and θ . This gives

$$\begin{aligned} P_i(z) &= \mathbb{E}[P_{ij}(z, r_{ij}, \theta)] \\ &= \lim_{R \rightarrow \infty} \int_0^{2\pi} \int_0^R P_{ij}(z, r_{ij}, \theta) f(r_{ij}) f(\theta) dr_{ij} d\theta, \end{aligned} \quad (5.9)$$

where $f(r_{ij}) = 2r_{ij}/R^2$ and $f(\theta) = 1/2\pi$.

5.3.3 Network-wide Connectivity due to a Small Movement

Based on the result in the previous section, the impact of the small movement to the whole network is investigated. Within a circular region of radius R around node i , the number of nodes (including node i), k , is known to follow a Poisson distribution

with a rate

$$\Lambda = \lambda \pi R^2 \quad (5.10)$$

where λ is the average node density. The PDF of k is therefore

$$\Pr(k; \Lambda) = \frac{e^{-\Lambda} \Lambda^k}{k!}. \quad (5.11)$$

By assuming the links between node i and the other $k - 1$ nodes (for $k \geq 2$) are independent, the network-wide probability of “no *connectivity* change” w.r.t node i is

$$P_i(k, z) = \prod_{j=1}^{k-1} P_{ij}(z, r_{ij}, \theta). \quad (5.12)$$

The expected value of (5.12) can be expressed in terms of (5.9), i.e.

$$\begin{aligned} \mathbb{E}[P_i(k, z)] &= \prod_{j=1}^{k-1} \mathbb{E}[P_{ij}(z, r_{ij}, \theta)] \\ &= [P_i(z)]^{k-1}. \end{aligned} \quad (5.13)$$

Note that when $k = 0$ or 1 , the *connectivity* information remains the same. Hence,

$$P_i(k, z) = \begin{cases} 1 & \text{if } k = 0, 1, \\ [P_i(z)]^{k-1} & \text{if } k \geq 2. \end{cases} \quad (5.14)$$

As a result, the network-wide probability of “no *connectivity* change” for a random node in the network is

$$\begin{aligned} P(z) &= \sum_{k=0}^{\infty} P_i(k, z) \Pr(k; \Lambda) \\ &= e^{-\Lambda} + e^{-\Lambda} \Lambda + \sum_{k=2}^{\infty} [P_i(z)]^{k-1} \frac{e^{-\Lambda} \Lambda^k}{k!} \\ &= \frac{e^{\Lambda(P_i(z)-1)}}{P_i(z)} - \frac{e^{-\Lambda}}{P_i(z)} + e^{-\Lambda}. \end{aligned} \quad (5.15)$$

If $R \rightarrow \infty$, then $\Lambda \rightarrow \infty$, $e^{-\Lambda} \rightarrow 0$ and $P_i(z) \rightarrow 1$. Thus (5.15) becomes

$$P(z) \approx \exp \{ \Lambda [P_i(z) - 1] \}. \quad (5.16)$$

5.3.4 Theoretical Resolution

Now consider a RV, Z , representing the distance that node i can move without changing the *connectivity* of the network. The distribution function $F(z)$ that $Z \leq z$ is defined as

$$F(z) = \Pr(Z \leq z) = 1 - P(z). \quad (5.17)$$

The resolution for the class of range-free localization algorithms is therefore the expected value of Z , which is given by

$$\mathbb{E}[Z] = \int_0^\infty z \dot{F}(z) dz. \quad (5.18)$$

5.4 Relation to Circular Coverage Model

The authors in [33, 109] present their derivations of the theoretical resolution based on the circular coverage model. In contrast, the use of the log-normal shadowing model has led to a more general result as presented in (5.16). Obviously the circular coverage model is a special case of the log-normal model. By assuming $\sigma_s \approx 0$ and $d_{cor} = 0$ (essentially this implies s_1 and s_2 are i.i.d.), the proposed model is equivalent to the circular coverage model with a transmission range of R_o (which is defined as the *nominal range* in Section 4.3.1). As such, (5.5) can be simplified into

$$\begin{aligned} P_{ij}(z, r_{ij}, \theta) &= \Pr [P_r(r_{ij}) \leq P_{th}] \Pr [P_r(r'_{ij}) \leq P_{th}] \\ &\quad + \Pr [P_r(r_{ij}) \geq P_{th}] \Pr [P_r(r'_{ij}) \geq P_{th}] \\ &= \frac{1}{2} \left[\operatorname{erf} \left(\frac{P_{th} - \bar{P}_r(r_{ij})}{\sigma \sqrt{2}} \right) \operatorname{erf} \left(\frac{P_{th} - \bar{P}_r(r'_{ij})}{\sigma \sqrt{2}} \right) + 1 \right]. \end{aligned} \quad (5.19)$$

Geometrically, when the movement z of node j crosses the circle of radius R_o around node i , there is a *connectivity* change. Consider the two cases illustrated in Fig. 5.5. Node j enters the circle around node i if $R_o < r_{ij} < R_o + z \cos \theta$ and $0 < \theta < \frac{\pi}{2}$ or $\frac{3\pi}{2} < \theta < 2\pi$. Similarly, node j leaves the circle around node i if $R_o + z \cos \theta < r_{ij} < R_o$ and $\frac{\pi}{2} < \theta < \frac{3\pi}{2}$. In these two cases, $\text{erf}\left(\frac{P_{th} - \bar{P}_r(r_{ij})}{\sigma\sqrt{2}}\right)$ and

Fig. 5.5: (a) Node j enters the circle around node i . (b) Node j leaves the circle around node i .

$\text{erf}\left(\frac{P_{th} - \bar{P}_r(r'_{ij})}{\sigma\sqrt{2}}\right)$ have opposite signs, and their product is equal to -1^1 . Therefore, $P_{ij}(z, r_{ij}, \theta) = 0$. In other cases where node j does not cross the circle around node i , there is no *connectivity* change and hence $P_{ij}(z, r_{ij}, \theta) = 1$.

Using (5.19), (5.9) becomes

$$\begin{aligned}
 P_i(z) = & \lim_{R \rightarrow \infty} \int_0^{2\pi} \int_0^R f(r_{ij}) f(\theta) dr_{ij} d\theta \\
 & - \int_0^{\frac{\pi}{2}} \int_{R_o}^{R_o + z \cos \theta} f(r_{ij}) f(\theta) dr_{ij} d\theta \\
 & - \int_{\frac{\pi}{2}}^{\frac{3\pi}{2}} \int_{R_o + z \cos \theta}^{R_o} f(r_{ij}) f(\theta) dr_{ij} d\theta \\
 & - \int_{\frac{3\pi}{2}}^{2\pi} \int_{R_o}^{R_o + z \cos \theta} f(r_{ij}) f(\theta) dr_{ij} d\theta
 \end{aligned}$$

¹When $\sigma_s \approx 0$, $\text{erf}(\infty) = 1$ and $\text{erf}(-\infty) = -1$

$$\begin{aligned}
&= \lim_{R \rightarrow \infty} 1 - 2 \left(\frac{2R_o z + z^2 \pi / 4}{2\pi R^2} \right) - \left(\frac{4R_o z - z^2 \pi / 2}{2\pi R^2} \right) \\
&= \lim_{R \rightarrow \infty} 1 - \frac{4R_o z}{\pi R^2}.
\end{aligned} \tag{5.20}$$

Substituting (5.20) into (5.16), it yields

$$\begin{aligned}
P(z) &= \lim_{R \rightarrow \infty} \exp \left[\lambda \pi R^2 \left(-\frac{4R_o z}{\pi R^2} \right) \right] \\
&= \exp(-4\lambda R_o z)
\end{aligned} \tag{5.21}$$

which is equivalent to the result in [33].²

5.5 Numerical Results and Simulations

In this section, the proposed theoretical bound for the class of range-free localization algorithms as described in Section 5.3 is evaluated. Two realistic scenarios based on empirical studies are considered. Extensive simulations are conducted to validate the model.

Table 5.1 lists the values of the parameters used across all analyses and simulations. d_o is the close-in reference distance (e.g. 1 m). R_o and P_{th} are set according to typical

Table 5.1: Parameter values used in simulations

Parameters	Values
d_o	1 m
R_o	30 m
P_{th}	−90 dBm
d_{cor}	10 m

IEEE 802.15.4 transceivers without loss of generality. d_{cor} assumes a value in line with the reference data [161, 164, 166]. With regard to the log-normal radio model,

²In [33], the probability of a change in the *connectivity* information effected by a movement z by a node is $1 - e^{-4\rho r z}$, where ρ is the node density and r is the communication range.

two sets of parameter values are extracted from the literature.

Scenario 1: Measurements taken in an office environment show that $n = 2.3$ and $\sigma_s = 3.92$ [154].

Scenario 2: Measurements taken inside a room show that $n = 1.64$ and $\sigma_s = 6.82$ [167].

5.5.1 Optimal value of R

A key component to the computation of the theoretical bound $P(z)$ in (5.16) is $P_i(z)$ in (5.9). The lack of closed-form solution for $P_i(z)$ in general calls for numerical integration. However, $P_i(z)$ is an improper integral as $R \rightarrow \infty$. Therefore, some finite value for R is required. Intuitively, a larger R yields a more accurate result, but it also incurs more computational efforts. Thus, for practical purpose, a suitable value for R has to be selected carefully.

In the following experiments, different values of R are used, and their effects on $P(z)$ are evaluated. The first result is obtained when $R = R_o$. Then, $R = 2R_o$ for Scenario 1 and $R = 10R_o$ for Scenario 2 are shown. Following the definition in Section 4.3.1, *effective range* is denoted by R_e in this chapter, i.e.

$$R_e = R_o 10^{0.4\sigma_s/n}. \quad (5.22)$$

Note that a slightly different notation is used in order to distinguish it from the limit of integration R in (5.9). Further tests are conducted with $R = R_e$, $3R_e$ and $5R_e$.

First Scenario

In the first scenario, λ assumes four values, namely 0.0001 m^{-2} , 0.0005 m^{-2} , 0.001 m^{-2} and 0.005 m^{-2} . The effect of R is presented in Fig. 5.6–5.9.

Fig. 5.6: (Scenario 1) Effect of R on $P(z)$ when $\lambda = 0.0001 \text{ m}^{-2}$.

Fig. 5.7: (Scenario 1) Effect of R on $P(z)$ when $\lambda = 0.0005 \text{ m}^{-2}$.

Fig. 5.8: (Scenario 1) Effect of R on $P(z)$ when $\lambda = 0.001 \text{ m}^{-2}$.

Fig. 5.9: (Scenario 1) Effect of R on $P(z)$ when $\lambda = 0.005 \text{ m}^{-2}$.

Second Scenario

In the second scenario, the four values of λ used are 0.0001 m^{-2} , 0.0005 m^{-2} , 0.001 m^{-2} and 0.002 m^{-2} . The effect of R is presented in Fig. 5.10–5.13.

Fig. 5.10: (Scenario 2) Effect of R on $P(z)$ when $\lambda = 0.0001 \text{ m}^{-2}$.

Fig. 5.11: (Scenario 2) Effect of R on $P(z)$ when $\lambda = 0.0005 \text{ m}^{-2}$.

Fig. 5.12: (Scenario 2) Effect of R on $P(z)$ when $\lambda = 0.001 \text{ m}^{-2}$.

Fig. 5.13: (Scenario 2) Effect of R on $P(z)$ when $\lambda = 0.002 \text{ m}^{-2}$.

Remarks

In both scenarios, the results indicate a general downward trend of $P(z)$ as R increases. As illustrated, when $R = R_o$, the resulting $P(z)$ is significantly higher than the rest. When R increases to $2R_o$ in Scenario 1 or $10R_o$ in Scenario 2, $P(z)$ drops significantly. Nodes within these ranges are those most likely effect a change in the *connectivity*. Hence, the inclusion of them pull the $P(z)$ low significantly.

$P(z)$ continues to drop as R grows, but convergence is evident in the experiments. For instance, in Fig. 5.6 and 5.7, $R = 3R_e$ and $R = 5R_e$ yield almost the same value for $P(z)$, while the simulation effort for the latter is nearly threefold as that for the former. Another observation is that higher sensor node density seems to encourage more rapid convergence. As shown in Fig. 5.8 and 5.9, $R = R_e$ overlaps with $R = 3R_e$ and $R = 5R_e$. As for Scenario 2, convergence is more prominent once R reaches R_e as shown in Fig. 5.10–5.13. Further increase in R has no significant effect on $P(z)$. The reason for faster convergence can be attributed to the larger σ_s (6.82 dB in Scenario 2 compared to 3.92 dB in Scenario 1) and the smaller n (1.64 in Scenario 2 compared to 2.3 in Scenario 1), which result in R_e being much larger.

The results support that a larger R is generally desirable, but the gain becomes insignificant after a certain point. This optimal value of R depends on the system parameters. From the experiments, $R = 3R_e$ is selected for the computation of $P(z)$.

5.5.2 Theoretical Bound

Simulations are conducted for the two scenarios in MATLAB to validate the analytical model described in Section 5.3. For each simulation run, nodes are randomly deployed in a $2000\text{ m} \times 2000\text{ m}$ and $5000\text{ m} \times 5000\text{ m}$ square area according to the node density, λ , for the first and second scenario respectively. Assuming a node is initially deployed at the center of the square, it is allowed to travel a small distance z in a random direction. *Connectivity* information before and after the movement are then compared.

In the following results, each data point is the average of 100 000 simulation runs.

First Scenario

For the first scenario, λ assumes four values, namely 0.0001 m^{-2} , 0.0005 m^{-2} , 0.001 m^{-2} and 0.005 m^{-2} . Results from the proposed model and simulation are plotted in the Fig. 5.14. Simulation results agree with the theoretical values over a wide range of z .

Fig. 5.14: (Scenario 1) Overall network-wide probability of “no *connectivity* change” due to small movement z with different sensor node densities λ .

Second Scenario

For the second scenario, the four values of λ used are 0.0001 m^{-2} , 0.0005 m^{-2} , 0.001 m^{-2} and 0.002 m^{-2} . Results from the proposed model and simulation are compared in Fig. 5.15. Again, the two graphs are in accord with each other for the range of z being tested.

Fig. 5.15: (Scenario 2) Overall network-wide probability of “no *connectivity* change” due to small movement z with different sensor node densities λ .

Remarks

Simulation results confirm the derivation based on the log-normal radio model. As expected, increasing the node density, λ , results in a drop in $P(z)$. This in turn implies a smaller theoretical resolution. For instance, in Scenario 1, it is nearly impossible to retain the same *connectivity* information with a movement of 2 m when $\lambda = 0.005 \text{ m}^{-2}$, whereas the chance of not detecting a change is as high as 0.88 when $\lambda = 0.0001 \text{ m}^{-2}$.

Moreover, a high level of shadow fading, σ_s , reduces the bound significantly. For the same $P(z)$ and λ , z can be several orders of magnitude smaller in Scenario 2 than in Scenario 1. This is because, as σ_s gets larger, the randomness in shadow fading dominates, and it becomes more difficult to maintain the same *connectivity* information for any $z > 0 \text{ m}$. As a case in point, when $\lambda = 0.0001 \text{ m}^{-2}$, $z = 6 \text{ m}$ yields a $P(z) = 0.8$ for Scenario 1, whereas for Scenario 2, $z \approx 0.06 \text{ m}$ is enough to obtain the same $P(z)$ for the same node density.

5.5.3 Special Case: Circular Coverage Model

In order to confirm the proof in Section 5.4, the model in (5.15) is numerically evaluated, and simulations are conducted with a careful choice of parameters.

Let us assume $d_{cor} = 0.01$ m and $\sigma_s = 0.01$ dB which give a scenario approximating a circular coverage model. As σ_s approaches 0 dB, however, singularity starts to appear at $z = 0$ m in (5.9), and it causes accuracy problem for standard numerical integration function routines, e.g. `dblquad.m` in MATLAB calls `quad1.m`, which implements a recursive adaptive Lobatto quadrature. As a result, a new function routine based on the Monte Carlo integration method is implemented.

Simulation results and Nagpal's result from [33] are plotted in Fig. 5.16. It is clear that they line up perfectly for every z evaluated. In addition, numerical results from the new integration function routine are also presented. Three different numbers of samples N are used. The magenta and blue dash lines are results when $N = 10^5$ and $N = 10^6$ respectively. The green dash lines with square markers represents the case for $N = 10^7$. As shown, the oscillations subside and the plots converge to Nagpal's result and the simulation result as N increases. One would expect even better results if N increases further or a more sophisticated integration algorithm is available. Nevertheless, the results are sufficient to confirm the claim that the proposed model can generalize the circular coverage model.

5.6 Concluding Remarks

In this chapter, the fundamental limit of *accuracy* and the theoretical bounds for the class of range-free localization algorithms for WSN are investigated. This class of algorithms is important because it holds a clear advantage of being lean in the hardware requirement over the others. Based on *connectivity* information only, a range-free localization algorithm is able to provide a location estimate. The theoretical bound is established from a geometric point of view. Consider when a node travels a

Fig. 5.16: $P(z)$ computed with Monte Carlo method for the approximated circular coverage model. Convergence is evident as N increases. In this test, $n = 1.64$, $\lambda = 0.001 \text{ m}^{-2}$.

small distance without breaking or establishing any link. As there is no change in the *connectivity* information, a range-free localization algorithm is not able to distinguish the new location from the old and gives the same location estimate for both cases. This small movement of the node then defines the theoretical resolution for *all* range-free localization algorithms.

Based on the log-normal radio model and by taking into account of correlation of shadow fading, the probability of maintaining the same *connectivity* for a pair of nodes is established. The result is then extended to cover a network of nodes. Extensive simulations are presented to validate the derivations. Two scenarios, extracted from published empirical studies, are considered. In addition, mathematical proof and numerical results are shown here to confirm that the proposed scheme is more general and is able to generalize a previous work that is based on the more restrictive circular coverage model.

The proposed scheme allows one to compute efficiently the resolution for the class

of range-free localization algorithms without relying on expensive simulations. In addition, the performance of range-free localization algorithms (e.g. [150]) can be evaluated by comparing the error distribution with the results presented in this chapter.

Chapter 6

Conclusions and Future Works

6.1 Conclusions

Statistics have shown that, on a global scale, the buildings sector is taking up most of the energy consumption and people tend to spend most of their time indoors, it is therefore imperative that smart buildings are able to deliver useful building services efficiently, and at the same time, make sure that the occupants are productive by ensuring their visual comfort, thermal comfort, etc. By closely monitoring every internal conditions of the building, the BAS is able to intelligently manage and control various subsystems so as to achieve energy saving without compromising the comfort of the occupants. The core of real-time monitoring is the ubiquitous sensing capability facilitated by large scale deployment of sensors in buildings. Enabled by the recent development of WSN and IoT technologies, widespread wireless connectivity between these sensors and other devices is becoming a reality.

While lighting plays an essential role in the operation of smart buildings, it also takes up a significant portion of the total electricity consumption. Different measures have been adopted to reduce the energy usage. A design of daylight-responsive lighting and shading control system is proposed in Chapter 3. By utilizing daylight intelligently, the energy consumed by electric lighting can be reduced, while at the

same time ensuring sufficient illumination and preventing glare. The proposed model leads to a mixed integer linear programming formulation, which can readily be solved. Furthermore, a survey of available technologies for illuminance measurement is conducted. As a result, high accuracy analog illuminance sensors are integrated with the ZigBee-based platform. The improved wireless sensing platform is subsequently assessed in a life-sized test bed, where a daylight emulator is used to emulate different test scenarios. Compared against a professional grade lux meter, the results show that the new wireless sensing platform is able to automatically and continuously measure the illuminance level with a deviation within 3.3%.

Envisaging large scale deployment of WSNs in buildings, the Discrete Weighted Centroid Localization algorithm (dWCL) is proposed in Chapter 4 as a WSN-based IPS. Leveraging the underlying WSN infrastructure, dWCL can provide the positioning service in buildings. Comparing with the original Weighted Centroid Localization algorithm [32] and its subsequent variants, one can claim that dWCL is superior for two reasons. First, it is more compliant with the current state of digital electronics. The weighting function is discrete in nature, rendering it suitable for the RSS values available in any typical transceivers. Moreover, by decoupling the definition of weight from range, dWCL is more capable of accommodating different performance requirements due to its flexibility. The analytical framework to characterize the performance of dWCL in terms of *accuracy* and *precision* is presented alongside with the closed-form expressions for the distributions of localization errors. The effect of several system parameters and their implications are also demonstrated via simulations. Furthermore, two optimization approaches are introduced in order to further elevate the performance of dWCL. Finally, a simple rule is established to compute the optimal weighting factor when the RSS level boundaries are known.

Continuing the discussion on the importance of *accuracy* and *precision* for localization algorithms, the fundamental limit of *accuracy* is investigated in Chapter 5. In particular, the theoretical bound for the class of range-free localization algorithms for

WSN is established. From a geometric perspective, a range-free localization algorithm is oblivious of any node movement as long as there is no change in the *connectivity* information, i.e. not breaking or establishing any link. The distance of the movement then defines the theoretical resolution of *all* range-free localization algorithms. Starting from a pair of nodes and then extending to the whole network, the mathematical model for the probability of “no *connectivity* change” due to the small node movement is established. The analysis is conducted based on a log-normal radio model and it also takes into account the correlation of shadow fading. The proposed model is validated with the simulations of two test scenarios. Moreover, mathematical proof and numerical results are presented to show that the proposed scheme is able to generalize a highly-cited work [33], which is derived based on the more restrictive circular coverage model.

6.2 Future Works

This thesis focuses on two important services, namely the lighting and the IPS, in smart buildings. The investigation and development presented in this work contribute to the larger goal of energy management optimization in smart buildings. There are still some unanswered questions and a few related research directions worth pursuing:

- (i) *Heterogeneous network*: In Chapters 4 and 5, it is assumed that all transceivers are identical and operate in the same way. In reality, there may exist some variations in the hardware design, perhaps due to different manufacturing techniques. Alternatively, there may be some protocols allowing the coexistence of multi-class devices, which therefore have different specifications in the same network. In either case, the modelling and the analytical framework will need a substantial overhaul, and it will lead to a more interesting conclusion.

- (ii) *Indoor correlated shadow fading model*: The correlation model adopted in Chap-

ter 5 is more oriented towards mobile radio systems. As pointed out in [168], correlation exhibits some form of periodic pattern, probably due to the indoor structures, such as windows, doors, tables and especially parallel walls along corridors. Recently there are new correlation models developed specifically for indoor environment, e.g. [169]. Combining the new correlation model and the proposed framework may yield results more applicable for indoor scenarios.

- (iii) *Cross-correlation:* The model for theoretical resolution proposed in Chapter 5 assumes that the cross-correlation between different pairs of sensor nodes is relatively insignificant, when compared with the autocorrelation between the same pair of nodes. However, this assumption may be too strong in some cases. Hence, it would be interesting to see an extension of the model by including the effect of cross-correlation.
- (iv) *Alternate propagation models and experimental validation:* The analysis of dWCL in Chapter 4 assumes a fairly idealized propagation model that may not be able to handle sophisticated effects such as multipath reflections. Hence alternative models such as stochastic channel models can be considered. Furthermore, an implementation of dWCL in a real WSN would provide a significant validation of the proposed scheme.
- (v) *Dealing with solar heat gain:* In Chapter 3, daylighting is adopted in order to supplement the indoor lighting system. While daylight can certainly reduce energy consumption due to lighting, it also causes solar heat gain. This, in turn, may heat up the indoor space and increase the cooling load for the HVAC system. Thus, a holistic approach, which considers both the lighting and heating domains simultaneously, is required when designing a better control system.
- (vi) *Synergy of IPS and lighting:* Once the intelligent lighting system discussed in Chapter 3 and the IPS in Chapter 4 are fully implemented and integrated into

the BAS in smart buildings, they can complement each other in increasing the energy efficiency and occupant satisfaction in buildings. For instance, when an occupant leaves one point for another, the IPS informs the lighting system, which automatically turns off the lights at the prior point and adjusts the lighting at the new point according to the occupant's personal preference.

Appendix A

Derivations for dWCL

A.1 Distribution of Sensor Node Coordinates

This section shows the detailed derivation of the statistical properties, namely the mean and variance, of the the x-coordinates of the sensor nodes of the WSN as described in Section 4.3.2. Those of y-coordinates are omitted as they are independent and identical to the x-coordinates.

A.1.1 Mean $\mathbb{E}[X_i]$

First, we expand the integral

$$\begin{aligned}
 & \iint_{\mathcal{D}} x \Pr[P_r(r) \geq \gamma_i] dA \\
 &= \int_0^{2\pi} \int_0^R r \cos \theta \Pr[P_r(r) \geq \gamma_i] r dr d\theta \\
 &= \int_0^{2\pi} \cos \theta \int_0^R r^2 \Pr[P_r(r) \geq \gamma_i] dr d\theta
 \end{aligned} \tag{A.1}$$

Since the inner integral of (A.1) is independent of θ and the outer integral inte-

grates $\cos \theta$ from 0 to 2π , (A.1) reduces to 0. Similarly,

$$\iint_{\mathcal{D}} x \Pr [\gamma_{i+1} \geq P_r(r)] dA = 0$$

Therefore the mean

$$\begin{aligned} \mathbb{E} [X_i] &= \frac{1}{\mathcal{A}_i} \iint_{\mathcal{D}} x \Pr [\gamma_{i+1} \geq P_r(r) \geq \gamma_i] dA \\ &= \frac{1}{\mathcal{A}_i} \iint_{\mathcal{D}} x \{ \Pr [P_r(r) \geq \gamma_i] - \Pr [P_r(r) \geq \gamma_{i+1}] \} dA \\ &= 0. \end{aligned}$$

A.1.2 Variance $\text{Var} [X_i]$

Let us first consider the following integral

$$\begin{aligned} & \iint_{\mathcal{D}} x^2 \Pr [P_r(r) \geq \gamma_i] dA \\ &= \int_0^{2\pi} \int_0^R r^2 \cos^2 \theta \Pr [P_r(r) \geq \gamma_i] r dr d\theta \\ &= \int_0^{2\pi} \cos^2 \theta \int_0^R r^3 \Pr [P_r(r) \geq \gamma_i] dr d\theta. \end{aligned} \tag{A.2}$$

From [152], one knows that

$$\Pr [P_r(r) \geq \gamma_i] = \frac{1}{2} - \frac{1}{2} \text{erf}(a_i + b \ln \frac{r}{R}) \tag{A.3}$$

where

$$a_i = (\gamma_i - P_r(R)) / \sqrt{2} \sigma_s$$

$$b = 10n \log_{10} e / \sqrt{2} \sigma_s.$$

Using (A.3), the inner integral of (A.2) now becomes

$$\begin{aligned} \int_0^R r^3 \Pr[P_r(r) \geq \gamma_i] dr &= \int_0^R \frac{r^3}{2} dr - \int_0^R \frac{r^3}{2} \operatorname{erf}(a_i + b \ln \frac{r}{R}) dr \\ &= \frac{R^4}{8} - \int_0^R \frac{r^3}{2} \operatorname{erf}(a_i + b \ln \frac{r}{R}) dr. \end{aligned} \quad (\text{A.4})$$

Let $t = a_i + b \ln \frac{r}{R}$, then $t = a_i$ when $r = R$, and $t \rightarrow -\infty$ when $r \rightarrow 0^+$. The integral term of (A.4) expands into

$$\begin{aligned} \int_0^R \frac{r^3}{2} \operatorname{erf}(a_i + b \ln \frac{r}{R}) dr &= \int_0^R \frac{r^3}{2} \operatorname{erf}(t) dr \\ &= \frac{r^4}{8} \operatorname{erf}(t) \Big|_{r=0}^{r=R} - \int_{r=0}^{r=R} \frac{r^4}{8} d \operatorname{erf}(t) \\ &= \frac{R^4}{8} \operatorname{erf}(a_i) - \int_{-\infty}^{a_i} \frac{2r^4}{8\sqrt{\pi}} e^{-t^2} dt. \end{aligned} \quad (\text{A.5})$$

Since $r = R \exp(\frac{t-a_i}{b})$, the integral term in (A.5) can be rewritten as

$$\begin{aligned} \int_{-\infty}^{a_i} \frac{2r^4}{8\sqrt{\pi}} e^{-t^2} dt &= \int_{-\infty}^{a_i} \frac{R^4}{4\sqrt{\pi}} \exp\left(\frac{4t-4a_i}{b}\right) e^{-t^2} dt \\ &= \frac{R^4}{4\sqrt{\pi}} \int_{-\infty}^{a_i} \exp\left\{-\left[t^2 + 2\left(-\frac{2}{b}\right)t + \frac{4a_i}{b}\right]\right\} dt \\ &= \frac{R^4}{4\sqrt{\pi}} \left(\frac{\sqrt{\pi}}{2}\right) \exp\left(\frac{4}{b^2} - \frac{4a_i}{b}\right) \operatorname{erf}\left(t - \frac{2}{b}\right) \Big|_{-\infty}^{a_i} \\ &= \frac{R^4}{8} \exp\left(\frac{4-4a_i b}{b^2}\right) \left[\operatorname{erf}\left(a_i - \frac{2}{b}\right) - \operatorname{erf}(-\infty)\right] \\ &= \frac{R^4}{8} \exp\left(\frac{4-4a_i b}{b^2}\right) \left[1 - \operatorname{erf}\left(\frac{2-a_i b}{b}\right)\right]. \end{aligned} \quad (\text{A.6})$$

Substituting (A.4), (A.5) and (A.6) into (A.2),

$$\begin{aligned} &\iint_{\mathcal{D}} x^2 \Pr[P_r(r) \geq \gamma_i] dA \\ &= \frac{R^4}{8} \left\{ 1 - \operatorname{erf}(a_i) + \exp\left(\frac{4-4a_i b}{b^2}\right) \left[1 - \operatorname{erf}\left(\frac{2-a_i b}{b}\right)\right] \right\} \int_0^{2\pi} \cos^2 \theta d\theta \\ &= \frac{R^4}{8} \left\{ 1 - \operatorname{erf}(a_i) + \exp\left(\frac{4-4a_i b}{b^2}\right) \left[1 - \operatorname{erf}\left(\frac{2-a_i b}{b}\right)\right] \right\} \cdot \pi \end{aligned}$$

$$= \frac{\pi R^4}{8} \left\{ 1 - \operatorname{erf}(a_i) + \exp\left(\frac{4 - 4a_i b}{b^2}\right) \left[1 - \operatorname{erf}\left(\frac{2 - a_i b}{b}\right) \right] \right\}. \quad (\text{A.7})$$

The variance is therefore

$$\begin{aligned} & \operatorname{Var}[X_i] \\ &= \mathbb{E}[X_i^2] - (\mathbb{E}[X_i])^2 \\ &= \frac{1}{\mathcal{A}_i} \iint_{\mathcal{D}} x^2 \Pr[\gamma_{i+1} \geq P_r(r) \geq \gamma_i] dA - (0)^2 \\ &= \frac{1}{\pi R^2 (U_i - U_{i+1})} \iint_{\mathcal{D}} x^2 \left[\Pr[P_r(r) \geq \gamma_i] - \Pr[P_r(r) \geq \gamma_{i+1}] \right] dA \\ &= \frac{R^2}{8(U_i - U_{i+1})} \left\{ \left\{ 1 - \operatorname{erf}(a_i) + \exp\left(\frac{4 - 4a_i b}{b^2}\right) \left[1 - \operatorname{erf}\left(\frac{2 - a_i b}{b}\right) \right] \right\} \right. \\ & \quad \left. - \left\{ 1 - \operatorname{erf}(a_{i+1}) + \exp\left(\frac{4 - 4a_{i+1} b}{b^2}\right) \left[1 - \operatorname{erf}\left(\frac{2 - a_{i+1} b}{b}\right) \right] \right\} \right\} \\ &= \frac{R^2}{8(U_i - U_{i+1})} \left\{ \operatorname{erf}(a_{i+1}) - \operatorname{erf}(a_i) + \exp\left(\frac{4 - 4a_i b}{b^2}\right) \left[1 - \operatorname{erf}\left(\frac{2 - a_i b}{b}\right) \right] \right. \\ & \quad \left. - \exp\left(\frac{4 - 4a_{i+1} b}{b^2}\right) \left[1 - \operatorname{erf}\left(\frac{2 - a_{i+1} b}{b}\right) \right] \right\}. \quad (\text{A.8}) \end{aligned}$$

A.2 Approximations for Ratio Distribution

The formulation of dWCL in (4.14) leads to a ratio of two Gaussian RVs. Among a few available approximation methods to obtain the distribution of the said ratio, two are highlighted here.

For the ratio distribution of two independent Gaussian RVs, of which the numerator has a zero mean, a closed-form PDF and CDF can be found in [1]. Let $X_1 \sim \mathcal{N}(\bar{X}_1, \sigma_1^2)$ and $X_2 \sim \mathcal{N}(0, \sigma_2^2)$ be independent Gaussian RVs. The PDF and CDF of the ratio $X = X_2/X_1$ are:

PDF:

$$p_x(x) = \frac{\sigma_1 \sigma_2}{\pi(\sigma_1^2 x^2 + \sigma_2^2)} \exp\left(-\frac{\bar{X}_1^2}{2\sigma_1^2}\right) + \frac{\bar{X}_1 \sigma_2^2}{\sqrt{2\pi}(\sigma_1^2 x^2 + \sigma_2^2)^{3/2}} \times \exp\left(-\frac{\bar{X}_1^2 x^2}{2(\sigma_1^2 x^2 + \sigma_2^2)}\right) \left[1 - 2Q\left(\frac{\bar{X}_1 \sigma_2^2}{\sigma_1 \sigma_2(\sigma_1^2 x^2 + \sigma_2^2)^{1/2}}\right)\right] \quad (\text{A.9})$$

CDF:

$$P_x(x) = \begin{cases} \frac{1}{\pi} \tan^{-1}\left(\frac{\sigma_2}{\sigma_1 |x|}\right) - 2V\left(\frac{\bar{X}_1 |x|}{\sqrt{\sigma_1^2 x^2 + \sigma_2^2}}, \frac{\bar{X}_1(\sigma_2/\sigma_1)}{\sqrt{\sigma_1^2 x^2 + \sigma_2^2}}\right) & \text{if } x < 0 \\ 1 - \frac{1}{\pi} \tan^{-1}\left(\frac{\sigma_2}{\sigma_1 x}\right) + 2V\left(\frac{\bar{X}_1 x}{\sqrt{\sigma_1^2 x^2 + \sigma_2^2}}, \frac{\bar{X}_1(\sigma_2/\sigma_1)}{\sqrt{\sigma_1^2 x^2 + \sigma_2^2}}\right) & \text{if } x \geq 0 \end{cases} \quad (\text{A.10})$$

where

$$V(u, v) \triangleq \frac{1}{2\pi} \int_0^u \int_0^{vx/u} \exp\left(-\frac{x^2 + y^2}{2}\right) dy dx. \quad (\text{A.11})$$

The two functions are plotted in Fig. A.1a and Fig. A.1b.

However, one has to take note the range when using the CDF. In the example shown in Fig. A.1b, (A.10) is only valid for $x \in (-2, 2)$. Outside this range, its value goes either below 0 or above 1, where the CDF becomes invalid.

Alternatively, Hayya *et al.* propose a much simpler normal approximation to the ratio distribution in [153]. Moreover, the two Gaussian RVs are not required to be statistically independent. They show that for the ratio $W = Y/X$, where $X \sim \mathcal{N}(\mu_x, \sigma_x^2)$ and $Y \sim \mathcal{N}(\mu_y, \sigma_y^2)$,

$$\begin{aligned} \mathbb{E}[W] &\approx \mu_y/\mu_x + \sigma_x^2 \mu_y/\mu_x^3 - \rho \sigma_x \sigma_y/\mu_x^2, \\ \text{Var}[W] &\approx \sigma_x^2 \mu_y^2/\mu_x^4 + \sigma_y^2/\mu_x^2 - 2\rho \sigma_x \sigma_y \mu_y/\mu_x^3. \end{aligned} \quad (\text{A.12})$$

Further numerical evaluations are conducted to verify this approximation. The result shows that the proposed method is able to approximate the actual ratio distribution with little deviation.

(a)

(b)

Fig. A.1: PDF and CDF for ratio distribution approximation [1].

A.3 Proof of Positive-Definiteness of Hessian Matrix

The proof of positive-definiteness of the Hessian matrix introduced in Section 4.4.1 is presented here.

The Hessian matrix $\mathbf{H}[\boldsymbol{\sigma}^2]$, when $M = 2$, is a scalar and is equivalent to $\frac{\partial^2 \sigma^2}{\partial w_1^2}$. From (4.27), it can be shown that

$$\begin{aligned}\mathbf{H}[\boldsymbol{\sigma}^2] &= \frac{2\lambda_1(\sigma_1^2 + \sigma_\xi^2)(\sum_k w_k \lambda_k - w_1 \lambda_1)}{(\sum_m w_m \lambda_m)^3} \\ &= \frac{2w_2 \lambda_1 \lambda_2 (\sigma_1^2 + \sigma_\xi^2)}{(\sum_m w_m \lambda_m)^3} \\ &> 0.\end{aligned}$$

Therefore $\mathbf{H}[\boldsymbol{\sigma}^2]$ is positive-definite, and the $\mathbf{w}^*$ in (4.31) when $M = 2$ is a local minimum.

When $M = 3$, the Hessian matrix is

$$\mathbf{H}[\boldsymbol{\sigma}^2] = \begin{bmatrix} \frac{\partial^2 \sigma^2}{\partial w_1^2} & \frac{\partial^2 \sigma^2}{\partial w_1 \partial w_2} \\ \frac{\partial^2 \sigma^2}{\partial w_2 \partial w_1} & \frac{\partial^2 \sigma^2}{\partial w_2^2} \end{bmatrix}. \quad (\text{A.13})$$

Similar to the case of $M = 2$, it can be shown that $\frac{\partial^2 \sigma^2}{\partial w_1^2} > 0$. Moreover, rewriting (A.13) yields

$$\mathbf{H}[\boldsymbol{\sigma}^2] = \frac{2}{(\sum_m w_m \lambda_m)^3} \mathbf{H}' \quad (\text{A.14})$$

where

$$\begin{aligned}\mathbf{H}' &= \begin{bmatrix} \lambda_1 s_1 (\sum_k w_k \lambda_k) - \lambda_1^2 C & -\lambda_1 \lambda_2 C \\ -\lambda_1 \lambda_2 C & \lambda_2 s_2 (\sum_k w_k \lambda_k) - \lambda_2^2 C \end{bmatrix}, \\ C &= w_i (\sigma_i^2 + \sigma_\xi^2),\end{aligned}$$

$$s_i = \sigma_i^2 + \sigma_\xi^2.$$

Since

$$\begin{aligned}
 |\mathbf{H}'| &= \left[\lambda_1 s_1 \left(\sum_k w_k \lambda_k \right) - \lambda_1^2 C \right] \left[\lambda_2 s_2 \left(\sum_k w_k \lambda_k \right) - \lambda_2^2 C \right] - (-\lambda_1 \lambda_2 C)^2 \\
 &= \lambda_1 \lambda_2 s_1 s_2 \left(\sum_k w_k \lambda_k \right)^2 - \lambda_1 \lambda_2^2 s_1 C \left(\sum_k w_k \lambda_k \right) - \lambda_1^2 \lambda_2 s_2 C \left(\sum_k w_k \lambda_k \right) \\
 &\quad + \lambda_1^2 \lambda_2^2 C^2 - \lambda_1^2 \lambda_2^2 C^2 \\
 &= \lambda_1 \lambda_2 \left[s_1 s_2 \left(\sum_k w_k \lambda_k \right)^2 - \lambda_2 s_1 C \left(\sum_k w_k \lambda_k \right) - \lambda_1 s_2 C \left(\sum_k w_k \lambda_k \right) \right] \\
 &= \lambda_1 \lambda_2 \left(\sum_k w_k \lambda_k \right) \left[s_1 s_2 \left(\sum_k w_k \lambda_k \right) - \lambda_2 s_1 C - \lambda_1 s_2 C \right] \\
 &= \lambda_1 \lambda_2 \left(\sum_k w_k \lambda_k \right) \left[s_1 s_2 \left(\sum_k w_k \lambda_k \right) - \lambda_2 s_1 w_2 s_2 - \lambda_1 s_2 w_1 s_1 \right] \\
 &= \lambda_1 \lambda_2 s_1 s_2 \left(\sum_k w_k \lambda_k \right) \left(\sum_k w_k \lambda_k - w_2 \lambda_2 - w_1 \lambda_1 \right) \\
 &= \lambda_1 \lambda_2 s_1 s_2 w_3 \lambda_3 \left(\sum_k w_k \lambda_k \right) \\
 &> 0,
 \end{aligned} \tag{A.15}$$

$|\mathbf{H}[\boldsymbol{\sigma}^2]| > 0$. Therefore $\mathbf{H}[\boldsymbol{\sigma}^2]$ is also positive-definite, and the $\mathbf{w}^*$ in (4.31) for $M = 3$ is also a local minimum.

Appendix B

Correlation Models for Shadow Fading

Numerous research studies have demonstrated that shadow fading losses exhibit certain amount of correlation when two wireless links are in close proximity. In this appendix, a few well-known and relevant correlation models for shadow fading are highlighted. For a more comprehensive overview of the topic, interested readers are referred to a recent survey paper [170] by Szyszkowicz *et al.* and the references therein.

Since most of the literature focuses on mobile radio systems, the following scenario is used as an example for illustration. In Fig. B.1, two base stations (BS1 and BS2) are transmitting signals to two mobile radios (M1 and M2). Alternatively, one may also consider that M1 and M2 represent the two locations of the same mobile radio, which is travelling at a certain speed, at two different time instances. Following the log-normal radio model, the shadow fading for the four paths are represented by X_{11} , X_{12} , X_{21} and X_{22} . Furthermore, their values are correlated due to their proximity to each other.

Some insights into the general behaviors of correlation are apparent from the literature. Regarding a pair of links, the ratio of their lengths, the angle in between, and the distance between the end points of the two paths are important factors in

Fig. B.1: A four-path example to illustrate correlated shadow fading.

determining the correlation coefficient. In addition, it should be a non-increasing function of these three factors [171]. Although there is no one well-agreed model for the correlation prediction, two types of correlations are identified, namely the autocorrelation and the cross-correlation, in [163].

B.1 Autocorrelation

Autocorrelation, or serial correlation, applies to situations where two mobile radios are receiving signals from a single base station. Referring to Fig. B.1, X_{11} and X_{12} , or X_{21} and X_{22} , fall into this type, and the correlation is defined by

$$\rho_a(r_m) = \frac{E[X_{11}X_{12}]}{\sigma_1\sigma_2} \quad (\text{B.1})$$

where σ_1 and σ_2 are the location variabilities corresponding to the two paths. Typically, r_m is assumed to be sufficiently small when compared with the two path lengths. Hence one can assume σ_1 and σ_2 are approximately equal to the same value σ , and (B.1) can be simplified into

$$\rho_a(r_m) = \frac{E[X_{11}X_{12}]}{\sigma^2}. \quad (\text{B.2})$$

Based on an empirical study, a simple exponential model has been proposed by

Gudmundson in [161] for the autocorrelation function. In the example shown in Fig. B.1, the correlation between X_{11} and X_{12} is

$$R(r_m) = \exp\left(-\frac{r_m}{d_{cor}} \ln 2\right) \quad (\text{B.3})$$

where d_{cor} is the decorrelation distance at which correlation drops to 0.5. d_{cor} depends on the environment and can vary from several meters to scores of meters [161]. In [166], it is found to be about 20 m in an urban environment. Other works suggest values as high as hundreds of meters [162, 163].

The model is then modified by Giancristofaro so as to accommodate the continuous-time case [172]. In another study [162], Algans *et al.* is able to obtain empirical data in agreement with the Gudmundson's model in certain environments. They also suggest a double exponential decay function that better fit the data. Considering a direct path between two mobile radios, which are travelling in different directions or at different speeds, Wang *et al.* [166] extend (B.3) to a joint spatial correlation function.

B.2 Cross-correlation

On the other hand, cross-correlation, or site-to-site correlation, arises when the two ends of two joint paths are further apart. X_{11} and X_{21} , or X_{12} and X_{22} in Fig. B.1 are be good examples. The correlation is given by

$$\rho_c = \frac{E[X_{11}X_{21}]}{\sigma_1\sigma_2} \quad (\text{B.4})$$

Field measurements by Graziano [160] has demonstrated that the correlation of this type depends on the angle between the links. The ratio of the two path lengths is also shown to be a key variable. Based on these two factors, a simple piecewise function is proposed by Saunders and Aragón-Zavala in [163] to model the correlation. In another work by Graziosi and Santucci [173], a new model is proposed to capture the

essence of both autocorrelation and cross-correlation. Agrawal and Patwari [174] argue that the correlation models above assume the lengths of the links are large compared with r_m , and hence, they are only suitable for long range communications such as cellular networks. For short range multi-hop networks such as ad hoc, mesh and sensor networks, they present a non-site-specific statistical model with an underlying Gaussian spatial loss field to account for the correlations.

B.3 Feasibility of Correlation Models

Most of the above correlation models consider a pair of paths only. When these models are applied to several paths at the same time, the resulting correlation matrix may become mathematically invalid [170,174]. This poses a challenge for network simulation or mathematical analysis. Szyszkowicz *et al.* [170] survey a large body of literature on shadow fading correlation models and devise the feasibility, i.e. positive semidefiniteness, test for the models. Based on their criteria, they recommend one particular model derived from an existing work, and also suggest appropriate parameter values.

B.4 Impact of Correlated Shadow Fading

Correlated shadow fading has been applied in a number of research areas. A few published works that take into account of the correlation are presented here. Patwari and Agrawal in [175] show that the CRB for sensor localization decreases when link correlation is considered. Using the correlation model in [166], Yamamoto *et al.* study the impact of correlated shadowing on the coverage of multi-hop cellular systems [176]. With the correlation known, Alouini and Simon [177] study the SNR output of dual branch diversity receivers operating over correlated log-normal fading channels. In [178], correlated shadow fading is considered in the study of call dropping in cellular networks. Min *et al.* develop a secure cooperative sensing protocol for opportunistic

spectrum use in dynamic spectrum access networks by exploiting the shadow fading correlation [179]. Based on their recommended model in [170], Szyszkowicz *et al.* [171] propose an alternative simulation approach using shadowing fields, together with random sample reuse and extrapolation, in order to speed up the simulation for the total interference distribution.

Author's Publications

Journal Articles

- (i)* **Y. W. E. Chan** and B. H. Soong, "A new lower bound on range-free localization algorithms in wireless sensor networks," *IEEE Commun. Lett.*, vol. 15, no. 1, pp. 16–18, 2011.
- (ii) Q. D. La, **Y. W. E. Chan**, and B. H. Soong, "Power management of intelligent buildings facilitated by smart grid: A market approach," *IEEE Trans. Smart Grid*, vol. 7, no. 3, pp. 1389–1400, 2016.
- (iii)* **Y. W. E. Chan** and B. H. Soong, "Discrete weighted centroid localization (dWCL): Performance analysis and optimization," *IEEE Access*, vol. 4, pp. 6283–6294, 2016.

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- (x)* S. C. Chien, Y. L. Sum, **Y. W. E. Chan**, S. H. Chew, B. H. Soong, and K. J. Tseng, “An integrated cyber-physical model towards high-performance lighting systems operation,” in *Proc. CIE 2016*, 2016.
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