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**SCHOOL OF ELECTRONIC ENGINEERING**

**Characterization of Reflectors in a Wireless Channel to Aid Low-Power Indoor Localization**

**Project Portfolio**

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Supervised by C. Brennan

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Characterization of Reflectors in a Wireless Channel to Aid Low-Power Indoor Localization

Aidan Smyth

*Abstract*— Modern wireless communication systems for the Internet of Things (IoT) increasingly require both long battery life and accurate indoor localization. Bluetooth Low Energy is heavily adopted in emerging wireless sensor networks as it meets the energy constraints. However, reflectors present in an indoor wireless channel cause multipath fading at the receiver, reducing accuracy and increasing the required energy for accurate indoor localization. Characterizing reflectors in a wireless channel can greatly enhance the accuracy of such low-power indoor localization systems. This paper proposes a low-energy approach to characterizing the wireless channel using power delay profiles (PDPs) and several novel ray tracing techniques which are implemented to verify the PDPs and predict the location of a reflector in an indoor wireless channel.

The selected solution successfully generates low-energy PDPs for several indoor positions, which are processed using ray tracing scripts to identify and verify a suspected reflector in the indoor environment.

# INTRODUCTION

T

HE key research question investigated in this paper and subsequent literature review is the following:

*“Which wireless technology and propagation model can provide the best trade-off between high accuracy and low computational cost for the characterization of a reflector in a wireless channel?”*

Use of the Global Positioning System (GPS) complimented with cellular provides precise positioning information outdoors [1]. Despite its popularity and accuracy outdoors, GPS suffers strong attenuation when passing through walls and is not sufficiently accurate indoors [2] [3]. In [4] it was stated that GPS systems “are not perfect as they rely on faint radio signals that can be blocked or reflected by man-made structures”. Wireless technologies such as Wi-Fi, Bluetooth or ZigBee are all competing to be the default implemented solution for indoor localization applications.

One of the main challenges faced by wireless technology indoors is the presence of reflectors in the wireless channel. In both line-of-sight (LoS) and non-line-of-sight (NLoS) transmitter-receiver situations, a source of error is the reflection of signal caused by reflectors in the channel. These reflectors crate delayed multipath signals which can cause interference at the receiver. Characterizing the wireless channel and its reflectors enables integration of this normally troublesome multipath signal as useful data to enhance the accuracy of indoor localization systems.

A diverse set of modern indoor localization applications exist which require submeter accuracy in harsh propagation environments. These include security, presence detection, automotive, medical services, logistics, emergency services, smart home appliances and military systems [5]. IoT technology avails of wireless sensor networks (WSNs) that require a long battery life to reduce the frequency of costly maintenance. As a result, indoor localization systems should target low energy consumption.

In this research, Bluetooth Low Energy is chosen to perform frequency sweeps of the wireless channel at several indoor locations as it best satisfies the low-energy constraint. Note that NLoS scenarios are not in the scope of this investigation. The proposed solution uses the PDPs obtained from these frequency sweeps as inputs to two different 2D ray tracing models. The first ray tracing model takes the real-world PDPs obtained from frequency sweeps at several positions in a room and verifies that they match the expected PDPs generated during a ray tracing simulation for a known geometry and reflector. The second ray tracing model has no prior knowledge of the indoor geometry, and uses each real-world PDPs to generate a locus of possible reflectors in the wireless channel. The intersection of several PDP’s locus indicates the location of a suspected reflector in the room.

The literature review in Appendix A documents the technical background, existing research, project development and results. This paper is the centre-piece of the research portfolio, and presents a focused summary of the literature review. It describes the leading-edge research in the field, a technical description of the technology and theory applied to the problem, analysis of the investigation’s findings, and the author’s conclusions and proposals for future research.

# Existing Research

Different approaches outlined in this section have been implemented for wireless indoor localization, many achieving satisfactory accuracy. Since energy consumption is a constraint, recent research is focused on also implementing low-energy solutions [6].

## Estimation Techniques

There are several popular localization techniques for analyzing received signals. Received signal strength (RSS) models the path loss of the signal over distance transmitted. The primary disadvantage of RSS is that it performs poorly in indoor environments where other propagation phenomena distort the relationship between distance and received signal [5]. Angle of arrival (AoA) estimation determines the angle of incidence at which signals are received by antenna arrays. High resolution AoA solutions require large antenna arrays, therefore accurate AoA localization is energy inefficient and costly to implement. AoA is also limited by the fact that it requires strong LoS conditions [7] [8]. Another multiple antenna solution is time difference of arrival (TDoA), which pairs antennas and triangulates using the delay time each antenna experiences relative to a reference anchor [9]. Wi-Fi incorporates a similar approach, “Finite Time Measurement”, using the round-trip time to estimate the distance to the receiver [10].

Each estimation technique implemented in isolation fails to characterize multipath components or reflectors, an essential requirement for low-energy accurate sub-meter indoor localization.

## Wireless Technology

Numerous low-energy wireless technologies have shown promise in indoor localization applications [11]. BLE is the most popular IoT wireless technology due to its short range, small data rate and low power consumption. ZigBee and ultra-wideband (UWB) signals have made less of an impact in industry and research primarily due to the fact that both are more costly and less energy-efficient than BLE [12]. However, in applications where energy efficiency and cost are not hard constraints, UWB provides the best resolution and most accurate indoor localization solutions [8] [13].

Research in [12] investigates the low-energy performance of BLE in contrast to ZigBee. The study indicates that BLE is highly energy efficient in terms of number of bytes transferred per Joule, but could be improved by increasing the data rate per connection event and implementing adaptive frequency hopping to combat interference. Opportunistic listening [11] can leverage responses from other devices’ requests to allow sharing of the channel among scanning devices.

## Indoor Localization Techniques

Multipath can be detected using delay times and anchor receivers in a known room geometry in [14], assisting indoor localization by characterizing the wireless channel. Machine learning techniques can be applied to existing wireless communications structures, motivating the continued research in this area. Machine learning enhances indoor localization and characterizes multipath in a wireless channel in [1] [2]. Both of these experiments use BLE technology.

## Automotive Applications

The automotive industry relies on WSNs to provide real-time data on peripherals and essential features. Research in [15] declares BLE as the industry’s leading technology for maximizing the energy-latency trade-off in automotive applications. Passive Keyless Entry (PKE) is explored in [16] using a Cypress Semiconductor Programmable System on a Chip (PSoC), with a BLE peripheral as the host and the user’s smartphone as a client.

## Propagation Models

Propagation modelling aims to obtain an estimation of field strength given a set of parameters from the wireless channel [17]. Propagation models can be classified into two categories: deterministic or empirical models.

Deterministic models use Maxwell’s equation along with detailed information about the environment. Deterministic models compute highly accurate PDPs and do not require local measurements. A drawback is that they require high computational effort [18]. A ray tracing model is an example of a deterministic model. A 2D ray tracing model is implemented in [19] to identify unmanned aerial vehicles flying in an urban environment. A wireless channel can be simulated using beam-forming and other deterministic methods in [20] and [21] respectively, with both predicting effects such as multipath propagation accurately.

Empirical propagation models are more widespread that deterministic models due to their simplicity and speed. Examples include the COST231 and Motley-Keenan models compared in [22]. Empirical models require less environment data. This reduces the computational effort and produces simplified mathematical expressions to calculate path loss between the transmitter and receiver [18]. However, empirical methods are limited by the fact that they are range-based and are valid only to similar environments [17]. Empirical models can be enhanced to include greater detail (wall thickness etc.) as shown in [18], but they still lack the accuracy and complete PDPs generated by deterministic models.

# Technical Description

An overview of the theory implemented in this research is presented in this section, providing the reader with insight into the results and analysis that follows in later sections.

## Hilbert Transform

Direct measurements of the phase during the frequency sweep may be avoided by using the Hilbert transform to extract the phase response from the measured magnitude response. This is true only if the channel is minimum-phase [23]. Experience dictates that in scenarios where LoS is present the channel can be confidently assumed to be minimum-phase. The advantage of not directly measuring phase is the ability to characterize the channel using low-energy and low-cost instrumentation.

Hilbert transformers shift all positive frequency components by π/2 radians and all negative frequency components by -π/2 radians [24]. In the (1) it is shown that if is assumed to be real and casual, the Hilbert transform of the real part of an analytic signal produces its imaginary part,

|  |  |  |
| --- | --- | --- |
|  |  | (1) |

where denotes the Hilbert transform operation, defined by a convolution in (2).

|  |  |  |
| --- | --- | --- |
|  |  | (2) |

This research implements a Hilbert filter (using the optimal Parks-McClellan approach) to convert the natural log of the magnitude response to the phase response (3). A FIR filter with a passband from 0.1 to 0.9 normalized frequency sufficiently models the Hilbert transform, and is shown in Figure 1.



Figure 1 - Hilbert filter magnitude frequency response.

If is assumed minimum phase, then it is also causal, giving the Hilbert relation to the phase and the wireless channel frequency response characterization (4).

|  |  |  |
| --- | --- | --- |
|  |  | (3) |
| and |  | (4) |

## Power Delay Profile

The power delay profile represents the distribution of signal power received over a multipath channel as a function of time, also referred to as the spatial average of the impulse response [25]. It can be obtained from the frequency response using the Inverse Fourier Transform (5).

|  |  |  |
| --- | --- | --- |
|  |  | (5) |

The signal power of each multipath is plotted against their corresponding propagation delays. The multipath component typically sees destructive interference as it propagates through the channel, i.e. increased channel loss. The PDP provides useful information that characterizes a wireless channel and helps identify multipath components to assist indoor localization [25].

An alternative way to consider the PDP is as the sum of ray paths in the time domain, that reach a receiver with different delay times (6).

|  |  |  |
| --- | --- | --- |
|  |  | (6) |

This representation in (6) is the basis for PDP generation from ray tracing simulations. The selection of N taps depends on the wireless channel’s coherence time , and the number of signal paths present [26].

The PDP consists of three separate components: direct path, reflected paths, and noise. Each peak represents a ray path that reaches the receiver. The reflections that occur in a room can be characterized as specular or diffuse. Typically, the PDP becomes diffuse after the early multipaths at the receiver. Since reflections tend to scatter instead of being ideally specular, the number of reflections grows exponentially. Reflections cease carry important information as they attenuate [27].

## Ray Tracing

Ray tracing is based on the ray concept from the Geometrical Theory of Propagation, an extension of geometrical optics to radio frequencies. Ray tracing methods derive models for wireless channel prediction [17] [28]. A previous limitation of ray tracing was its high computational effort. This concern is less relevant today due to increased computing capacity available in modern computer networks [28]. The principle of ray tracing is to emit rays from a source, recursively reflect the transmitted rays toward the receiver, then follow the paths of each ray. The reflected paths that reach the receiver within the coherence time are stored as valid paths.

The first 2D ray tracing model designed in this paper simulates the multipath distributions of an indoor environment with a known geometry. Reflectors are defined as straight lines, and multipath reflections are modeled on AoA and angle of departure (AoD) theory at the reflector surface. The program’s output is a series of simulated PDPs, using the speed of light and length of ray path to create the delay times. The PDPs verify the delay times of the other PDPs obtained from the Hilbert transform and frequency sweep in the previous sub-section.

The second ray tracing solution in this paper implements a novel solution to identify or verify reflectors in a room with no prior knowledge of the geometry, using only real-world PDPs as input. Based on the multipath delay times, a locus of possible reflector locations is generated for each PDP, and where they intersect suggests that a common reflector may exist. The reflector geometry considerations are illustrated in Figure 2.

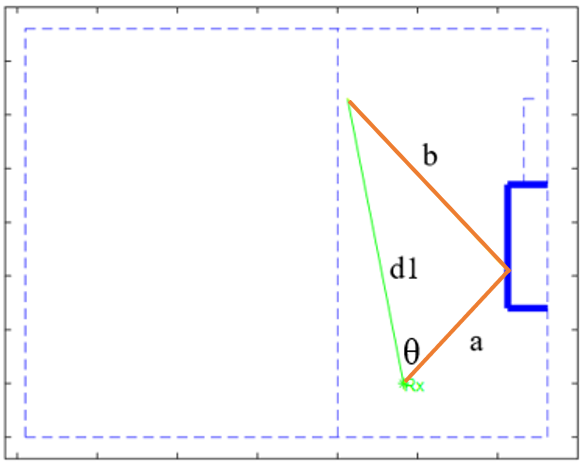


Figure 2 – Geometry used to characterize a potential reflector.

# Experiment Plan

## Data Acquisition

Five locations are chosen in an indoor auditorium to perform frequency sweeps of the 2-3 GHz frequency channel (see Figure 3). The receiver (signal analyzer) is fixed and the transmitter (signal generator) changes position for each different sweep.

## Automated Instrument Program

The receiver and transmitter need to sweep the frequencies in a coordinated and automated manner. This is achieved by scripting control of the signal generator and signal analyzer using the PyVISA package (Appendix E.1). The signal generator is connected to the laptop via a GPIB-USB connection and the signal analyzer uses an Ethernet connection to communicate to the network. The signal generator sweeps in steps of 500 kHz while transmitting at a constant power of -14 dBm, strong enough to overcome most weaker signals competing in the channel. Simultaneously the signal analyzer sweeps the same frequency steps, storing the averaged peak value of the received signal magnitude in a CSV file.

## PDP Generation and Ray Tracing Simulation

The frequency sweeps measured at each location are post processed to generate PDPs for each position, using the MATLAB script in Appendix E.2. The script is based on the theory in Section III, using the Hilbert filter to acquire the phase response of the channel from the magnitude response. The complete frequency response is reconstructed from the phase and magnitude response, and the Inverse Fourier Transform produces the time-domain PDP representation. From observing the common peaks in the PDPs, the delay times for the LoS and multipath components can be determined.

# Experimental Results and Analysis

## Channel Frequency Magnitude Response

The positions with longer transmission distances suffer larger path loss than those with shorter transmission distances. For all positions there exists a tap in all the magnitude frequency responses typically between 2.1-2.2 GHz. The positions with longer transmission distances all display several smaller taps and magnitude frequency response variations. The magnitude frequency responses can be found in Appendix D.

If the signal generator is not transmitting, a frequency sweep can be performed using just the signal analyzer to observe channel noise. The noise measurement in Figure 3 show a large noise signal in the channel in the 2.4-2.5 GHz range strong enough to interfere with the signal at the receiver. Smaller narrowband signals are also present, but are easily overpowered once transmission begins.

A screenshot of a social media post

Description generated with very high confidence

Figure 3 - Manual sweep of channel noise.

## PDP Analysis

To avoid the unwanted noise in the channel characterization, the effective bandwidth is reduced from the 2-3 GHz swept to 2.0-2.4 GHz. The decision to take the lower half of the bandwidth is arbitrary, from 2.5-3 GHz is equally effective.

The PDPs generated for all five sweeps positions can be found in Appendix D. Each PDP has a clear LoS pulse of high path loss amplitude. Transmission positions further away from the receiver experience greater relative path loss (i.e. have a greater amplitude) than those closer to the receiver.

The scope of this investigation focuses on the most dominant multipath reflection since it has the strongest path loss and likely originates from the strongest reflector in the channel. The PDPs at the transmitter positions 1 and 3 do not experience any common multipath path that positions 5, 7 and 9 do, so are disregarded in the following multipath investigations.

Figure 4 compares the PDPs for remaining positions. The common multipath pulses are observed in the purple box. Significant noise in the PDPs makes it difficult to determine where the first multipath pulses exists. This noise is mostly attributed to Gibb’s phenomenon. According to [29], the phenomenon is an overshoot of Fourier series occurring at simple discontinuities.

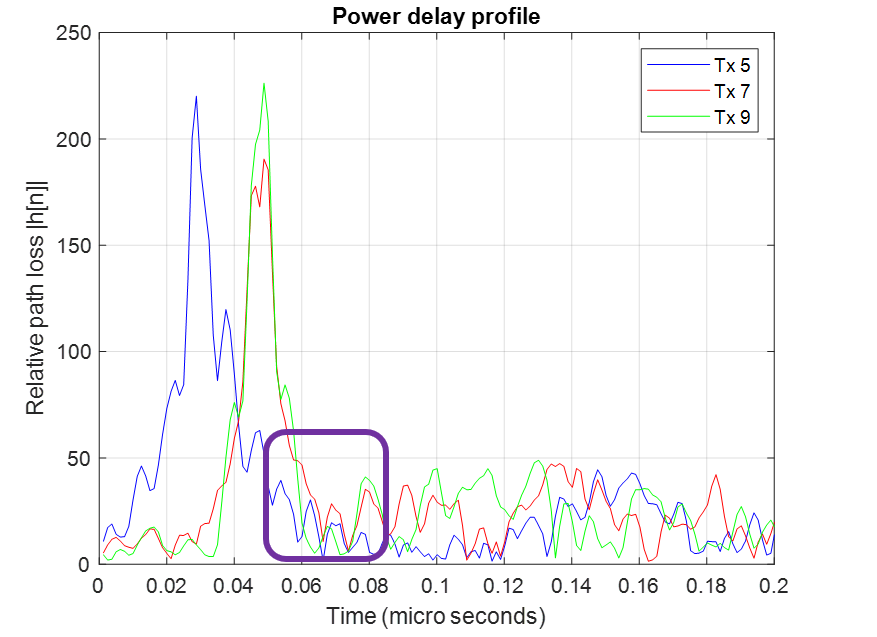


Figure 4 – PDPs comparison for positions that experience multipath.

Figure 5 compares the purple box region of the three PDPs, using the logarithmic scale to circle the first multipath pulses. Comparing the PDPs of the three nearby transmitter locations reveals that there is a common multipath pulse between the PDPs. The delay time of this pulse varies slightly depending on PDP location.

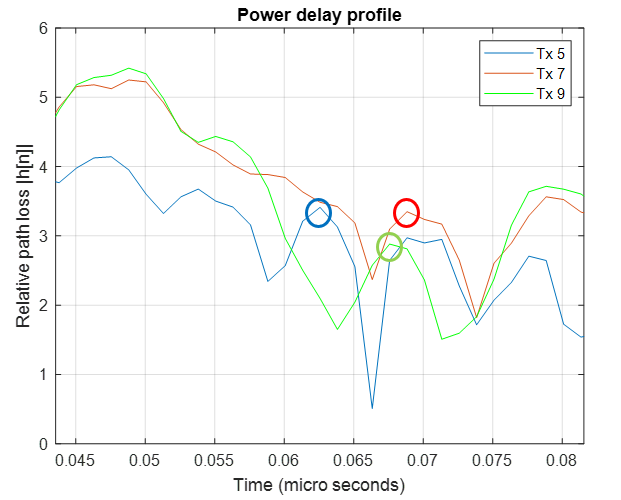


Figure 5 - Closer inspection of log PDP comparison.

The PDP observed delay times are listed in Table 1.

|  |  |  |
| --- | --- | --- |
| Position | LoS (µs) | Reflected (µs) |
| 1 | 0. 01877 | NaN |
| 3 | 0.01877 | NaN |
| 5 | 0.02879 | 0.06258 |
| 7 | 0.04881 | 0.06884 |
| 9 | 0.04881 | 0.06758 |

Table 1 – PDP time delays observed from sweep measurements.

## Validating PDPs Using Ray Tracing

The objective of the ray tracing program in this section is to verify or predict the PDPs captured in the previous section (Table 1). The ray distributions for all five positions can be found in Appendix D. Figure 6 displays the ray tracing simulation for transmission from position 7. Note that the co-ordinate system is in inches, but is converted to meters for PDP delay time calculation.



Figure 6 - Ray tracing simulation for transmitter position 7.

Table 2 lists the ray tracing generated PDP delay times. Note that positions 1 and 3 do not receive a multipath reflection, matching their PDPs measured in the previous section.

|  |  |  |
| --- | --- | --- |
| Position | LoS (µs) | Reflected (µs) |
| 1 | 0.016467 | NaN |
| 3 | 0.016763 | NaN |
| 5 | 0.028363 | 0.052372 |
| 7 | 0.046306 | 0.055463 |
| 9 | 0.046412 | 0.071667 |

Table 2 – PDP time delays from ray tracing with one reflector.

For the LoS paths, both ray tracing and measured PDP delay times match closely. This verifies that a reflector exists in the wireless channel where it is suspected (the elevator shaft). The measured PDP time delays are slightly slower (~2 ns), possibly due to possible attenuation and energy reduction.

The multipath reflection varies more (~9 ns), with position 9 experiencing especially long multipath delay in the ray tracing compared to the other positions. Possible reasons for this may be an unknown second reflector influencing the transmitted signal at position 9, or incorrect identification of PDP multipath delay times.

## Identify the Reflector Using Ray Tracing

The next part of the research is a novel to attempt to identify a reflector in an unknown indoor geometry. To first test the functionality of the script, the ray tracing PDPs in the previous section are used as an input (see Table 2). The ray tracer produces a locus of points whose geometry correctly match the distances suggested by the delay time inputs. In Figure 7 two loci intersecting correctly identifies the reflector to an accuracy of less than a meter.



Figure 7 - The PDP delay times generated using the ray tracer for a known reflector.

With the script correctly estimating the known reflector for ideal ray tracing PDPs, the next step is to use the real-life measured PDPs as an input (Table 1). Less accurate prediction is expected compared to the results in Figure 7, due to multiple possible reflectors indoors, incorrect identification of the multipath delay time, and the fact that a 2D simulation does not model the real-life 3D environment.



Figure 8 – Ray tracing reflector estimation for measured PDPs

In Figure 8, two of the reflector position loci intersect in the region where the elevator shaft is (indicated with a blue rectangle). This confirms that the suspected reflector exists in that region, adding greater detail to the characterization of the wireless channel. This novel solution is most effective in indoor environments where a single reflector is suspected and where a LoS condition exists.

# Future Work

There are several areas in which the work in this research could be extended in future implementations [17].

* Extending the novel ray tracing solution to identify multiple reflectors in a 3D space, and improve the multipath identification process by removing Gibb’s phenomenon in the PDPs.
* Deep learning can be applied to intuitively characterize reflectors and other features in the wireless channel for indoor environments and determine suitable levels of detail depending on the environment.
* Implementation of real-time capabilities and geospatial awareness will result in the wireless channel models being adopted by wireless communication systems to enhance performance and reduce power consumption. Cognitive radio can benefit from real-time channel characterization to allocate the spectrum.

In summary, I conclude that ray tracing integrated with BLE technology and machine learning can serve as an accurate generalizable solution for wireless channel characterization and indoor localization in a real-time low-power system.

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**Appendix A**

**Literature Review**



**DUBLIN CITY UNIVERSITY**

**SCHOOL OF ELECTRONIC ENGINEERING**

**Characterization of Reflectors in a Wireless Channel to Aid Low-Power Indoor Localization**

**Literature Review**

**Aidan Smyth**

ID Number: 13452192

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MASTERS OF ENGINEERING

IN

Electronic Systems

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**Declaration**

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* **Abstract**

Modern wireless communication for Internet of Things (IoT) systems requires both long battery life and accurate indoor localization. Bluetooth Low Energy is heavily adopted in emerging wireless sensor networks (WSNs) as it meets the energy constraints. However, reflectors present in an indoor wireless channel cause multipath fading at the receiver. Characterizing such reflectors in a wireless channel can greatly enhance the accuracy of such low-power indoor localization systems. This paper proposes a low-energy approach to characterizing the wireless channel using power delay profiles (PDPs) and several novel ray tracing techniques which are implemented to verify the PDPs and predict the location of a reflector in an indoor wireless channel.

The selected solution successfully generates low-energy PDPs for several indoor positions, which are processed using ray tracing scripts to identify and verify a suspected reflector in the indoor environment.

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**Glossary**

|  |  |
| --- | --- |
| IoT | Internet of Things |
| PDP | Power Delay Profile |
| BLE | Bluetooth Low Energy |
| UWB | Ultra-wideband |
| LoS | Line of Sight |
| NLoS | Non Line of Sight |
| AoA | Angle of Arrival |
| ToA | Time of Arrival |
| TDoA | Time Difference of Arrival |

1. **Introduction**

It is important that the reader is familiar with the key research question of this project. The question investigated in this literature review is:

*“Which wireless technology and propagation model can provide the best trade-off between high accuracy and low computational cost for characterization of a reflector in a wireless channel?”*

Localization using radio frequency signals dates to World War II. It was originally deployed to locate personnel in the case of an emergency. The Vietnam War introduced the Global Positioning System (GPS) to the world. Today in outdoor applications GPS complimented with cellular can be used to provide precise positioning information [1]. Although it is the most popular positioning system, GPS suffers great attenuation and do not reliably work indoors [2][3]. In [4], it was stated that GPS systems “are not perfect as they rely on faint radio signals that can be blocked or reflected by man-made structures”.

Alternative localization systems are required that are accurate in indoors environments. Emerging high-definition self-aware applications can operate in harsh propagation environments and require submeter accuracy. Reliable localization is essential to a diverse set of applications including security tracking, medical services, logistics, emergency services, home appliance control and military systems [5].

IoT wireless sensor networks (WSNs) used in modern applications require a long battery life to reduce the time and financial cost of replacing and maintaining them. Therefore, WSNs require low-energy communication technology. Two such candidates are BLE and ultra-wideband signals, with BLE enjoying rapid progress and integration into modern IoT applications.

This literature review investigates the existing solutions available for wireless channel and reflector characterization to assist localization systems operating indoors (such as car parking lots). Current range-based, angle-based and time-based technologies require a line-of-sight (LoS) path between the transmitting and receiving antennas to operate at a reasonable accuracy, and experience signal distortion due to the multipath effect and signal fading.

Deterministic and empirical propagation models are investigated and evaluated in this literature review as solutions to improve the localization accuracy, with an emphasis placed on minimizing the power consumption and computational time of the system. The scope of this project is on indoor propagation environments where reflection, diffusion and scattering of the signal is common. The solution is targeted at indoor environments. The success criterion of this project is to sweep and characterize the wireless channel, verify the obtained power delay profile of the channel, identify reflectors that are present, simulate and deploy the channel data in a localization system that can perform to sub-meter accuracy, while preserving a relatively low power consumption.

The literature review is organized as follows. Section 2 describes in detail the problems encountered by radio frequency waves indoors, such as non-line-of-sight (NLoS) and multipath effects on the signal. Section 3 outlines the existing range-based (RSS), angle-based (AoA) and time-based (ToA/TDoA) solutions. The empirical and deterministic propagation models are described and evaluated in Section 4. Section 5 compares the wireless technology (GPS, Wi-Fi, ZigBee, Bluetooth, BLE and UWB) and highlights the preferred choice wireless communication technology for low-power IoT and localization systems. The critical evaluation of the research investigated as part of the literature review is presented in Section 6. Section 7 provides an overview of the hardware that will be required to implement and test the proposed solution. A project plan and timeline are presented in Section 8. The project development and procedural steps are documented in Section 9, followed by the research conclusions in Section 10. Further Appendices are located at the end of the portfolio.

1. **Problem Description**

**2.1 Indoor Localization**

In outdoor applications, several wireless methods can be used to calculate distance between a transmitter and a receiver. However, in indoor environments the received signal suffers severe interference due to other electromagnetic waves and the obstacles it encounters [1].

Reflectors in the wireless channel cause multipath interference which greatly reduces the usability of received signal data. One source of error is multipath or the excess delay, caused by the propagation of a partially blocked LoS components that travel at different speeds depending on different obstacles they encounter [5].

Another source of error occurs when a propagation path between transmitter and receiver is completely blocked, and only NLoS components can be observed. This results in a positive bias in distance estimates just like the excess delay. An important condition for any localization system is NLoS identification. Once identified, NLoS effects can be mitigated or included in a model to improve localization accuracy [5].

Based on radio wave propagation technology, there are four types of characteristics that can be used to distinguish indoor positioning systems: received signal strength (RSS), time of arrival (ToA) uses the time of signal propagation, time difference of arrival (TDoA) is concerned with the differences in radio signal time of arrival, and angle of arrival (AoA) utilizes the different incident angles of a received radiation pattern to the antenna [30].

For direction-based systems, the AoA is a popular metric. However, this method requires additional hardware to measure the angle of incidence of the received signal. The RSS methods use the signal propagation models to estimate the distance between the transmitter and the receiver. Unfortunately, RSS suffers greatly in the presence of multipath. ToA and TDoA both require expensive hardware and clock synchronization [2].

In indoor environments these techniques fail to provide accurate location estimation. The main reason in all cases is insufficient knowledge and the ability to characterize the wireless channel. With knowledge of the reflectors in a wireless channel, indoor localization models can be extended to produce more accurate results by processing multipath information.

**2.2 Wireless Channel Characterization**

Knowledge of wireless channel characteristics is desirable, as they indicate the amount of interference which should be expected and hence mitigated in the wireless channel. A detailed tutorial in [26] provides the basis of much of the wireless channel description in this section. The channel refers to the medium between transmitter and receiver. The characteristics of a signal changes as it travels from transmitter to receiver, i.e. through the wireless channel. The change depends on the:

* distance between transmitter and receiver,
* nature of the channel’s environment (buildings, obstacles),
* existence of a LoS path,
* effects of multipath propagation.

The power delay profile (PDP) of a received signal is considered the result of convolving the transmitted signal and the channel’s impulse response in the time domain, or equivalently multiplication in the frequency domain. The transmitted signal is given in (1),

|  |  |  |
| --- | --- | --- |
|  |  | (1) |

where is the channel response and is the channel noise.

The wireless channel’s three main components are path loss, multipath, and shadowing.

**2.2.1 Path Loss**

The transmitted signal attenuates with increased distance as its energy spreads spherically around the transmitting antenna. A common empirical formula for path loss is given in (2),

|  |  |  |
| --- | --- | --- |
|  |  | (2) |

where is the power at distance and is the path loss exponent.

**2.2.2 Shadowing**

Obstacles in the path of the signal cause the transmitted signal to suffer path loss through absorption, reflection, scattering and diffraction. This effect is called shadowing. Net path loss accounting for shadowing is given by (2), but can also be expressed as a function of distance (3),

|  |  |  |
| --- | --- | --- |
|  |  | (3) |

where is the mean path loss in dB at distance , and is a normally distributed random variable (in dB) representing the shadowing effect.

Shadowing is also known as large-scale or deep fading, and can cause temporary failure of signal reception due to a severe drop in the channel signal-to-noise ratio (SNR) [31] [32].

**2.2.3 Multipath Fading**

Objects may reflect the wireless signal on its way to the receiver. Multipath refers to the phenomenon that results in radio signals from multiple paths reaching the receiver’s antenna. Since each reflected signal takes a different path, each has a different phase and amplitude. Depending on the phase, this results in constructive or destructive interference at the receiver. Distortion experienced in a wireless system due to multipath propagation is referred to as small-scale or multipath fading. Multipath fading is also known as small-scale fading, as it occurs on a scale of the order of the carrier wavelength and is frequency dependent [31] [32].

Since different paths have different transmit times, a single impulse from the transmitter results in multiple impulses received at different times. The maximum delay after which the received signal becomes negligible is called the maximum delay spread, . A large maximum delay spread indicates a highly dispersive channel. It is common that the root-mean-square (rms) value of the delay spread, , is used instead of the maximum [26].

Multipath fading is frequency-selective since the coherence bandwidth is less than the bandwidth of the signal. Different frequency components experience decorrelated fading. Frequency-selective fading is dispersive, i.e. the signal associated with each symbol is spread out in time. Intersymbol interference can occur, and equalizers are often deployed to mitigate this effect [31].

Multipath can easily be modelled for two-ray analysis. The two-ray analysis can be extended to the *n*-ray multipath model. It is assumed that *n* separate signals arrive at the receiver. Multipath fading occurs as expected when the sum of the direct and *n* reflected signals is close to zero. The n-ray model is a useful representation for indoor multipath channels. Ray tracing is useful for simulating the multipath distribution in a room. Two-ray rat tracing simulation of AoA based multipath fading can be found in Appendix A.

An environment without reflectors, or one that reflects signals with high loss, experiences less multipath propagation. The multipath propagation is particularly prevalent in urban areas, where there is a dense collection of strong reflectors such as windows, tall metallic structures and many moving objects. The multipath in a city usually is less dynamic than over water. Inside office buildings the effect is very strong, with many moving people and changing landscapes.

An antenna receives many reflected rays from different directions. These conditions result in a rapidly fluctuating RF environment. In the case where a LoS exists, the received signal experiences Rician fading. The Rician distribution probability density function causes the RSS to vary widely and rapidly for a large amount of time [33].

If all received reflections are NLoS, the receiver experiences Rayleigh fading. Signals from all paths have comparable strengths, and the instantaneous received power becomes a random variable depending on antenna location [34]. The full mathematical model and a detailed description of multipath can be found in Appendix A.

***2.2.3.1 Fading Mitigation***

Fading does not reduce the average energy of the RSS, rather it redistributes the signal energy over time and space. By designing communication links that are insensitive to this energy redistribution, the channel can approach the performance of an additive white Gaussian noise (AWGN) channel. The remainder of the research in this chapter is based from a summary of ray tracing and multipath mitigation found in [33].

In general, multipath mitigation techniques require diversity. The transmitter sends information over multiple channels which are statistically separate. The separate channels can implement frequency diversity, time diversity and space diversity. The receiver can manipulate and recover the original transmitted signal.

1. **Receiver Antenna Pattern**

By limiting the number of signals the receiver antenna views, the probability of receiving two separate signals from the same transmitter is reduced. This can be implemented by using a narrow-beamwidth, low-sidelobe antenna. In some applications the receiver may be mobile and required to be omni-directional. Omni-directional antennas introduce problems in a multipath environment as they receive signals from every direction.

1. **Frequency Diversity**

A signal fade occurs when the difference in path lengths between the direct and reflected wavelengths is an odd multiple of . The length of the transmission path determines the phase of the arriving signals. By transmitting two slightly different frequencies along the same path, the resultant phase difference between the two reflected signals is no longer . There is a strong likelihood that one of the frequencies will not fade. However, there is no guarantee that this will be the case for every scenario. A drawback to using frequency diversity is that it is inefficient and wastes spectrum.

1. **Spatial Diversity**

As previously discussed, the geometry of the transmitter, receiver and reflector can produce a 180◦ phase shift, causing multipath deep fade. Slight geometrical change results in dramatic RSS increase. Using this fact, multipath statistics can be improved. Using one transmitter and two physically separate receivers, the receiving equipment chooses the best signal from the two antennas.

1. **Polarization Diversity**

Polarization can affect the way in which waves reflect off objects. Vertically polarized waves reflect off vertically oriented objects, whereas horizontally polarized waves tend to reflect off horizontally polarized objects. The paths taken by polarized paths are likely to vary depending on polarization nature. If the channel experiences a fade in one polarization, it may not in the other polarization. Polarization diversity poses some practical implementation problems. Both the transmitter and receiver require dual-polarized antennas, which can be expensive and physically cumbersome.

Unfortunately, these fading mitigation techniques are costly to implement on a large scale, do not match size constraints, or fail to achieve low-energy operation.

**2.2.4 Frequency Response**

For all the time domain phenomena mentioned above there exists corresponding frequency domain phenomena. The Fourier transform of the PDP enables the calculation of the coherence bandwidth, which is also inversely related to the delay spread. The larger the delay spread, the smaller the coherence bandwidth becomes. With a small coherence bandwidth, the channel is then said to be frequency selective [26].

The PDP gives the statistical power distribution of the channel over time for an impulse transmission. Similarly, the Doppler power spectrum gives the statistical power distribution of the channel for a signal transmitted on a single frequency f. The Doppler power spectrum is non-zero for , where is the Doppler spread. Coherence time is inversely proportional to the Doppler spread [26].

**2.2.5 Hilbert Transform**

Direct measurements of frequency phase response may be avoided using the Hilbert transform to extract the phase response from the frequency magnitude response of the channel . The Hilbert transform can derive the phase response from the amplitude response, and vice versa, if the channel is known to be minimum phase. An inverse discrete Fourier transform (IDFT) of yields the time domain representation *h(t)*. The Hilbert transform is applicable provided is minimum phase, and provides a useful lower bound on the time-spread of a non-minimum phase impulse response [23].

Major advantages of using this method are the possibility of characterizing the wireless channel using low-cost instrumentation, and the possibility to extend the technique to outdoor radio channels. The measurement of the transfer function can be performed using a spectrum analyzer without the need for cable or synchronization between the transmitter and the receiver [35].

The time-domain signal can be determined using the Hilbert filter only if is assumed to be minimum phase. Although strictly speaking the radio channels are not minimum phase systems, experience dictates that in certain circumstances the estimated value of under the minimum phase hypothesis gives results close to the exact value. This can be of practical use in the estimation of the real value [35].

If the energy of the first path is larger than the spectral density of all subsequent paths, the impulse response of a channel is considered minimum phase. Experimentally, it has been proven that the condition is more likely to be met if the transmitter and receiver are in LoS. The Hilbert may give unreliable results if the first path is highly attenuated in a NLoS environment [36].

Properties of the Hilbert transform include

* linearity,
* use of multiple HTs can produce the inverse Hilbert transform,
* the Hilbert transform of a function is equivalent to the Hilbert transform of the derivative of the Hilbert transform of that function,
* a real function and its Hilbert transform are orthogonal,
* it can create an analytic signal from a real signal.

**Theory**

The following explanation of the Hilbert transform is based on [35].

The channel is considered linear and time invariant (LTI). Since the impulse response of the frequency sweep is measured for many instances, the impulse response is a discrete signal given by (4), where is the approximate time interval between each sample.

|  |  |  |
| --- | --- | --- |
|  | , | (4) |

The Fourier transform of the channel is given by (5), where is a complex function which can be written as shown in (6).

|  |  |  |
| --- | --- | --- |
|  | , | (5) |
|  |  | (6) |

In this case can be determined real and casual,

|  |  |  |
| --- | --- | --- |
|  |  | (7) |

where denotes the Hilbert transform operation, defined as a convolution in (8)

|  |  |  |
| --- | --- | --- |
|  | . | (8) |

Converting the magnitude to the phase of the transfer function involves applying the complex natural logarithm to in exponential form (9)

|  |  |  |
| --- | --- | --- |
|  | . | (9) |

The minimum phase condition is satisfied if , the inverse Fourier transform of , is also causal. This condition is the equivalent to having no poles or zeros outside the unit circle. This hypothesis is assumed true for a typical wireless channel [37].

If is assumed minimum phase, then it is also causal, giving the Hilbert relation to the phase (10).

|  |  |  |
| --- | --- | --- |
|  |  | (10) |
| and |  | (11) |

The Hilbert transform in (7) can be achieved using a convolution in the frequency domain through the use of FFT, using the following relationship (12)

|  |  |  |
| --- | --- | --- |
|  |  | (12) |
| where |  | (13) |
| Note |  | (14) |

A full derivation of the Hilbert transform can be found in Appendix A.1.

**2.2.6 Power Delay Profile**

The power delay profile (PDP) represents the distribution of signal power received over a multipath channel as a function of time (or propagation delays). It is often referred to as the spatial average of the complex baseband channel impulse response [25].

***Ray Tracing Representation***

The PDP of a multipath channel can be mathematically represented in (15):

|  |  |  |
| --- | --- | --- |
|  |  | (15) |

The selection of N taps depends on , or the number of signal paths present. The time for which the channel characteristics are constant is known as the coherence time [26]. The PDP consists of three separate components: direct path, reflected paths, and late reverberations. Each peak represents a ray path that reaches the receiver. The reflections that occur in a room can be characterized as specular or diffuse [27].

Typically, the PDP becomes diffuse soon after the early multipaths at the receiver. Since reflections tend to scatter instead of being ideally specular, the number of reflections grows exponentially. As a result the reflections cease to longer carry important information as they attenuate [27].

***Inverse Discrete Fourier Transform Representation***

A PDP can be determined from the Inverse Discrete Fourier Transform of the frequency magnitude and phase response of a channel (16). The signal power of each multipath is plotted against their respective propagation delays. The multipath typically sees destructive interference as it propagates through the channel. The PDP provides useful information to help characterize a wireless channel [25].

|  |  |  |
| --- | --- | --- |
|  |  | (16) |

1. **Existing Solutions**

There are several wireless technologies that have been successfully deployed to characterize the wireless channel and aid in indoor localization. Recent research and technological advances have implemented the following technologies for indoor localization in our everyday interactions with reasonable accuracy depending on the environment [6].

**3.1 RSS**

RSS ranging is based on the principle that received signal experiences loss with increased distance between two nodes. The technique is prevalent in low-cost systems, such as wireless sensor networks, as it is cheaper and easier to implement than time-based solutions. The logarithmic path loss model translates the RSS measurements into distance estimates is given by (17) [5] [30]:

|  |  |  |
| --- | --- | --- |
|  |  | (17) |

is the received power, is the power level at a known reference distance, n is the propagation coefficient and d is the unknown distance between receiver and transmitter. S represents the deep fading variations, and it is commonly modelled as a Gaussian random variable with zero mean. The parameter *n* is the path loss exponent, and usually takes a value between 2 and 6 [5]. The value indicates the rate at which the path loss increases with distance. This value depends on the radio wave frequency and the environment [7].

Such models are inaccurate in environment that are not free-space, and suffer due to reflection, refraction, diffusion and scattering [30]. The primary disadvantage of RSS is that it performs poorly in cluttered environments with propagation phenomena which act to distort the relationship between distance and received signal [5].

|  |  |
| --- | --- |
| Partition | Loss (dB) |
| Fixed walls | 3.0 |
| Door | 2.0 |
| Windows | 2.0 |
| Metal Partitions | 5.0 |
| Basement Wall | 20.0 |

*Table 3 - Typical attenuation factors of signal* [38]

**3.2 AoA**

AoA provides a location estimate by determining the angle of incidence at which signals are received by the antennas. Two or more receivers are required for location estimation, more receivers often increase the accuracy of the system. Multiple element antenna arrays or mechanically agile directional antennas are required for AoA localization systems. AoA works best in LoS environments, but suffers significantly in multipath situations. In dense urban areas, AoA is not viable as the LoS between two transceivers is seldom present [7].

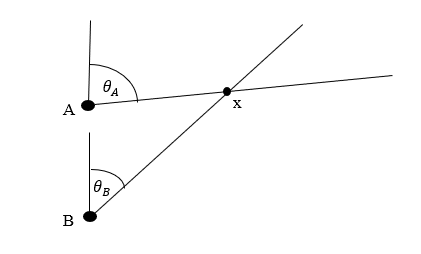


Figure 9 – AoA location estimation principle.

Narrow-beamed antennas are best for achieving precise AoA measurements. By combining two AoA measurements or one AoA and one range measurement, the location of a target can be determined. For high resolution, AoA solutions require large antenna arrays to realize narrow beams with large dimensions of received signal. Consequently, such schemes are costly to implement. Accurate AoA also requires strong LoS conditions. Spatial smoothing and redundancy techniques may help distinguish multipath components for several coherent signals, but are difficult and cumbersome to implement in practice [8].

**3.3 ToA/TDoA**

ToA measurements define spheres which are used for triangulation. For ToA measurements, the estimated parameter vector is extended by the unknown time of emission. TDoA is calculated by the relative difference between two ToA measurements from spatially independent sensors. TDoA is often referred to as hyperbolic positioning [9].

Recent focus has been directed at the use of ToA measurements without TDoA processing. Currently, ToA localization cannot be provided by a single sensor. The signals are transmitted to a sensor fusion centre to obtain TDoA measurements by cross correlation. This is motivated by the fact that prior to acquiring TDoA measurements, sensors must first be paired. TDoA measurements are then received using a common reference sensor, or by considering all possible sensor pairings [9].

TDoA-based localization systems do not rely on absolute distance estimates between pairs of nodes, rather it employs two schemes. In the first, multiple signals are transmitted from anchor nodes at known positions and agents measure the TDOA. In the second scheme, an agent broadcasts a reference signal which is received by several anchors. The anchors share their estimated ToA and compute the TDoA. At least three anchors are required to triangulate the target, and two TDoA measurements are taken [5].

Wi-Fi-based positioning has incorporated a similar Time-of-Flight (ToF) approach in the recent Fine Timing Measurement protocol defined as part of the 802.11 (mc 4.0+) standard. ToF is based on estimating the position using the distances from access points acting as FTM responders. The protocol uses Round-Trip Time (RTT) to estimate the distance from each responder. The FTM approach compensates for the lack of synchronization by measuring RT delays. FTM-based localization approaches must also include algorithms for detecting multipath and LoS components of signals [10].

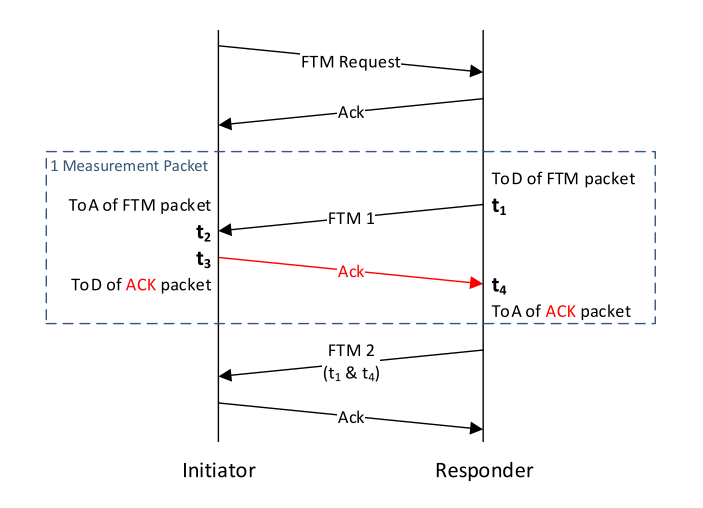


Figure 10 - FTM protocol, 4 FTMs per burst [10]

1. **Propagation Models**

Propagation modelling aims to obtain an estimation of field strength given a set of parameters of the wireless system (frequency, antenna heights, terrain etc.) [17]. Propagation models can be classified into two main extremes: deterministic or empirical models. Some models fall in-between the two ends of the spectrum and are called semi-empirical models [39]. Deterministic models and empirical models are in general simple and fast to implement.

Deterministic models contain information about the environment, structure materials and the existent furniture present. Deterministic models produce high accuracy results and do not require local measurements, but require high computational effort [18].

Empirical models need less information about the environment, reducing the computational effort and producing simplified mathematical expressions to calculate path loss between the transmitter and receiver [18]. However, empirical methods are limited by the fact that they are range-based and are valid only to similar environments [17].

**4.1 Empirical**

Empirical models are based on practically measured data and use few parameters. These models are simple but in general not as accurate as deterministic models. Such models are represented by mathematical equations which provide the path loss as output [22]. Model tuning and environment data collection are simplified when empirical models are used [22]. They include the Okumura and Hata models, the COST231 Hata model, and the Motley-Keenan model [39].

Empirical models are very similar since they both calculate the propagation loss based on the path loss due to obstacles. Extensions of these models can be more detailed, such as knowledge of the number of walls between the transmitter and the receiver [22].

**4.1.1 Okumura and Hata Models**

The Okumura model for Urban Areas was built on data collected in 1968 in Tokyo, Japan. The model is targeted at dense urban areas with few tall blocking structures. The model was designed as a base for others, and was built on by subsequent Hata models. The Okumura models consists of three modes: urban, suburban and open area modes [39].

In 1980 the Hata model established empirical relationships to describe the graphical information of the Okumura model in greater detail. The Hata model approximates the Okumura model for distances greater than 1km, and is intended for large cells with BS placed on a height. Both models were designed for 150-1500 MHz frequency bands [26]. The Hata model is limited in its ranges and input parameters. The model is applicable only over smooth relatively terrain [39].

**4.1.2 COST231 Hata and COST231 Multi-Wall Models**

The European Cooperative for Scientific and Technical (COST) research extended the Hata model for use in the 1.5-2.0 GHz range. A drawback of this model noted in [39] is that it often underestimates path loss.

The path loss for COST231-Hata model is (2):

|  |  |  |
| --- | --- | --- |
|  |  | (2) |

Where:

|  |  |  |
| --- | --- | --- |
|  |  |  |
|  |  |  |
|  | C = 0 *for medium and suburban areas* |  |
|  | = 3 *for urban areas* |  |

The COST231 Multi-Wall model modifies COST231 to account for the effect of multiple walls on the propagation channel. The model can be enhanced to include floor penetration, but for this project floor propagation effects are not required.

|  |  |  |
| --- | --- | --- |
|  |  | (3) |

Where M is the total number of walls through which the signal penetrates, and is the wall loss factor for the ith wall [40]. Other notable extensions of the COST231 model include the COST 231-Walfish-Ikegami Model (distinguishes cases for LoS and NLoS), Erceg Model, and Stanford University Interim (SUI) Channel Model [26].

**4.1.3 Motley-Keenan Model**

The Motley-Keenan multiple walls model extends the COST231 Multi-Wall model. The model calculates the path loss when the signal reflects off several types of walls [18].

|  |  |  |
| --- | --- | --- |
|  |  | (4) |

is the reference loss (dB) taken at a known distance (1 meter) along the transmitter and receiver path, n is the path loss exponent or decay rate of the signal level, N is number of walls, is the number of type i walls, and is the penetration loss in type *i* walls. The penetration loss is the same for each type of material, independent of its thickness [18].

The term can be modified to consider the width of the walls. The walls have built in type i material and have a thickness of e, resulting in an adjusted term given by (5).

|  |  |  |
| --- | --- | --- |
|  |  | (5) |

* 1. **Deterministic**

Empirical models such as the COST231 Multi-Wall model are popular due to their speed and simplicity but limited in its accuracy. Research is focusing more on ray tracing deterministic models and minimizing their runtime [41]. Deterministic models contain more parameters than empirical models, and therefore more accurate in general [39]. These are computational models which simulate the behaviour of propagation radio signals [22]. Two of these models are the full wave frequency domain model and ray tracing.

**4.2.1 Full Wave Frequency Domain Models**

Full wave propagation models are based on the numerical solution of Maxwell’s equations. Such models can provide exact solutions the indoor propagation problem except for numerical inaccuracies or missing environmental factors. Indoor propagation models should include as much of the physics affecting the environment as possible, while also running in a reasonable computational time. The suggested approach is to start with a highly accurate full wave propagation model and reduce its computational time [21].

Two integral equation formulas for two-dimensional analysis of indoor propagation channels are volume and surface electric field integral equations (VEFIE and SEFIE). These are discretized by the Method of Moments (MoM), resulting in dense linear systems which can be solved iteratively using acceleration techniques. The convergence of VEFIE is significantly faster than that of SEFIE [42].

The two-dimensional form of the VEFIE is discretized using the method of moments and solved using an iterative solver. Accurate knowledge of the propagation is vital to the recent development of indoor localization systems. Propagation models should include as much geometry as possible while also running in a reasonable time [41].

The power delay profile (PDP) data can be computed by solving the discretized frequency domain VEFIE over a wide range of frequencies. The solutions for each frequency are independent and gives the total field for all points. As a result, the PDP can be computed for multiple points within the building at no extra computational cost, since the VEFIE contains the electric field for all domain points. The VEFIE is solved using an iterative solver, and PDPs are generated from the solved VEFIE by using the Fourier transform to convert the solutions to the time domain. The generated PDPs match the predicted geometric optics closely [21]. The VEFIE model can provide information about the power arriving at each angle over ray tracing [41].

See Appendix E for the VEFIE formulations.

**4.2.2 Ray Tracing**

Full wave frequency domain models are based on numerical equations. In contrast, ray tracing is based on the ray concept from the Geometrical Theory of Propagation. Ray tracing methods are stochastic and perform Monte Carlo sampling of possible reflection paths, with the main purpose to derive models for RF channel characterization [17] [28]. The RT model is popular due to its ability to simulate multipath propagation including the time and space dispersion characteristics of the channel. A previous limitation was high computational effort is less relevant today due to improved computational ability in modern processors [28].

A model for an empty office is created in **Error! Reference source not found.**, with a single transmitter receiver pair in the middle of the room. The ray tracing is based on AoA, and the code can be found in Appendix C. The simulation for LoS with multipath 1st order reflections is shown in Figure 12**Error! Reference source not found.**, the Rayleigh distribution for only second multipath reflections (no LoS) is found in Figure 13. The Rician distribution for both LoS and NLoS components is pictured in Figure 14.

|  |  |
| --- | --- |
| Figure 11 - LoS between transmitter and receiver. | Figure 12 - Multipath with first reflections. |
| Figure 13 - Rayleigh distribution of second reflections multipath. | Figure 14 - Simulation of Rician distribution of multipath LoS and NLoS reflections. |

***4.2.2.1 Principle of Operation***

The main principle of ray tracing is to emit rays from a source, then follow the paths of each ray. Some are reflected and registered as valid paths. The emission is either pre-defined or via Monte Carlo. The propagation of each ray is traced, with the ray changing direction every time it hits a surface and is reflected.

Energy attenuation in the wireless channel is related to ray termination. Each simulated ray carries energy information and when the ray is reflected, its energy is attenuated according to the attenuation coefficient of the reflector. The ray terminates when its energy falls below a threshold for all frequency bands, or if a maximum travelling distance is reached [27].

In contrast to empirical and numerical methods, Ray tracing does not provide simple formulas for calculating of path loss. The ray concept provides information on the different propagation mechanisms and interactions of EM waves, and is summarized as follows [17]:

1. A ray travels in a straight line in homogenous medium.
2. It obeys the laws of reflection and refraction, as well as the law of diffraction.
3. A ray carries energy, and can be treated as a tube in which energy is contained and propagated.

***4.2.2.2 Ray Types***

We can classify a ray as one of three types [17]:

* **Direct Rays**: LoS ray directly from transmitter to receiver.
* **Reflected and Transmitted Rays**: If ray is reflected before reaching the transmission point.
* **Diffracted Rays**: one incident ray spawns many rays due to diffraction.

The three types of rays are illustrated in Figure 15.

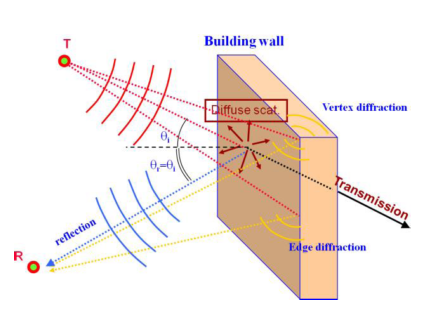


Figure 15 – Reflected, transmitted and diffracted rays on a wall surface [28]

***4.2.2.3 Ray Tracing Algorithms***

The ray tracing algorithms in the following section are discussed in detail in [17], and are listed below:

1. General Theorem: Fermat’s Principle of Least Time
2. Image Method
3. Shooting and Bouncing Ray Method
4. Hybrid methods
5. **General Theorem: Fermat’s Principle of Least Time**

Fermat’s Principle of Least Time summarized simply state that the ray will take the route which takes the least possible time to travel between two points. This principle is used to derive the laws of reflection, diffraction and transmission. It is extended by the image method used to commonly determine the paths of rays.

1. **Image Method**

This algorithm is recursive and can be extended for multiple reflections., in real-world indoor environments this may not be efficient due to the large number of surfaces and the resulting high computational cost.

This method is illustrated in Figure 16. First, the image of the receiver with respect to the reflector is determined. A connection is subsequently established between the transmitter and receiver reflected image . The point of intersection between the connector and the reflector surface is denoted by . By connecting to , the ray path can be traced.

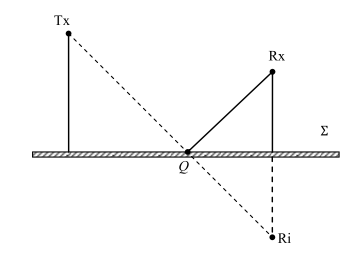


Figure 16 - The image method [17]

1. **Shooting and Bouncing Ray (SBR) Method**

The basic idea of SBR is to launch rays from a source and trace each one to determine if they reach a field point. It consists of three steps: ray launching, ray tracing and ray reception. Ray launching requires a uniform distribution of rays emitted from the source point so that each carry similar power.

Ray tracing allows for the ray to go directly or indirectly from source to destination, depending on whether it intersects any object in the environment. On intersection, the ray is reflected, scattered or diffracted. Ray intersection tests consume close to 90% of computational time in an unsophisticated ray tracing implementation. is deemed to be within the sphere of radius r, where r is defined as (18),

|  |  |  |
| --- | --- | --- |
|  |  | (18) |

where is the angular space between neighboring rays and d is the unfolded path length [43]. The reception of the ray occurs when the ray tube associated with the ray illuminates the receiving point. The respective field can then be calculated. The test determines whether the field point is inside the ray tube of increasing cross-section.

1. **Hybrid Method**

The SBR is simple to implement, but the trajectory may not be as accurate as the image method. Hybrid methods exist which take advantage of both algorithms. For example, in [44] SBR’s faster computational speed is used to determine valid rays received, and then the image method adjusts the chosen ray trajectories. The imaging method can perform quite fast in this setup and has a negligible overhead while improving accuracy.

1. **Wireless Technology**

New advances in the miniaturization of low-power wireless communication are driving the growth of the Internet of Things (IoT). The IoT is designed around small devices capable of operating for long periods on a single battery, whilst transmitting intermittent data about the surrounding environment. Finding a single wireless technology capable of ultra-low-power and an effective communication range is complicated [11].

Numerous wireless technologies have shown promise, including NFC, RFI, Bluetooth Classic, BLE, UWB and ZigBee [11]:

* NFC is limited to a proximity range in the order of several inches, limiting the ease of user interaction.
* Radio Frequency Identification (RFID) has a longer range, but the current cost of an RFID reader limits its practical deployment in commercial environments.
* Bluetooth Classic satisfies the low-power criteria and is available on all smartphones, however its complex discovery and pairing features make it an unsuitable platform for IoT devices.
* BLE has a short range, short data rate and low power consumption, ideal for many IoT applications.
* ZigBee is promising but has not been included in the smartphone industry so is of little use in a public environment.
* UWB has low power consumption but a large data rate and very short range of transmission.

**5.1 GPS**

The Global Positioning System (GPS) is a position and navigation and timing (PNT) utility developed and maintained by the US Air Force. The GPS space segment consists of a constellation of 24 satellites transmitting signals which contain information on the satellite’s position and time. GPS operates at a frequency band between 1550MHz and 1600MHz. The receivers in the user device use geometric triangulation to calculate its location [45].

Currently GPS is the most commonly used localization technique. The advantage of GPS is that its receivers can determine latitude, longitude and altitude to a high degree of accuracy. However, LoS is required for the system to function [46]. Unfortunately, due to its significant attenuation in the RSS, it is infeasible indoors. Therefore an alternative for indoor localization systems is required [3] [47].

**5.2 Wi-Fi**

IEEE 802.11 standard is more commonly known as Wi-Fi. Indoor positioning using Wi-Fi fingerprinting and sensor fusion methods are well established due to the omnipresence of Wi-Fi signals, and typically provide accuracy to within a few metres provided full Wi-Fi coverage of a well-surveyed environment. However, it is time consuming to plan and deploy access points with ideal density and geometry for indoor localization. Furthermore, Wi-Fi is a power-hungry protocol, which is undesirable for many IoT applications [48].

Wi-Fi positioning systems take advantage of the dense Wi-Fi deployment in indoor environments. Wi-Fi technology uses the 2.4 GHz radio frequency band in a wireless local area network (WLAN) to communicate with other devices. These systems use the RSS of different access points (APs) for trilateration, however this approach yields a low accuracy. Fingerprinting can improve the location estimation using a database of RSS value descriptions for a known environment. In addition, sensor fusion using accelerometers, gyroscopes and magnetometers (all available on most smartphones) can further improve the accuracy of the system. The AoA technique uses an array of antennas to receive multiple signals at the access points and triangulates the calculated angles to determine the location of the user [6]. As discussed previously, FTM can also calculate distance using RTT measurements of ToF.

**5.3 ZigBee**

ZigBee protocol stack consists of MAC and Physical layers specified by the 802.15.4 standard, and a set of layers above them specified by the ZigBee alliance. Unlike Bluetooth, which uses frequency hopping, channels are accessed using CSMA/CA. The data rate (250kbps) is much lower than BLE (1Mbps) and other low-rate technologies [12].

ZigBee topology can be star or peer-to-peer. A network can consist of end devices, routers and coordinators. End devices can connect to routers or coordinators which can connect to each other. The router or coordinator listens continuously for the end device to transmit, which is a lot less energy efficient than BLE [12].

ZigBee is a narrow band signal with a 3MHz bandwidth, but only 16 channels spaced by 5MHz. It uses Carrier Sense Multiple Access with Collision Avoidance (CSMA/CA) to avoid interference by sensing if a channel is busy before transmitting. If the channel is busy, a random back off period is waited until transmission is attempted again [49].

An important feature of ZigBee is dynamic channel selection. A scan function iterates through supported channels, and a feature called frequency agility specified in the ZigBee standard is measured to indicate whether ZigBee should move to clear a channel. Frequency agility makes the use of the 16 channels easier, allowing the network to move and adapt over time to changing RF environments [49].

**5.4 Bluetooth Classic**

Excellent summaries of Bluetooth technology basics can be found in [50] and [38], and are the sources of much of the information in this section. Bluetooth is a wireless communication technology designed to connect to peripherals and computers. It is an inexpensive, short-range, low-power radio technology. Because it relies on radio waves, Bluetooth devices can range up to 10m and do not require LoS between each other.

Bluetooth devices operate on the 2.4 GHz licence-free radio frequency band. The band is available worldwide, however devices must compete with other RF emitters. To overcome potential noise, Bluetooth employs frequency-hopping and uses shorter packets than other standards in the RF band. Frequency hopping allows Bluetooth devices to use the entire band, ensures interference will be short lived, and provides a level of security as it makes eavesdropping difficult.

Connected devices must agree on a selected frequency, so a master-slave relationship is established. A Bluetooth device operating in master mode may communicate with a maximum of seven slave devices. The master sends its own address and value of its internal clock to ensure synchronization.

**5.4.1 Protocol Stack**

By providing well-defined protocol layers of functionality, Bluetooth specification ensures interoperability and adaption.

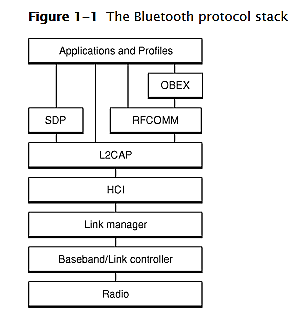


Figure 17 – Bluetooth protocol stack [50]

At the base of the protocol stack is the radio layer. This is responsible for the modulation and demodulation of data into RF signals.

Above this layer is the baseband and link controller layer. The baseband portion of the layer formats data for transmission to and from the radio layer, and handles synchronization of links. The link controller portion carries out the link manager’s command and maintains the link specified by the link manager. The link manager translates the host controller interface (HCI) commands into base-band level instructions.

Bluetooth specifies two types of links: synchronous connection oriented (SCO) and asynchronous connectionless (ACL). An ACL is established between a master and slave at connection. Data packets transmitted over ACL links have 142 bits of encoding in addition to a payload up to 2712 bits.

The HCI layer acts as a boundary between the lower and the upper stack layers. The lower layer is known as the module, and the upper layer is known as the host.

The first upper layer is the logical link control and adaption protocol (L2CAP) layer, which is responsible for establishing ACL connections across existing ACL links, multiplexing between different higher layers, and repackaging data packets from the higher layers into the format required for the lower layers.

The serial discovery protocol (SDP) defines actions for both servers and clients of Bluetooth services, maintaining records of services and their respective universally unique identifier (UUID). OBEX is a transfer protocol that defines data objects and communication protocol two devices may use to exchange those objects.

**5.5 UWB**

Ultra-Wideband (UWB) is a wireless technology that can be employed in indoor localization systems to enhance the overall performance [13]. For high-accuracy localization, UWB is the best solution offered by real-time locating systems, with accuracy in the order of 10-20cm [8] [5]. UWB is authorized to operate unlicensed in the 3.1-10.6 GHz frequency range.

The main advantages of UWB over narrowband RF technologies is its insensitivity to multipath and its high data rate [51]. The transmission pulses of high resolution in the order of a few nanoseconds guarantee high localization accuracy, high data rates and accurate measurements. In such scenarios, methods based on ToA/AoA/phase measurements can theoretically provide higher accuracy than RSS-based approaches [8].

For narrow-band signals, angle/phase measurements take advantage of high SNR but suffer from deep fading. For UWB, time measurements (ToA/TDoA) are sufficient to extract all necessary information from the received signals. ToA-based ranging techniques exploit the fine delay resolution property of UWB signals. This enables centimetre-level accuracy. Moreover, the large bandwidth helps resolve the multipath components, reducing the effect of fading. Localization techniques based on ToA estimation are susceptible to multipath, interference and clock drift, making estimation of the TOA challenging in harsh propagation environments where LoS may not always exist [5] [8].

UWB lost out to the adoption of Wi-Fi and Bluetooth in smartphones and modern electronic devices, and suffered a decline in the last decade. The low device compatibility and unrequired high data rate are factors which limit its deployment for indoor localization systems.

**5.6 BLE**

BLE (also called Bluetooth Smart) is developed, specified and marketed as part of the Bluetooth Special Interest Group. It was introduced with version 4.0 of the Bluetooth Standard as an addition to the Bluetooth Classic. BLE is characterized by its simple pairing, low cost, low data rate and low energy consumption using coin cells. Bluetooth Classic targets higher data rate applications (up to 2.1 Mbps), whereas BLE targets applications with a much lower data rate (up to 0.3 Mbps effective) and with a reduced range [52].

BLE has emerged as a potential candidate to dominate the IoT community, capitalizing on the flaws of the other wireless technologies. BLE eliminates the pairing and simplifies the complex discovery of Bluetooth Classic. Its main advantages are short message exchanges and low power consumption. The fact BLE can be bundled with Bluetooth Classic chips on smartphones makes it easy to implement, and experts predict large spaces will deploy hundreds or even thousands of BLE tags, for localization applications or advertising services and products [11].

There are various vendors which offer system on chips (SoCs) containing a BLE radio and a low power microcontroller capable of running the BLE protocol stack with user application. Such SoCs require very few external components and can be linked relatively easily with C language software and scripts. For smartphones, both iOS and Android offer BLE APIs. As a result of these factors, the development of BLE devices connected to the IoT is increasing considerably [52].

**5.6.1 Principle of Operation**

BLE occupies the same 2.4 GHz radio band as Wi-Fi, and addresses many of Wi-Fi’s shortcomings. Designed for short range, low power messages, it defines many core capabilities including proximity sensing. Proximity applications such as targeted advertising already exploit this technology. However, for more tradition indoor localization applications such as tracking and navigation, the BLE signal needs to be dense at every point in the environment, not just when in close proximity to a beacon [48].

The coexistence between Bluetooth Classic and BLE on the same device is assured using a common MAC layer. The MAC layer also performs channel QoS, RSS measurements and packet loss rate for Bluetooth to maintain an up-to-date collection of working channels. In order to achieve QoS, tests for coexistence with competing 2.4 GHz signals must be performed [49].

Like Bluetooth, BLE uses adaptive frequency hopping spread spectrum to access the shared channel. However, the difference is the hop size for BLE is 43 and the channel width is 2MHz, in contrast to a hop size of 79 for Bluetooth and a channel width of 1MHz [12]. It incorporates 40 channels, each 2 MHz wide, and moves pseudo randomly between these channels to transmit data in short messages. Because of its commitment to low energy, BLE only uses 3 of these channels to advertise its identifier. The advertisement channels are labelled 37, 38 and 39 and are centred on 2402 MHz, 2426 MHz and 2480 MHz, respectively. The receiving device scans over the advertisement channels, pausing every few milliseconds to listen for advertisements. The scan continues indefinitely, and every sighting of an advertisement is reported.

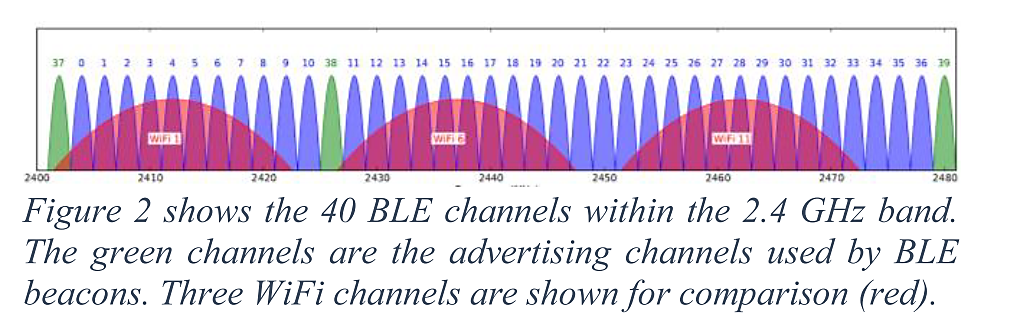


Figure 18 - Green channels represent BLE advertising channels, Wi-Fi channels in red [48]

**5.6.3 Advertising**

BLE employs an advertising (or beaconing) mode that enables short, unsolicited messages to be sent at flexible update rates [48]. The BLE advertising state controls the power consumption of beacons, BLE-based sensors and general device discovery [52].

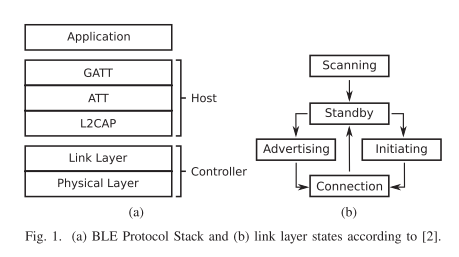


Figure 19 – BLE Protocol Stack and link layer states [52]

The BLE protocol stack in Figure 19 is consists of two main parts, the host and controller. Focusing on the controller, its lower layer (physical layer) is a 40-channel frequency hopping radio in the 2.4 GHz ISM band using GFSK modulation at 1 Mbps data rate. Three channels are dedicated to advertising and the remainder are used for data transmission at a power between 20 dBm and 10 dBm. The radio consumes a large amount of power when in active receive or transmit mode.

The link layer controls the physical layer radio. It is best described as a state machine in Figure 19. In advertising mode, a device broadcasts advertising packets, announcing its presence to nearby devices to connect. Advertisements are periodically repeated on the three advertising channels with intervals of 20ms-10ms. The advertising interval determines the frequency of the transmit phases of a transmitter. Advertising packets consist of a frame and the packet data unit (PDU). This adds a 10 byte overhead to the 37-byte maximum available payload. Packet length influences the duration of transmitter and receiver phases [52].

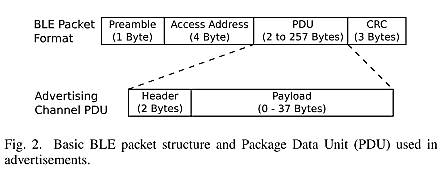


Figure 20 – BLE packet structure and PDU used in advertisements [52]

When performed successfully, advertising and scanning results in a connection establishment between nodes. In Figure 21, node m1 is advertising and node m2 is scanning. *T\_advEvent* is the sum of *advInterval* and *advDelay*, the latter being a pseudo-random time between 0ms and 10ms [15].

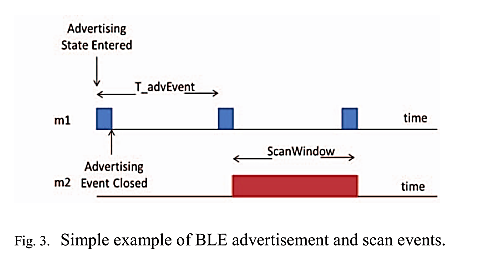


Figure 21 – Example of BLE scan and advertisement events [15]

A BLE device can be connected to any number of peripheral devices at any time, unlike Bluetooth Classic which can only support a maximum of seven devices. BLE uses profiles rather than the protocols of Bluetooth Classic, with the two main profiles being Generic Access Profile (GAP) and Generic Attribute (GATT) profile [16].

GAP profile defines pairing and connection parameters for BLE, whereas GATT on the other hand defines the various traits and features of the BLE device. Every profile consists of services and characteristics. A service defines the behaviour of a device. Characteristics are a subset of services and relates to the data that is sent over the connection [16]. The L2CAP profile multiplexes the data channels and assembles chunks that belong to large packets [12].

GAP defines two roles, Central and Peripheral. Peripheral devices advertise BLE packets at predefined time intervals. Central devices are scanning devices which scan for the advertised BLE packets and data that follows. Central devices initiate connection and update parameters. Both central and peripheral devices can terminate the established connection. When the device is not scanning it enters a power-saving deep-sleep mode. Modes for BLE devices include deep-sleep, hibernate and stop mode [16].

**5.6.4 Power Consumption**

IoT is extending the scope of the internet to include physical objects not considered as traditional networked devices. BLE is a promising solution that enables sensors to feed small data to the internet efficiently for long durations of time [12].

BLE topology is a star, since devices can act as a slave or a master. The slaves advertise on one or more of the three advertising channels, and the master scans these channels to discover slaves. At discovery time, both wake up in synchrony and exchange data. Both devices sleep at all other times, conserving power [12].

As battery life is a key selling point of BLE, power consumption plays a major role in the future success of the technology. Consider a large scale indoor localization system using hundreds of BLE beacons. Replacing dead batteries regularly would be both time consuming and expensive. Typical power supplies range from CR2032 coin cells to AA batteries. With a typical target lifespan up to ten years, the power budget must be strictly limited. BLE beacons cyclically broadcast messages at intervals ranging from 100ms-10s. It is critical to find the perfect trade-off between performance and power consumption [52].

**5.6.5 Ranging Precision**

The measurement of distance using RSS strength is accurate when within a meter of the transmitter and when there is LoS. The RSS decreases proportional to the inverse of the square of the distance to the source [48].

However, the ranging performance degrades drastically with range. The human body also attenuates 2.4 GHz radio signals which impact the ranging estimation. Figure 22 shows that when within 10 cm of the transmitter, the ~10 dB reduction caused by the body does not drastically affect the proximity estimation, whereas out by 1 meter the ranging error is ~5 meters [48].

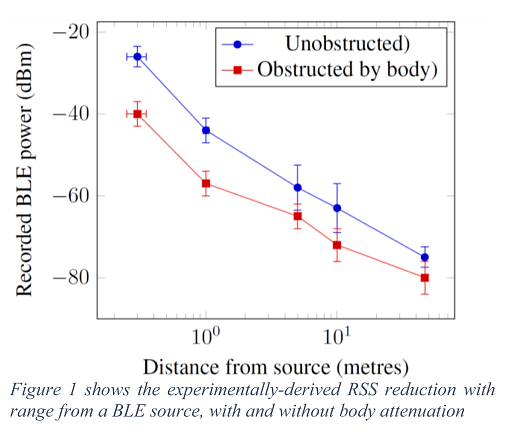


Figure 22 – Experimental RSS attenuation loss from a BLE source, with and without body attenuation [48]

The Friis radio link formula uses antenna power and gain to calculate the transmission distance. The logarithmic attenuation model analyses the relationship between the RSSI values and the transmission distances as show in [6]. The distance can be determined from the logarithmic attenuation model as follows in (6) and (7), where is the RSS at do, which is 1 meter from the transmitter.

|  |  |  |
| --- | --- | --- |
|  |  | (6) |
|  |  | (7) |

Once distances between receivers and transmitter have been determined, trilateration can determine the receiver’s location. A system of equations can solve the location if the ranges of each beacon and their locations are known [6].

Rather than selecting location based on data from the beacon of highest RSS, it is possible to estimate position based on multiple RSS values from different beacons. The range of a beacon is estimated based on its RSS, and a position that minimizes the error between measured and actual distances. This greatly improves resolution and offers potential for localization between beacons. However, it comes at a cost: a signal propagation model is required to transform multiple RSS measurements to distances, which is influenced significantly by disturbances. With limited number of beacons per room, disturbances result in a tracking error in the order of several meters, unsuitable for indoor localization [53].

1. **Related Work**

This section investigates the recent research and literature that is relevant to this project. The literature is grouped under separate areas of interest related to this project.

**6.1 Low power consumption**

Low energy consumption is the main theme throughout the research referenced in this literature review. One such study is [52], which investigates the power consumption of BLE devices in advertising state on a SoC independent system. The study highlights the large impact of the receive phase, which can result in denial of sleep attacks. Research in [12] [54] investigates the low-energy performance of BLE in contrast to ZigBee. The results of these studies agree to indicate that BLE is highly energy efficient in terms of number of bytes transferred per Joule spent, but could be improved by increasing the data rate per connection event and implementing adaptive frequency hopping to combat interference.

Another approach to conserving energy is presented in [11], which investigates the potential problem of BLE deployment in dense IoT environments with high collision rates. The impact of such collisions had been largely ignored before this article. The first issue is BLE’s active scanning mode, where control messages can overwhelm a wireless channel even with only a few scanning devices. Opportunistic Listening is proposed, which leverages responses from other device’s requests and allows scanning devices to better share the channel. The second source of contention is passive advertisement devices degrading the channel due to the increased number of advertising tags. An aggregate advertisement can silence redundant passive devices and reduce wasted energy.

**6.2 Indoor Localization**

There are several novel implementations of BLE in indoor localization and target tracking systems. These systems employ techniques such as machine learning, sensor fusion, beaconing and signal error mitigation.

**6.2.1 Machine Learning**

Machine learning is commonly applied to indoor localization techniques to enhance the BLE localization accuracy. Research in [1] investigates the improvement of localization accuracy using fingerprint information from different channels, and implementing machine learning techniques such as SVM and KNN algorithms. [2] also studies the indoor localization problem in the machine leaning framework. The influence of geometry and the quantity of access points (APs) on localization error is demonstrated. The probabilistic approach (Gaussian kernel) has a slightly lower localization error than the non-probabilistic method (k-nearest neighbours). The results are encouraging, and perhaps could be further improved with the correct application of more robust machine learning methods (support vector machines or deep neural networks may be possibilities). The fact that this method can be applied on existing wireless communication infrastructure should drive continued research in this area.

**6.2.2 Sensor Fusion**

Noise reduction and estimation algorithms such as the Kalman filter are frequently applied to indoor localization methods [6] [51] [55] [56]. Research in [55] proposes implementing a Kalman filter to fuse indoor localization data using an inertial measurement unit (IMU) and BLE. This approach has great advantages for deployment in wearable devices which include IMUs. The key advantages of using an IMU in such technology is that it does not suffer from a signal blockage. However, they suffer from long-term accumulation of drift due to sensor bias. RSS from a low-power technology such as BLE can perform trilateration but suffers in multipath and NLoS environments. Combining BLE with IMU readings provides a highly accurate localization estimation.

**6.2.3 Beacons**

BLE beacons are low cost, low energy and are attractive for industrial and retail applications. An asset tracking using BLE technology is presented in [57], explicitly designed, implemented and tested for use on construction sites. The research focuses on the use of an ad hoc sensor network comprised of BLE beacons, RFID tags and smartphones. The paper demonstrates a satisfactory energy/accuracy trade-off that exists to optimize performance while battery time lasts long enough for a typical work shift (8 hours).

Similarly, [6] develops a BLE personnel tracking system using four beacons and a smartphone with BLE support. A Kalman filter is used to reduce the Gaussian noise in the model and improve accuracy. Trilateration using RSS measurements provides an estimation to an average error of 1.8m at an update rate of 0.5s. This error is relatively high, and requires fingerprinting and sensor fusion to improve the accuracy.

Targeted advertisements commonly use cameras to tailor advertisements to a user’s presumed gender and other features. Research in [58] proposes the use of BLE beacons for targeted advertising using digital signage. The user inputs their desired attributes into their device, and when they approach signage the data is broadcast. The server parses the data and replies with a targeted advertisement relevant to the user. The accuracy is superior to the camera-based method of targeted advertising, but requires a greater level of application configuration and does not include some useful features such as eye tracking or facial reactions to advertisements.

**6.2.4 Signal Error Mitigation**

Multipath can assist in indoor navigation systems, as demonstrated by [14]. Errors can be mitigated by detecting NLoS situations and matching the travel times of specular multipath components to the geometry by introducing virtual anchors, assuming the floor plan environment is known.

Spatial and frequency diversity are utilized to mitigate multipath effects to improve accuracy of indoor localization systems in [59]. IMUs are included in a hybrid localization system using sensor fusion. The solution to multipath error is the use of diversity, combining redundant and decorrelated RF channels. This simultaneous diversity approach is shown to compensate fade, reduce the maximum error for all eight combined RSS values by more than 34%, and lead to a more reliable localization technique in the presence of multipath and external interference signals.

[49] analyses the impact of a BLE sensor network on a crowded 2.4GHz environment, containing multiple ZigBee sensors, Wi-Fi routers and Bluetooth technology. All measurements are carried out in a full anechoic chamber. It is found that the human body absorbs part of the signal, and that BLE coexists well with other technologies in the 2.4GHz range due to its use of frequency hopping.

[60] presents a method for position localization in an ad hoc network using AoA measurements between neighbouring nodes. The absolute coordinates and orientations that it provides neighbouring nodes is ideal for disconnected networks, which suffer from NLoS.

**6.3 Automotive**

The modern automotive industry requires many different sensors to provide information on peripherals and essential features. The increased complexity of wiring such sensor networks has driven the motivation for cable replacement with low-energy wireless communication candidates such as BLE. This reduces the cost of manufacturing and maintenance, and improves fuel efficiency greatly. Research in [15] investigates the trade-off between reducing BLE energy demands and the worst-case latency guarantee. BLE is declared as the leading technology for maximizing the energy-latency trade-off in automotive applications.

A car parking lot is an example of a dense multipath urban environment that this project aims to provide localization systems in. Keyless Entry (PKE) is explored in [16] using a Programmable System on a Chip from Cypress Semiconductor (PSoC-4 BLE) with a BLE peripheral as the host and the user’s smartphone as a client. A predefined whitelist on the client decides which host is granted access to the client. The solution is extremely energy efficient and sufficiently secure. A shield provides additional security inside the vehicle door by blocking BLE signals which produce false positives, acting like a Faraday cage on all sides except the side facing the door. However, the problem has yet to be satisfactorily demonstrated for NLoS situations.

Research in [61] evaluates BLE as a technology to implement sensor engines in modern automotive designs. A blind zone alert system is installed in the rear of the vehicle, detecting the presence of a target using the RSS of the packets broadcast by BLE sensors. The proposed system is simple to implement on existing sensor networks, but has a significant false positive rate of 15%.

**6.4 Fingerprinting**

Fingerprinting is a widespread trend of research in BLE technology in indoor localization systems. [48] explores the use of BLE for fingerprint indoor positioning. The lower bandwidth of BLE makes it more susceptible to fast fading and RSS fluctuations compared to Wi-Fi. This problem is diminished by batch filtering multiple RSS measurements, providing a smoothing effect on the BLE RSS signal. Position accuracy increases with the number of beacons up to around 6-8 beacons, after which there is no further improvement in position accuracy. In the four years since the study was published, there have been further advancements in fingerprinting positioning techniques, but in general the same problems persist which limit the practical deployment of fingerprinting in complex indoor environments.

Some of these indoor positioning problems are investigated further in [53], which details simple tests to measure the effects of distance, walls, doors, user’s body and antenna anisotropy on RSS throughout the day. The fingerprinting localization and site survey degrades throughout the day. The influence of walls and doors on observed RSS values is significantly less than the influence of antenna orientation or shadowing effect from user’s body. A supervised learning method using RSS measurements throughout the room is successfully implemented, using Principle Component Analysis and K-Nearest Neighbours. This method predicted the room label to a 99% accuracy. A drawback to this approach is the possible large training set that would be required for large indoor environments.

Fingerprinting can be enhanced by sensing and dynamically adapting to changes in the environment. Research in [30] incorporates a simple wireless vision sensor to enhance a fingerprinting solution by improving its overall accuracy. Ultimately the computational and power cost far outweigh the attempted enhancements.

**6.5 Propagation Models**

Research is trending in the direction of propagation model design, with ray tracing and full-wave frequency domain models the most popular in recent studies. In [19] a semi-deterministic channel 2D ray tracing model is tested on a UAV flying in a dense urban area, with the obtained parameters recorded. In a similar UAV application, [62] investigates a commercial-off-the-shelf (COTS) array for localizing stationary signal anchor nodes on the surface. The advantage of using this modular COTS-based approaches is the flexibility, low cost and simple deployment compared to traditional phased antennas. The challenge this approach faces is aligning the radios to ensure coherent phase detection.

Beams are similar to rays, the only difference being that they possess a thickness. [28] summarizes the recent implementations of large antenna arrays for pencil-beam forming to cope with the high throughput density requirements of future gigabit-wireless applications. [20] implements a fast and accurate beam-tracing algorithm that can simulate radio wave propagation, including effects such as multipath propagation due to reflection and refraction.

The full wave frequency domain models are investigated in [21] [41] [42]. [21] offers a preliminary investigation of power delay profile computation from a full wave frequency domain indoor propagation model. The generated PDP closely matches the GO model, and includes other interactions ignored by GO. Research in [41] [42] discusses integral equation approaches for indoor wave propagation modelling. The VEFIE convergence rate is shown to be significantly better than that of the SEFIE. VEFIE is applied to the problem of indoor localization in. The PDP contains more information than the GO model as it includes every electromagnetic interaction. Popular empirical methods, such as the Motley-Keenan model and the COST231 Multi-Wall model lack this model’s accuracy and reliability.

Empirical propagation models are equally popular in modern research. The COST231 model correction factors are tuned in [63], and the model is compared to Motley-Keenan in [22] for location estimation in indoor environments. The best results were achieved with the simple COST231 model. The Motley-Keenan propagation model is enhanced in [18] to include information on the nature and thickness of walls. This has the effect of increasing the model accuracy, although the computational processing required likely outweighs the benefit in this application.

**6.6 Ultra-Wideband Signals**

The use of UWB signals was investigated thoroughly as a possible alternative to using BLE. Research in [5] [8] [13] [64] [51] [56] demonstrates the high accuracy of UWB. [51] presents a dynamically adapting covariance Kalman Filter that implements sensor fusion of UWB and inertial sensor measurements. Machine learning approaches [13] and ToA based estimation [5] are the most promising in cluttered propagation environments, where the discrete separable nature of the signal lends itself well to accurate estimation. However, the cost of the hardware required to implement UWB localization systems, lack of practical implementation and lack of device compatibility compared to BLE are notable drawbacks.

One of UWB’s most promising application is in Impulse Radio (IR) UWB. Due to the short pulse width, high resolution when resolving multipath components, and its accurate estimation of ToA, the IR-UWB technology has received increasing attention in recent years [13] [64]. IR-UWB has been deployed in UAV platforms for GPS assisted navigation, high precision positioning systems based on the TDOA algorithm. Despite its intrinsic temporal resolution, IR-UWB signals have short wavelengths and are still subject to severe intra-channel interference caused by dense colliding multipath components [64].

**6.7 Security**

A topic often overlooked by researchers is privacy and security issues for BLE devices. [65] investigates the potential privacy threat of BLE devices. It is discovered that most BLE devices do not take advantage of the existing BLE privacy features such as elliptic curve cryptography. Similarly, [66] explores the security issues regarding the use of selective jammers on BLE beacons. The narrowband jammer works on the advertising channels and is difficult to detect. Despite the effectiveness of the jammer, it can be mitigated by choosing a pseudo-random channel hopping pattern based on a common key between the transmitter and the receiver.

1. **Hardware**

This section provides a summary and brief description of the proposed hardware to be tested in this project.

* 1. **Agilent 4432B Signal Generator**
* Capable of generating signals with frequencies ranging from 250kHz- 3.0GHz.
* Communicates to LAN network via a GPIB connection.
* The Python scripts for connection and control of signal generator can be found in Appendix E.1.
* Manual:
  + <https://literature.cdn.keysight.com/litweb/pdf/5989-4074EN.pdf?id=751061>



Figure 23 – Agilent 4432B signal generator

* 1. **Rohde & Schwarz FSV Signal Analyzer**
* Capable of analyzing signals with frequencies ranging from 10Hz-13.6GHz.
* Communicates to LAN network via Ethernet connection.
* The Python scripts for connection and control of signal analyzer can be found in Appendix E.1.
* Manual:
  + <https://cdn.rohde-schwarz.com/pws/dl_downloads/dl_common_library/dl_manuals/gb_1/f/fsv_1/FSVA_FSV_UserManual_en_10.pdf>



Figure 24 - R&S FSV Signal Analyzer

* 1. **Antennas**

The Taoglas GW.26 2.4 GHz Monopole Antenna SMA(M) is used during the frequency sweep to transmit and receive on the signal generator and signal analyzer respectively.



Figure 25 - Taoglas Monopole Antenna

* Datasheet: <http://www.taoglas.com/product/gw-26-2-4ghz-monopole-antenna-smam/>
* Operating temperature: -40/+85 °C
* Impedance: 50 Ω
* Omni-directional

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**Appendix A.1**

**Hilbert Transform Derivation**

The following derivation for the Hilbert transform is based on information from [67]. To recover a signal the Inverse Fourier Transform is required.

|  |  |  |
| --- | --- | --- |
|  |  | (27) |

Another form of the Fourier inversion theorem is that the signal in the time-domain is interpreted as a type of Cauchy Principle value.

|  |  |  |
| --- | --- | --- |
|  |  | (28) |

If f(t) is a real function, then

|  |  |  |
| --- | --- | --- |
|  |  | (29) |

Therefore, the positive frequency spectra is sufficient to represent a real signal. is a function that is zero for all negative frequencies and for all positive frequencies.

|  |  |  |
| --- | --- | --- |
|  |  | (30) |

The relationship between and can be seen. The inverse Fourier transform of is therefore

|  |  |  |
| --- | --- | --- |
|  |  | (31) |

where is a complex function given by (32).

|  |  |  |
| --- | --- | --- |
|  |  | (32) |

It can be shown that g(t) is real in (33).

|  |  |  |
| --- | --- | --- |
|  |  | (33) |

The definition of the Fourier Transform matches with , giving the Fourier transform (34).

|  |  |  |
| --- | --- | --- |
|  |  | (34) |

The result of the inverse transform of is . This gives the Hilbert transform, and a real result for signal .

|  |  |  |
| --- | --- | --- |
|  |  | (35) |

**Appendix A.2**

**Full Wave Propagation VEFIE Formulations**

VEFIE is derived from Maxwell’s equations using the volumetric equivalence principle and expresses the total electric field in terms of an incident electric field and a scattered electric field [41]. Advantages of 2D VEFIE is significantly quicker run time, despite introducing new inaccuracies in the model [41].

The VEFIE is discretized into N uniform cells. The electric field is expanded using the pulse basis functions and the method of moments (MoM) is applied to the VEFIE. The result is in matrix form which can be solved iteratively.

The PDP is computed by solving the VEFIE independently for many frequencies. Each solution gives the total field for all points, enabling the PDP to be computed for many points within the environment without any extra overhead after it has been solved for each frequency [41].

Geometrical Optics (GO) is used to validate the VEFIE PDP, determining when the pulse should arrive (36) [41].

|  |  |  |
| --- | --- | --- |
|  |  | (36) |

where R is the distance the wave travels and is the speed of light. The GO model predicts when the LoS pulse should arrive, in addition to various reflections. The VEFIE PDP includes more information than the GO because it includes every electromagnetic interaction. It can capture the effect on the received signal between major pulses, unlike the GO model. The VEFIE model also can provide detailed information on the power received at each angle of arrival over ray tracing as it considers every interaction and scatterer. Popular empirical models do not produce the detail that the full wave model approach produces [41].

**Appendix B**

**Project Plan**



**DUBLIN CITY UNIVERSITY**

**SCHOOL OF ELECTRONIC ENGINEERING**

**Characterization of Reflectors in a Wireless Channel to Aid Low-Power Indoor Localization**

**Project Plan**

**Aidan Smyth**

ID Number: 13452192

30th of August 2018

MASTERS OF ENGINEERING

IN

Electronic Systems

**1. Project Scope**

*“Which wireless technology and propagation model can provide the best trade-off between high accuracy and low computational cost for low energy wireless channel reflector characterization to aid in indoor positioning?”*

The scope of this project is indoor and dense urban propagation environments where reflection, diffusion and scattering of the signal is likely. The solution is targeted at indoor and dense environments.

**2. Selected Solution**

BLE is selected as the wireless technology that is most appropriate for a novel indoor localization system. As discussed in Section 5.6, there are several advantages that BLE has over other wireless communication technologies compared to other wireless communication technologies. It performs better than UWB in NLoS environments, has better device compatibility and is low power [8].

The indoor environment will be a large auditorium at Cypress Semiconductor. There should be several reflectors present in the indoor environment, which should be seen after the ray tracing algorithm is implemented. The initial main milestone will be to perform a frequency sweep of the channel chosen for several positions in the auditorium. The sweep will be between 2-3 GHz, although this can be later narrowed if required to suit the analysis of BLE and the ray tracing model inputs.

After the initial sweep, the frequency magnitude data stored in a CSV file will be post-processed on MATLAB. The signal’s phase can be calculated using the Hilbert transform. With both the magnitude and phase, the time representation of the sampled signal can be deconvolved from the sinc function induced by sampling. This gives the true power as a function of time seen at the receiver antenna, known as the power delay profile (PDP).

The power delay profile of several different locations is the input to both the ray tracing and other deterministic models. As previously in the Literature Review, ray tracing is an effective solution for characterizing wireless RF reflectors in an indoor environment. Its ability to simulate multipath propagation including the time and space dispersion characteristics of the channel is the reason that it is chosen ahead of the other propagation models.

**3. Deliverables**

The project plan in this section is a coarse framework for time management. The project plan begins in the first week after arrival at the industrial placement, Cypress Semiconductor in San Jose. Although the project plan is detailed, it is flexible and subject to change depending on conflicting academic duties or unexpected problems encountered. Contingency periods are included in the often-generous time allocation per task. As each deliverable is reached, the project plan is updated.

|  |  |  |  |
| --- | --- | --- | --- |
| Task | Time Allocated | Target Completion | Status |
| *SPRING SEMESTER 2018 - Beginning January 22nd* | | | |
| Begin industrial placement at Cypress in SJ. | 1 day | Start of Week 1 | Complete |
| Meet supervisor and team | 1 Week | End of Week 1 | Complete |
| Decide desired project problem to be solved | 1 Week | Start of Week 2 | Complete |
| Agree project with both academic and industrial supervisor | 1 day | Start of Week 2 | Complete |
| Research recent news and state of art in chosen project field | 1 Week | End of Week 3 | Complete |
| Read research papers | 3 Weeks | End of Week 6 | Complete |
| Simulate multipath effect on MATLAB | 2 days | End of Week 5 | Complete |
| Script hardware for remote setup |  |  | Complete |
| Write Literature Review | 2 Weeks | March 12th | Complete |
| Setup Indoor Test Environment | 1 Week | End of Week 8 | Complete |
| Acquire equipment necessary (antennas, platforms, switches etc.) |  |  | Complete |
| Oral Presentation | 1 week | April 2nd | Complete |
| Perform initial RF measurements | 2 Weeks | End of Week 10 | Complete |
| Obtain plan of room | 1 Week | End of Week 11 | Complete |
| Observe factors that affect channel inside room | 1 Week | End of Week 12 | Complete |
| *END OF SEMESTER - EXAM PERIOD* | | | |
| *SUMMER INTERNSHIP - Beginning May 28th* | | | |
| Hilbert Transform and PDP calculation | 4 Weeks | Early June | Complete |
| Model multipath effect in room | 2 Weeks | Mid-June | Complete |
| Ray Tracing Model Design | 1 Month | Mid July | Complete |
| Ray Tracing Model Enhancement | 3 Weeks | Early August | Complete |
| Testing, Critical Assessment and Writing of Thesis | 2 Weeks | Late August | Complete |
| Portfolio Submission | 1 day | September 1st | Complete |
| Final Interview & Assessment | 1 day | Mid-September | TBD |

**4. Success Criteria**

The success criteria of this project is to identify, simulate and deploy a localization system that can identify reflectors in a wireless channel that may aid in increasing indoor localization accuracy, while also maintaining a low energy cost:

* Acquisition of PDPs using the Hilbert transform which are realistic in the indoor geometry.
* Identification, confirmation and prediction of multi-path reflectors in indoor environment using novel ray tracing techniques.
* Identification of wireless channel characteristics.

**5. Revision Status**

The literature review and project plan in this portfolio are the second version submitted, and reflect the changes in research goals as the project evolved over time. The original research had the scope of real-time low-energy indoor localization using ray tracing. It focused on compare the energy consumption and accuracy of deterministic and empirical models in real-time applications using BLE technology.

During the pursuit of this goal, the benefit of characterizing reflectors in a wireless channel became apparent. Knowledge of the reflector locations could increase knowledge of the wireless channel and increase the accuracy of future indoor localization applications. This worthwhile goal of characterizing reflectors is achievable by the development of novel ray tracing simulations for characterizing reflectors in the channel.

**Appendix C**

**Testing & Results**

1. **Setup**

A frequency sweep is necessary to characterize of reflectors in a wireless channel. The most suitable environment available to perform this is an auditorium. It is a large open environment, has no obvious competing strong signals, and possesses at least one suspected reflector (an elevator shaft close to the perimeter). The walls and doors are light and mobile, so are not considered strong reflectors. In all subsequent frequency sweeps, PDP analysis and ray tracing simulations were carried out and modelled on the geometry of this room, pictured in Figure 26.



Figure 26 - Auditorium indoor environment and setup

1. **Apparatus**

The following hardware and software is used to characterization of the reflectors in the wireless channel:

* Agilent ESG-D Series Signal Generator, Ethernet cable and power source.
* Rohde Schwarz FSV Spectrum Analyzer and power source.
* GPIB-USB connection to connect signal generator, since no Ethernet connection to signal generator was available.

The roles of each apparatus are described in Table 4.

|  |  |
| --- | --- |
| Apparatus | Role |
| FSV | * Ethernet connection enabled to 1059 port D. * Fixed position on table. * Power source connected beside port D. * All control and sweep settings are configurable and scripted. |
| Signal Generator | * Need to manually turn RF on and modulation off, not scripted yet. * On trolley with laptop. * Power source connected to extension reel. * GPIB-USB connects sig-gen to laptop. * Tx at 14 dBm to overcome most garbage and competing signals. |
| PyCharm Text Editor | * Run python scripts to automate remote synchronized frequency sweep between the FSV and signal generator. * Fully programmable parameters * Stores results in CSV file. |
| MATLAB 2018 | * Performs post-processing on frequency sweep data, returning PDP for specified position and sampling parameters. * Performs ray tracing for the auditorium geometry. |

Table 4 - Apparatus and their role in the project setup

1. **Automation**

The signal generator and spectrum analyzer are scripted to be run in a parallel and automated manner. The main benefit achieved by adopting these scripts into a frequency sweep setup is performing a controlled sweep that carefully monitors the effect of the signal on each spectral line in a controlled and even manner. The automated configuration of the signal analyzer and signal generator reduces the time consuming manual setup of sweep setting. Table 5 lists the automated instrument control scripts and describes their functionality. The scripts can be found in Table 5.

|  |  |
| --- | --- |
| SCRIPT | DESCRIPTION |
| *main\_sweep\_script.py* | * Main run script * Specifies signal analyzer parameters:   + IPv6 address   + Frequency range   + Frequency step size   + Averaging of spectrum * Specifies sig-gen parameters:   + GPIB address   + Transmission power   + Frequency range and step size * Specifies CSV results parameters:   + Loops to average over   + Run time * Print CSV results |
| *SG\_CTRL\_function.py* | * Sig-gen class functions * \_\_init\_\_ (self, GPIB address, sg)   + List VISA resources   + Connect to GPIB address specified * connect (self)   + Clear instrument for use   + Print welcome message on console * set\_sg (self, frequency, power)   + Set start frequency of sweep in GHz   + Set in dBm |
| *SA\_CTRL\_function.py* | * Signal analyzer class functions * \_\_init\_\_ (self, LAN, resource string)   + List VISA resources   + Connect to LAN address specified   + Setup VXI-11 resource string * fsa\_connect (self)   + Clear instrument for use   + Print welcome message on console * fsa\_set\_fc\_GHz (self, frequency, power)   + Set start center frequency of sweep in GHz * fsa\_set\_fspan\_MHz (self, frequency span)   + Set frequency range of sweep in MHz * fsa\_measure\_peak (self)   + Measure peak of signal * fsa\_set\_average (self, averaging number)   + Set the signal output to be an average of a specified number of points |
| *pdp\_gen.m* | * Convert frequency sweep to power domain profile, i.e. time representation of wireless channel   + Find magnitude of channel   + Apply Hilbert filter to extract phase of channel   + Retrieve signal and IFT to get time domain representation, using discrete band-pass sampling   + Deconvolve sinc introduced by Gibb’s phenomenon due to band-pass sampling   + Plot figures |

Table 5 - Instrument automation scripts

1. **Frequency Sweep**

The automated scripts were used to perform a frequency sweep in the auditorium from 2-3 GHz in steps of 500 kHz. The frequency sweep returned the below wireless channel magnitude frequency responses. As expected, the positions that transmit a further distance are received with less magnitude at the spectrum analyzer. There is a tap in all the responses typically between 2.1-2.2 GHz. The positions that transmit further distances (positions 5, 7, 9) all display several smaller taps and magnitude frequency response variations.

|  |  |
| --- | --- |
| Figure 27 – Frequency sweep at position 1 | Figure 28 – Frequency sweep at position 3 |

|  |  |
| --- | --- |
| Figure 29 – Frequency sweep at position 5 | Figure 30 – Frequency sweep at position 7 |
| Figure 31 – Frequency sweep at position 9 |  |

To further highlighting the benefits of scripting the frequency sweep, a manual sweep trace on the signal analyzer is performed and can be seen in Figure 32 for transmission at position 9. The automatic sweep in Figure 31 clearly contains more information about the wireless channel characteristics than the manual maximum-hold type sweep performed by the signal analyzer. The manual signal analyzer sweep is not co-ordinated with the signal generator, and its maximum hold and lower data point count results in less information being retained during the sweep and susceptibility to short fluctuations in channel signal.

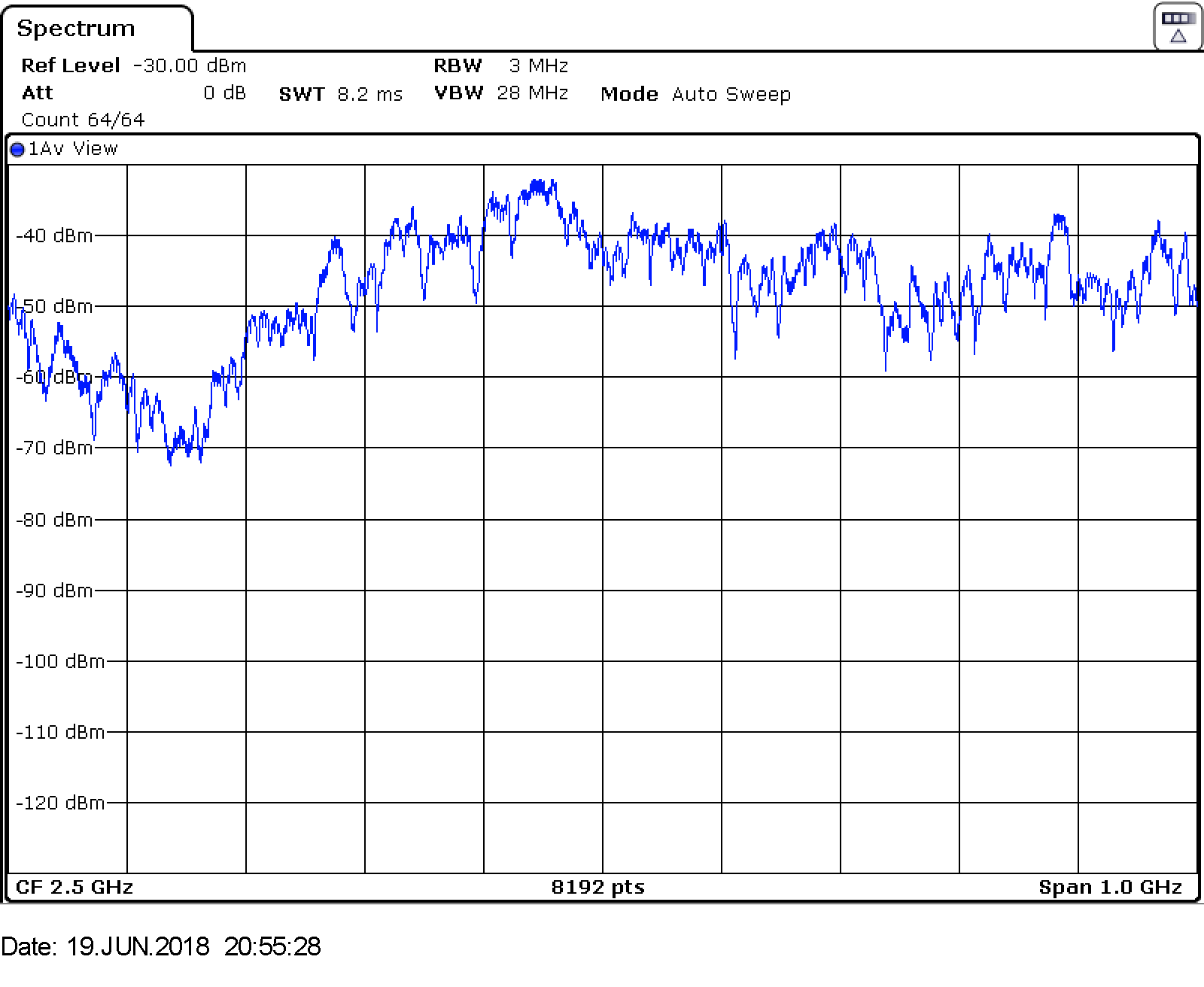


Figure 32 - Results of manual signal analyzer sweep for position 9

However, the manual signal analyzer sweep function is useful in this investigation. If the signal generator is powered off, a frequency sweep of the wireless channel with no signal transmitted from the generator can be performed to observe wireless channel noise. The results in Figure 33 show a noise signal in the channel in the 2.4-2.5 GHz range strong enough to interfere with the received signal at the antenna. Other smaller narrowband signals are present, but have negligible power once in the wireless channel characterization.

A screenshot of a social media post

Description generated with very high confidence

Figure 33 - Manual sweep of noise when no signal generated

1. **Power Delay Profile**

**5.1 Generation**

In Figure 33 it is shown that the channel experiences significant interference in the 2.4-2.5 GHz range. To mitigate this unwanted noise in the wireless channel characterization the effective bandwidth is reduced from the 2-3 GHz swept to 2.0-2.4 GHz. The decision to take the lower half of the bandwidth is arbitrary, from 2.5-3 GHz is equally effective.

The MATLAB script for PDP generation is found in Appendix E.3. The positions are listed using a co-ordinate system for the measured test environment in inches. Depending on the position case, different sweep results are loaded as the script’s input. The position is used to find the LoS distance between the chosen transmitter and the fixed receiver, which will be used for the time delay of the LoS path later in the program.

The bandpass nature of the frequency channel swept imposes certain requirements when converting and sampling the time domain representation of the data. The frequency resolution and bandwidth have been determined during the sweep. The bandwidth is 0.4 GHz, and the frequency resolution is 500 kHz. The sufficient sampling frequency parameter is chosen to be twice the sampling frequency to satisfy the Shannon-Nyquist sampling theorem [68]. The spectral lines are the number of distinct frequencies swept, i.e. the bandwidth divided by the resolution. The time sampling parameters are also declared. The time resolution is equal to the inverse of the sampling frequency, and the number of time samples is twice the spectral lines.

|  |
| --- |
| delta\_f = f(2) - f(1); % frequency steps  B = Fu - Fl; % Bandwidth  Fs = 2\*B; % Sampling frequency  SL = B/delta\_f; % increase B or reduce delta\_f    t\_samples = 2\*SL;  delta\_t = 1/Fs;  t\_span = t\_samples\*delta\_t;  t = delta\_t:delta\_t:t\_span; |

As outlined in Section 2, the PDP is the time domain characterization of the wireless channel, in this case given by the Inverse Fourier Transform (19):

|  |  |  |
| --- | --- | --- |
|  |  | (19) |

The IFT can only be performed if we know both the channel frequency magnitude and phase responses. This can be expensive to measure, particularly in cheap low-energy WSNs. This research proposes the use of the Hilbert transform to extract the phase directly from the magnitude measured, eradicating the need to measure both magnitude and phase. This is only the case if the signal is minimum phase. This is a safe assumption if there is LoS present.

The frequency magnitude response is straightforward to determine. The magnitude squared is equivalent to the absolute gain, that is the RSS minus the transmission power at the signal generator. This is described in (20) and the code snippet below below.

|  |  |  |
| --- | --- | --- |
|  |  | (20) |
| abs\_gain = abs(s - Tx);  abs\_Hfi = 10.^(abs\_gain./(2\*10)); | | |

The Hilbert transfer is applied to extract phase. Direct measurement of phase can be avoided using Hilbert transform, based on the safe assumption that signal is minimum phase (when LoS present). The Hilbert filter is implemented with a passband of normalised sampling frequency 0.1-0.9 radians per sample. The transition band of the filter is gradual. A filter order of 16 provides satisfactory smooth magnitude response in the passband.

|  |
| --- |
| fo = 16;  h = firpm(fo,[0.1 0.9],[1 1],'hilbert'); |



Figure 34 - Hilbert filter magnitude response

The group delay is the average delay of the filter as a function of frequency. The mean of the result of the function grpdelay(h)in Figure 35 indicates how many zeros to prepend to the complete phase and complete signal later in the program.



Figure 35 - Hilbert filter group delay

|  |
| --- |
| grpdel\_h = mean(grpdelay(h));  h\_delay = zeros(size(h));  h\_delay(grpdel\_h+1) = 1; |
|  |

As stated in Section 2.2.5, the phase of the signal can be retrieved using the Hilbert transform of the natural log of the magnitude of the signal response . The group delays are included for both the phase and magnitude responses, allowing the reconstruction of the signal .

|  |
| --- |
| fx = log(abs\_Hfi); % input to Hilbert: ln(|H(w)|)  phase = -conv(h,fx); % Apply filter to get phase  abs\_del1 = conv(h\_delay, fx); % Apply filter to get abs delay  % synchronize phase and mag delays  phase = phase(grpdel\_h + (1:length(fx)));  abs\_del = abs\_del1(grpdel\_h + (1:length(fx)));  Hw = exp((abs\_del + 1j\*phase)); % H(w) reconstructed! |

The next step is to convert to a discrete time PDP, or depending on time sampling preferences. This is achieved using the Inverse Fourier Transform (IFT). Prior to performing the IFT the frequency response must be ramped to introduce the time delay of its LoS component. The frequency is shifted once to allow for the ramping at 0 normalized frequency, then shifted back to its original position. The Inverse Discrete Fast Fourier (IDFFT) Transform converts the frequency response to a PDP like Figure 4. This MATLAB function is faster and as accurate as using the Inverse Fourier Transform in its full form.

|  |
| --- |
| Hw2 = ifftshift(Hw);  Hw2 = Hw2.\*exp(-1j\*2\*pi\*f\*t\_del);  Hw2 = ifftshift(Hw2);  hn = ifft(Hw2,length(t)); |



Figure 36 – PDP for transmitter position 5.

From Figure 4 it is notable that the first pulse is the LoS component, and has been delayed an amount of time as specified by the program’s parameters. There exists a lot of noise in the PDP, which makes it more difficult to see if a second pulse exists. This noise is partly due to Gibb’s phenomenon illustrated in Figure 37, a ringing effect introduced by sharp bandpass sampling. According to [29], the phenomenon is an overshoot of Fourier series occurring at simple discontinuities. The additive ringing is increases proportional to the number of harmonics in the system.

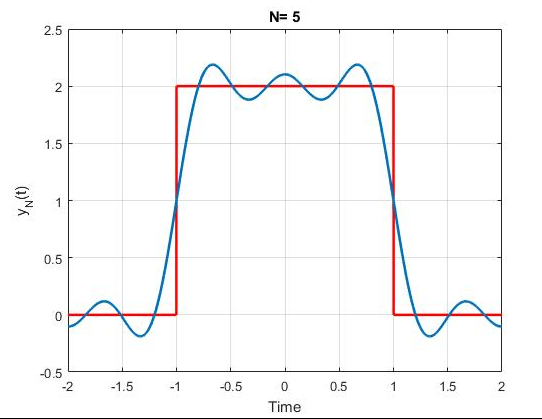


Figure 37 - Gibb's phenomenon

Ultimately, it is difficult to remove all bandpass sapling phenomena from the PDP. However, one solution to reduce the ringing introduced by Gibb’s is deconvolution. When sharp bandpass sampling occurs, a sinc function is convolved into the resulting time domain representation. Using a suitable large sampling frequency, some of the sinc function can be deconvolved from the PDP, resulting in a reduction in observable Gibb’s phenomenon. This is an imperfect solution to the reducing the unwanted effects introduced by bandpass sampling.

|  |
| --- |
| % Deconvolution of sinc to reduce Gibb's phenomenon  Fs = 2e9  Fc = (Fl+Fu)/2; % centre frequency for bandpass sinc  sc = Fs\*sinc(pi\*t\*Fs) .\* (cos(pi\*t\*Fc/Fs)); % sinc shifted to Fc  [q,r] = deconv([abs(hn)' zeros(1,length(abs(hn))-1)],sc\  q = q.\*sum(sc); r = r.\*sum(sc); % adjust magnitude changes |

* 1. **Observations**

The PDPs generated from the sweeps of the chosen five positions are displayed in the figures below. Each PDP in the figures below have a clear LoS component of high amplitude. Transmission positions further away from the receiver experience greater relative path loss (i.e. have a greater amplitude) than those closer to the receiver.

|  |  |
| --- | --- |
| Figure 38 – PDP for transmitter position 1 | Figure 39 – PDP for transmitter position 3 |

|  |  |
| --- | --- |
|  |  |
| Figure 40 - PDP for transmitter position 5 | Figure 41 – PDP for transmitter position 7 |
| Figure 42 – PDP for transmitter position 9 |  |

The most challenging aspect of this wireless channel characterization method is correctly differentiating between multipath delayed pulses and Gibb’s phenomenon. It is clear that there are several multipaths seen for each transmission problem. The scope of this investigation narrows it down to the most dominant multipath reflection, which would have the strongest effect and likely come from the strongest reflector in the channel.

Identifying a second pulse for the PDPs is difficult with the undesired presence of ringing introduced by Gibb’s phenomenon. A comparison between the PDPs is necessary to find a multipath component that is seen to change depending on the transmission distance. This will differentiate the multipath it from the Gibb’s phenomenon ringing. It can be argued from a brief viewing of the PDPs that the transmitter positions 1 and 3 do not experience the same second path that the other positions do. This makes sense, as they are close to the receiver and the suspected reflector does not lie near the LoS path.

Figure 43 compares positions 7 and 9 PDPs for the full sampling time duration. Figure 5 takes a closer look at the PDP comparisons for the first reflection. Comparing the PDPs of two nearby transmitter locations reveals that there is a second impulse response in the PDP.



Figure 43 - Natural log of PDPs for positions 7 & 9



Figure 44 - Closer inspection of log PDP comparison

Transmission from position 5 is debatable whether a second pulse is evident that is from the same reflector as positions 7 and 9. The PDP for position 5 is shown in Figure 45. The first multipath pulse that is clearly differentiable from the LoS pulse and ringing is chosen as a matching delay time.



Figure 45 – Closer view of PDP for transmitter position 5.

The PDP observations for LoS and first multipath delay times are listed in Table 1.

|  |  |  |
| --- | --- | --- |
| Position | LoS (µs) | Reflected (µs) |
| 1 | 0. 01877 | NaN |
| 3 | 0.01877 | NaN |
| 5 | 0.02879 | 0.06258\* |
| 7 | 0.04881 | 0.06884 |
| 9 | 0.04881 | 0.06758 |

Table 6 - Time delays observed from PDPs captured.

1. **Ray Tracing**

Ray tracing is an effective tool for wireless channel characterization and aids in the location of reflectors when an environment’s dimensions are known. A measure of the auditorium’s dimensions allows for a simple 2D ray tracing model to be designed. The applications of ray tracing in this investigation is two-fold:

1. To generate PDPs if a **reflector is known** in the wireless channel. This simulation can verify the PDPs captured in the previous section.
2. To **identify or verify a reflector** in the wireless channel based on the PDPs.

Both applications are scripted and explained in detail this section. The programs can be found in Appendix E.3 and Appendix E.4 respectively.

* 1. **PDP Simulation**

The ray tracing script requires a reflector to be declared in the room. Note that the room’s thin walls are not considered reflectors. A nearby elevator shaft is the main suspect reflector in the auditorium. This reflector assumption is the basis of this ray tracing method.

The LoS ray is the first to be traced. The simulation creates reflections based on updated AoA and AoD values. For one and two multipath reflections, if the ray reaches the receiver it is saved and plotted at the end of the simulation. Temporary rays that do not find the transmitter targets are discarded.



Figure 46 - Ray tracing simulation for position 7 with known reflector.

Figure 46 displays the ray tracing simulation for transmission from position 7. The results of all five positions are displayed below. Note that the co-ordinate system is in inches, but can easily be converted to meters for comparison with PDPs.

|  |  |
| --- | --- |
| Figure 47 – Ray tracing simulation for transmitter position 1. | Figure 48 - Ray tracing simulation for transmitter position 3. |
| Figure 49 – Ray tracing simulation for transmitter position 5. | Figure 50 - Ray tracing simulation for transmitter position 9. |

The PDP delay times generated are listed in Table 2.

|  |  |  |
| --- | --- | --- |
| Position | LoS (µs) | Reflected (µs) |
| 1 | 0.016467 | NaN |
| 3 | 0.016763 | NaN |
| 5 | 0.028363 | 0.052372 |
| 7 | 0.046306 | 0.055463 |
| 9 | 0.046412 | 0.071667 |

Table 7 – PDP delay times generated using ray tracing for LoS and multipath with known reflector.

The objective of this ray tracing program was to generate PDPs to verify the PDPs captured in the previous section, which can be found in Table 1. For the LoS path, the direct ray times match closely to the PDP data. This is as expected, as it is independent of declaring a reflector and should be similar. The PDP delays are slightly slower (~ 2 ns) due to possible path loss and energy reduction.

The first multipath varies much more (~ 9 ns) from the PDP delays, with position 9 experiencing especially long multipath delay in the ray tracing compared to the other positions. Possible reasons for this may be an unconsidered second reflector close to the transmitter at position 9, or incorrect observation of the PDP delay times.

* 1. **Reflector Prediction**

As mentioned previously, ray tracing can also be used to locate or confirm possible reflectors in a wireless channel. The script for the reflector validation can be found in Appendix E.4.

The program uses the difference in arrival times of the LoS pulse and the reflector’s multipath pulse (if present) for several PDPs generated from frequency sweeps at different positions. Observing the PDPs provide easy conversion to the distances d1 and d2 for the first and second (if present) pulses respectively. Like the previous ray tracing program, the geometry of the room is known in advance. However, this time there is no knowledge of where in the room the reflector lies.

Assuming there is only one reflection on the reflected path, the geometry in Figure 2 can be used to define the distance of that the second pulse travels.

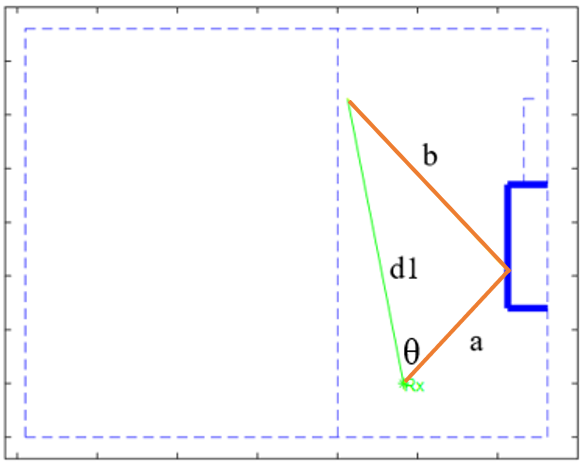


Figure 51 – Ray tracing geometry for predicting a reflector.

The red line, green line and angle Φ are known from the geometry of the room. The green line indicates the LoS distance d1, the red line indicates the multipath distance d2 and Φ is the angle that the LoS path makes with the horizontal. Note that the above geometry is displayed here for illustrative purposes, and is not part of this ray tracing program.

The time difference between the two pulses can be converted to a difference in distance, which must satisfy the conditions in the geometry specified by (21), (22), (23) and (24).

|  |  |  |
| --- | --- | --- |
|  |  | (21) |
|  |  | (22) |
|  |  | (23) |
|  |  | (24) |

The distance between the reflector and receiver is represented as , and the distance between the reflector and the transmitter is denoted as . A locus of all possible and combinations is generated with values varying between 0 and . If the combinations satisfy the above conditions the and pair is stored. This process is repeated for all the PDPs in the environment.

The distance for valid and pairs is known for each locations PDP, but the angle θ is also required to create the reflected path and locate/confirm the reflector. The Cosine Rule enables the calculation of θ for each pair in the locus. Point of the reflector is given by (25).

|  |  |  |
| --- | --- | --- |
|  |  | (25) |

Each PDP produces its own locus of points that represent its estimation of the position of possible reflectors. If two such loci intersect at a suspected reflector location, this confirms that there is a reflector at that location in the wireless channel.

To first test the functionality of the script, the input to this script is the output of the first ray tracing script, i.e. the ideal delay times for each position listed in Table 2. This should correctly identify the reflector, i.e. the elevator shaft. The ray tracer produces a locus of points whose geometry correctly match the distances suggested by the delay time inputs. Each locus belongs to a transmitter position. Assuming the reflector is a straight line, when two loci intersect the intersection is on the line of the locator. In Figure 7 the script correctly identifies the elevator shaft to an accuracy of less than a meter.

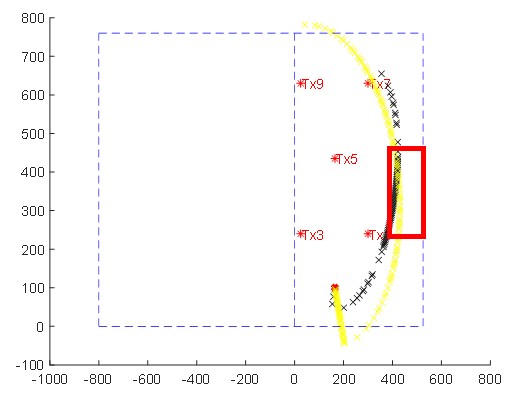


Figure 52 – Reflector prediction using PDP simulation data.

With the script correctly estimating the reflector position in an ideal ray tracing simulation with one reflector, the next step is to input the real-life captured PDP delay times in Table 1. It is expected that the identification of the reflector is less accurate than for the simulated PDP delay times, due to:

* Possible multiple reflectors in the room.
* Possible multiple reflectors outside the room.
* Incorrect identification of the delay times, especially the multipath delay.
* A 2D simulation does not fully model a 3D environment.

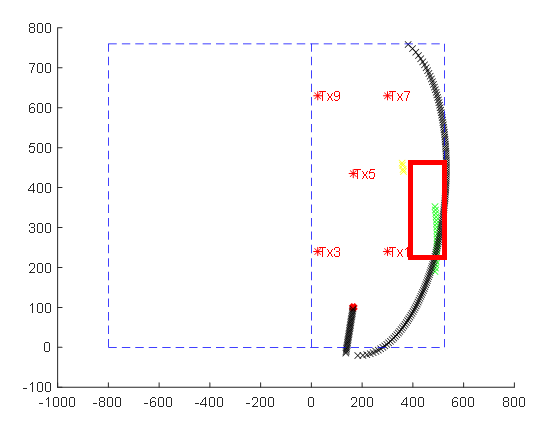


Figure 53 – Reflector prediction using measured PDPs.

In Figure 53, two of the PDP loci intersect in the region where the elevator shaft is (indicated with a red rectangle). This confirms that there is a reflector in that region, as previously suspected. Two further intersections occur in the purple rectangles, which were not previously predicted. Possible reasons for this may be reflectors in the ceiling or floor not modelled by the 2D wireless channel characterization, or because of incorrect multipath delay observation.

It is evident that the ray tracer is useful to confirm suspected reflectors in a wireless channel, although due to its many assumptions it cannot be a highly accurate reflector estimator in a complex environment. However, its ability to identify suspected reflectors is useful in low energy indoor localization applications that use PDPs and post processing techniques such as ray tracing.

1. **Conclusion & Future Prospects**

Wireless channel characterization is an essential element of wireless communication systems as well as low power indoor localization systems. In the past decades the field has progressed at an exciting rate. Encouraging research and applications has been applied in useful models and techniques in indoor localization, such as those mentioned in Section 6 [17].

In the future, wireless channel characterization will progress further to achieve intelligent, accurate, low power and real-time solutions. Indoor locations will be better mapped with higher resolution and increased geometrical data available to include in more flexible models [17].

The simulations will be intelligent in selecting which features should be included in the model to best characterize the wireless channel. Machine learning and big data inference will aid in the construction of such intelligent systems, which will be able to make simulations accurate and fast enough for deployment in real-time. Deep learning will intuitively identify features of wireless channel propagation in different environments and determine suitable levels of detail depending on the environment [17].

Such models will be integrated and commonly employed, heralding the arrival of faster computational speeds by using hardware acceleration and improve algorithms. This will eventually result in real-time simulation speeds of multiple scenarios. It is hoped that the new systems will be easier to use and less expensive [17].

Real-time capabilities and geospatial awareness will result in the wireless channel models being adopted by wireless communication systems to enhance performance and reduce power consumption. Cognitive radio can benefit from real-time channel characterization to determine spectrum availability [17].

Ray tracing is more general than other methods, especially empirical methods. It has a sound physical basis in high frequency solutions to Maxwell’s Equations and Geometrical Optics. It can be confidently deployed in wireless communications, and will play an important role in wireless channel characterization and low power indoor localization systems. In my opinion, ray tracing integrated with BLE technology and deep learning can serve as an accurate real-time low-power indoor localization [17].

**Appendix D**

**Acquired Data & Data Visualization**

This appendix contains all plots generated during this research.

* Frequency sweeps
* PDPs
* 2D Ray Tracing Ray Distributions for a Known Geometry
* 2D Ray Tracing Reflector Prediction

All raw data used to generate these plots is publicly available on GitHub:

<https://github.com/aidansmyth95/Masters-Project-Characterization-of-Reflectors-in-a-Wireless-Channel.git>

**D.1 Frequency Sweep Results**

|  |  |
| --- | --- |
| Figure 54 - Frequency Sweep Position 1 | Figure 55 - Frequency Sweep Position 3 |
| Figure 56 - Frequency Sweep Position 5 | Figure 57 - Frequency Sweep Position 7 |
| Figure 58 - Frequency Sweep Position 9 |  |

**D.2 Hilbert Filter PDP Results**

|  |  |
| --- | --- |
| Figure 59 - PDP Position 1 | Figure 60 - PDP Position 3 |
| Figure 61 - PDP Position 5 | Figure 62 - PDP Position 7 |
| Figure 63 - PDP Position 9 |  |



Figure 64 - PDP Multipath Comparison.

**D.3 Ray Tracing PDP Simulation**

|  |  |
| --- | --- |
| Figure 65 – Ray tracing simulation for transmitter position 1 | Figure 66 - Ray tracing simulation for transmitter position 2. |

|  |  |
| --- | --- |
| Figure 67 - Ray tracing simulation for transmitter position 3 | Figure 68 - Ray tracing simulation for position 4 |
| Figure 69 – Ray tracing simulation for transmitter position 5 | Figure 70 - Ray tracing simulation at position 6. |

|  |  |
| --- | --- |
|  |  |
| Figure 71 - Ray tracing simulation for transmitter position 7. | Figure 72 - Ray tracing simulation position 8. |
| Figure 73 - Ray tracing simulation for transmitter position 9. |  |

**D.4 Ray Tracing Reflector Prediction**



Figure 74 - Reflector Prediction for Ray Tracing Simulated PDPs



Figure 75 - Reflector Prediction for Measured PDPs

**Appendix E**

**Source Code**

This appendix contains source code used in the project. All code is also publicly available on GitHub:

<https://github.com/aidansmyth95/Masters-Project-Characterization-of-Reflectors-in-a-Wireless-Channel.git>

* **PyVISA Instrument Control**
  + ***SA\_CTRL\_function.py*** : Python class using PyVISA package to communicate with a signal analyzer/FSV
  + ***SG\_CTRL\_function.py*** : Python class using PyVISA package to communicate with a signal generator
  + ***main\_sweep\_script.py*** : Main script for performing a parallel frequency sweep.
* **PDP Hilbert Calculation**
  + ***pdp\_gen.m*** : Post processes frequency magnitudes obtained during sweep, converting to power delay profiles using the Hilbert filter.
  + includes frequency sweep input data.
* **Ray Tracing PDP Simulation**
  + ***auditorium\_test.m*** : creates simple 2D ray distribution for any specified room geometry and reflector location.
  + also contains classes for modeling AoA reflection etc. for ray tracer
* **Ray Tracing Reflcetor Prediction**
  + ***pdp\_locus.m*** : Novel 2D ray tracing using power delay profile delay times to predict the location of a reflector in a wireless channel.

**E.1 PyVISA Instrument Control**

**E.1.1 Main Script**

**import** csv  
**import** visa  
**import** socket  
**import** vxi11  
**import** time  
**import** sys  
**import** math  
**import** string  
**from** SA\_CTRL\_function **import** \*  
**from** SG\_CTRL\_function **import** \*  
  
*# sig gen settings*freq = 2.400000  
pwr = -20  
print(visa.ResourceManager().list\_resources())  
sg = SG\_CTRL\_function(**'GPIB0::13::INSTR'**, 0)  
  
*# VSA sattings*resourceString = **'TCPIP::10.198.141.237::INSTR'** *# Standard LAN connection (also called VXI-11)*LAN = **'10.198.141.237'**fc = 2.4  
fspan = 10  
  
*# connect and power sig gen*sg.connect()  
sg.set\_sg(freq, pwr)  
  
*# Create, connect and configure fsa*scope = SA\_CTRL\_function(LAN, resourceString)  
scope.fsa\_set\_fc\_GHz(fc)  
scope.fsa\_set\_fspan\_MHz(fspan)  
  
  
*# Start measuring peaks and record to CSV*print(**"Starting measurements..."**)  
**with** open(**'fsa\_markers.csv'**, **'w'**) **as** f1:  
 writer = csv.writer(f1, delimiter=**'\t'**, lineterminator=**'\n'**, )  
 columnTitleRow = **"Freq\tMagnitude\n"** writer.writerow(columnTitleRow) *# write headings for columns* **for** i **in** range(0, 1000):  
 scope.fsa\_measure\_peak() *# update measurements* writer.writerow(scope.res\_x + **'\t'** + scope.res\_y)  
 time.sleep(0.005) *# sleep (in seconds)*print(**"Finished measurements!"**)

**E.1.2 Signal Generator Class**

**import** time  
**import** sys  
**import** visa  
**import** time  
**import** sys  
**import** math  
**import** string  
  
  
**class** SG\_CTRL\_function:  
 **def** \_\_init\_\_(self,gpib\_addr,sg=0):  
 self.sg = sg  
 self.rm = visa.ResourceManager()  
 self.gaddr = gpib\_addr  
 print(self.rm.list\_resources())  
 self.my\_instrument = self.rm.open\_resource(self.gaddr)  
  
 **def** connect(self):  
 print(**"Connecting..."**)  
 self.my\_instrument.write\_termination = **'\n'** self.my\_instrument.clear()  
 print(**"Hello, I am "** + self.my\_instrument.query(**'\*IDN?'**))  
 self.my\_instrument.write(**'if {![info exists DEFGPIBADDR]} {s /usr/local/lib/epigram/gpib.tcl}'**)  
 self.my\_instrument.write(**'set DEFGPIBADDR(sg\_%s) %s'** % (self.sg, self.sg))  
 self.my\_instrument.write(**'set sg\_%s %s'** % (self.sg, self.sg))  
 self.my\_instrument.write(**'gpib set $gpibbn $sg\_%s "\*RST;\*CLS"'** % self.sg)  
  
 **def** set\_sg(self,freq,pwr):  
 self.my\_instrument.write(**'FREQUENCY:FIXED %se9'** % float(freq))  
 self.my\_instrument.write(**'POW:AMPL %s dBm'** % float(pwr) )  
 self.my\_instrument.write(**'FREQUENCY:FIXED %se9'** % freq)

**E.1.3 Spectrum Analyzer Class**

**import** csv  
**import** visa  
**import** socket, vxi11  
**import** time  
  
  
**class** SA\_CTRL\_function:  
  
 **def** \_\_init\_\_(self,LAN,resourceString):  
 self.LAN = LAN  
 self.resourceString = resourceString  
 self.scope = visa.ResourceManager().open\_resource(self.resourceString) *# Standard LAN connection (also called VXI-11)* self.instr = vxi11.Instrument(LAN)  
 self.res\_x = 0  
 self.res\_y = 0  
  
 **def** fsa\_connect(self):  
 self.scope.write\_termination = **'\n'** self.scope.clear() *# Clear instrument io buffers and status* idn\_response = scope.query(**'\*IDN?'**) *# Query the Identification string* print(**"Hello, I am "** + idn\_response)  
 print(self.instr.ask(**"\*IDN?"**))  
  
 **def** fsa\_set\_fc\_GHz(self,fc):  
 cmd = **'freq:center %se9;\*opc?'** % fc  
 self.instr.write(**'%s\n'** % cmd)  
  
 **def** fsa\_set\_fspan\_MHz(self,fspan):  
 cmd = **'freq:span %se6;\*opc?'** % fspan  
 self.instr.write(**'%s\n'** % cmd)  
  
 **def** fsa\_measure\_peak(self):  
 cmd = **':INIT:IMM;\*OPC?'** self.instr.write(**'%s\n'** % cmd)  
 cmd = **':calc:mark1:max:peak;\*OPC?'** self.instr.write(**'%s\n'** % cmd)  
 cmd = **':calc:mark1:y?'** self.res\_y = self.instr.ask(**'%s\n'** % cmd, 5)  
 cmd = **':calc:mark1:x?'** self.res\_x = self.instr.ask(**'%s\n'** % cmd, 5)

**E.2 PDP Calculation using Hilbert Filter**

%% Create impulse train

clear;clc;%close all;

%\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_

pos = 7;

c = 3e8; % m/s

freqStartGHz = 2.0; % GHz

freqEndGHz = 2.4; % GHz

posRx = 165+100j; %position of fixed receiver in inches

% Testcase for Tx position

% requires Excel formatted frequency sweep results

switch pos

case 1

filename = 't61801.xlsx';

posTx = 300+240j;

case 3

filename = 't61803.xlsx';

posTx = 25+240j;

case 5

filename = 't61805.xlsx';

posTx = 165+435j;

case 7

filename = 't61807.xlsx';

posTx = 300+630j;

case 9

filename = 't61809.xlsx';

posTx = 25+630j;

otherwise

error('PDP Generator:case#', ' invalid position number\n'); %#ok<CTPCT>

end

d = abs(posTx-posRx)\*0.0254; % distance of LoS path in meters

t\_del = d/c; % time delay for direct path

f\_all = xlsread(filename,'A2:A2003'); % GHz

s\_all = xlsread(filename,'C2:C2003'); % dBm

figure(1)

plot(f\_all,s\_all)

grid on;

title('Frequency Sweep')

xlabel('Frequencies')

ylabel('PRx (dBm)')

% choose frequencies that avoid the interference in auditorium

f = f\_all(find(f\_all>=freqStartGHz,1,'first'):find(f\_all<=freqEndGHz,1,'last'));

s = s\_all(find(f\_all>=freqStartGHz,1,'first'):find(f\_all<=freqEndGHz,1,'last'));

clear f\_all; clear s\_all;

f = f\*1e9; % represent in Hz

Tx = 14; % Transmission power in dBm

%% Hilbert filter to extract phase

fo = 16; % filter order

h = firpm(fo,[0.1 0.9],[1 1],'hilbert'); % Hilbert filter

grpdel\_h = mean(grpdelay(h)); % Account for group delay - for flat

h\_delay = zeros(size(h));

h\_delay(grpdel\_h+1) = 1;

abs\_gain = abs(s - Tx); % channel gain = |S(jw)| - Tx = log10(|H(jw)|^2) dBm

abs\_Hfi = 10.^(abs\_gain./(2\*10)); % |H(jw)|

fx = log(abs\_Hfi); % input to Hilbert: ln(|H(w)|)

phase = -conv(h,fx); % Apply filter to get phase

abs\_del1 = conv(h\_delay, fx); % Apply filter to get absoloute delay

% synchronize phase and mag delays

phase = phase(grpdel\_h + (1:length(fx)));

abs\_del = abs\_del1(grpdel\_h + (1:length(fx)));

Hw = exp((abs\_del + 1j\*phase)); % H(w) reconstructed!

%% Frequency and time sampling parameters

Fl = f(1);

Fu = f(end);

delta\_f = f(2) - f(1); % frequency steps

B = Fu - Fl; % Bandwidth

Fs = 2\*B; % Sampling frequency

SL = B/delta\_f; % increase B or reduce delta\_f

t\_samples = 2\*SL;

delta\_t = 1/Fs; % ns

t\_span = t\_samples\*delta\_t;

t = delta\_t:delta\_t:t\_span; % starts on delta\_t for strong first bin

%% Time Domain Representation

Hw2 = ifftshift(Hw);

% ramping to account for delay of direct path of signal

Hw2 = Hw2.\*exp(-1j\*2\*pi\*f\*t\_del);

Hw2 = ifftshift(Hw2);

hn = ifft(Hw2,length(t));

figure(4)

plot(t\*1e6, abs(hn));

grid on;

title('Power delay profile')

xlabel('Time (micro seconds)')

ylabel('Relative path loss |h[n]|')

xlim([0,1])

% plot h[n]

figure(2)

plot(t\*1e6, 10\*log10(abs(hn).^2./sqrt(mean(abs(hn).^2))));

grid on;

title('Power delay profile')

xlabel('Time (micro seconds)')

ylabel('Relative path loss |h[n]|')

xlim([0,1])

% % Deconvolution of sinc to reduce Gibb's phenomenon

% Fs = 10e9; % sampling frequency high enough for bandpass sinc

% Fc = (Fl+Fu)/2; % centre frequency for bandpass sinc

% sc = Fs\*sinc(pi\*t\*Fs) .\* (cos(pi\*t\*Fc/Fs)); % sinc function is shifted to centre frequency

% [q,r] = deconv([abs(hn)' zeros(1,length(abs(hn))-1)],sc); % deconvolution

% q = q.\*sum(sc); r = r.\*sum(sc); % adjust magnitude changes

%

% figure(3);

% plot(t\*1e6, abs(q));

% grid on;

% title('Power delay profile (deconvolved)')

% xlabel('Time (micro seconds)')

% ylabel('Relative path loss |h[n]|')

% xlim([0,1])

**E.3 PDP Simulation with Ray Tracing**

**E.3.1 auditorium\_tracer.m**

clear; close all; fclose all; clc;

%\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_

tx\_pos = 9; % options 1->9

z\_rx = 165+100j;

% Testcase for Tx positioning

switch tx\_pos

case 1

z\_tx = 300+240j;

case 2

z\_tx = 165+240j;

case 3

z\_tx = 25+240j;

case 4

z\_tx = 300+435j;

case 5

z\_tx = 165+435j;

case 6

z\_tx = 25+435j;

case 7

z\_tx = 300+630j;

case 8

z\_tx = 165+630j;

case 9

z\_tx = 25+630j;

otherwise

error('TxRx\_testcase:case#', ' invalid case number\n'); %#ok<CTPCT>

end

%%\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_

% escalator indent

L{1}=create\_line(425+240j, 425+470j);

L{2}=create\_line(425+240j, 525+240j);

L{3}=create\_line(425+470j, 525+470j);

% Keep lines reflections after 2nd path

tmp\_lines\_idx = 1;

figure(1);

% draw the geometry of ROOM

for i=1:length(L)

% Tx, Rx and reflector

L{i}.draw;

%text(real((L{i}.z\_min+L{i}.z\_max)/2), imag((L{i}.z\_min+L{i}.z\_max)/2), num2str(i));

if (i==1)

hold on

end

end

% 4 walls

plot([-780 525], [760 760],'b--');

plot([-780 525], [0 0],'b--');

plot([525 525], [0 760],'b--');

plot([-780 -780], [0 760],'b--');

plot([0 0], [0 760], 'b--')

plot([465 500], [630 630],'b--');

plot([465 465], [470 630],'b--');

% draw Tx, Rx

zall\_tx = [300+240j,165+240j,25+240j,300+435j,165+435j,25+435j,300+630j,165+630j,25+630j];

plot(real(z\_tx), imag(z\_tx), 'r\*');

for i=1:length(zall\_tx)

plot(real(zall\_tx(i)), imag(zall\_tx(i)), 'r\*');

text(real(zall\_tx(i))+3, imag(zall\_tx(i))-1, strcat('Tx',int2str(i)), 'Color', 'r');

%plot(real(zall\_tx), imag(zall\_tx), 'r\*');

end

plot(real(z\_rx), imag(z\_rx), 'g\*');

text(real(z\_rx)+3, imag(z\_rx)-1, 'Rx', 'Color', 'g');

% LoS

L\_LoS = create\_line(z\_tx, z\_rx); % create line from Tx to Rx

LoS\_valid = NaN(length(L),1); % NaN values for number of walls

AoA.LoS = struct('r', NaN, 'theta', NaN); %specify LoS for object AoA

AoD.LoS = struct('r', NaN, 'theta', NaN); % dito for AoD

for i=1:length(L) % for all walls

[~,tmp\_v] = L{i}.intersect(L\_LoS);

LoS\_valid(i) = tmp\_v(1) && tmp\_v(2); % needs to sum to 0

end

if (sum(LoS\_valid) == 0) % LoS is valid

% assign AoA & AoD angle and distance values

AoA.LoS.theta = L\_LoS.alpha;

AoD.LoS.theta = L\_LoS.alpha;

AoA.LoS.r = abs(z\_rx - z\_tx);

AoD.LoS.r = abs(z\_rx - z\_tx);

L\_LoS.draw('g-');

else

% doesn't reach here hopefully

tmp\_l(tmp\_lines\_idx) = L\_LoS.draw('r-.');

tmp\_lines\_idx = tmp\_lines\_idx + 1;

end

%% 1R

z\_1refl = NaN(length(L), 1);

%fill tmp with L number of NaNs

tmp = cell(length(L), 1); for i=1:length(L), tmp{i} = NaN; end

% structured arrays for AoA AoD

AoA.refl\_1 = struct('r', tmp, 'theta', tmp);

AoD.refl\_1 = struct('r', tmp, 'theta', tmp);

clear tmp;

for i=1:length(L) % every wall

[tmp\_aoa, tmp\_aod, tmp\_z] = multiple\_reflections(L, i, z\_tx, z\_rx);

if ( ~isnan(tmp\_aoa.theta) && ~isnan(tmp\_aod.theta) )

AoA.refl\_1(i) = tmp\_aoa;

AoD.refl\_1(i) = tmp\_aod;

z\_1refl(i) = tmp\_z;

plot(real([z\_tx; tmp\_z; z\_rx]), imag([z\_tx; tmp\_z; z\_rx]), 'r-')

else

tmp\_idx = find(~isnan(tmp\_z));

if (length(tmp\_idx) >= 1)

tmp\_l(tmp\_lines\_idx)=plot(real([z\_tx tmp\_z(tmp\_idx)]), imag([z\_tx tmp\_z(tmp\_idx)]), 'r--');

tmp\_lines\_idx = tmp\_lines\_idx + 1;

end

end

end

%% two reflections

z\_2refl = NaN(length(L), length(L), 2);

tmp = cell(length(L), length(L)); for i=1:length(L), for j=1:length(L), tmp{i,j} = NaN; end; end

AoA.refl\_2 = struct('r', tmp, 'theta', tmp);

AoD.refl\_2 = struct('r', tmp, 'theta', tmp);

clear tmp;

for i=1:length(L)

for j=setdiff(1:length(L), i)

[tmp\_aoa, tmp\_aod, tmp\_z] = multiple\_reflections(L, [i, j], z\_tx, z\_rx);

if ( ~isnan(tmp\_aoa.theta) && ~isnan(tmp\_aod.theta) )

AoA.refl\_2(i,j) = tmp\_aoa;

AoD.refl\_2(i,j) = tmp\_aod;

z\_2refl(i,j,:) = tmp\_z;

plot(real([z\_tx; tmp\_z; z\_rx]), imag([z\_tx; tmp\_z; z\_rx]), 'c-')

else

tmp\_idx = find(~isnan(tmp\_z));

if (length(tmp\_idx) >= 1)

tmp\_l(tmp\_lines\_idx)=plot(real([z\_tx; tmp\_z(tmp\_idx)]), imag([z\_tx; tmp\_z(tmp\_idx)]), 'r--');

tmp\_lines\_idx = tmp\_lines\_idx + 1;

end

end

end

end

axis([-830 600 -40 800])

hold off

title('Ray Tracing in Auditorium');

pause(4); delete(tmp\_l);

x\_ref = real(z\_1refl); y\_ref = imag(z\_1refl);

x\_ref = x\_ref(1);

y\_ref = y\_ref(1);

dr1 = sqrt( (real(z\_tx)-x\_ref)^2 + (imag(z\_tx)-y\_ref)^2 ); % inches

dr2 = sqrt( (real(z\_rx)-x\_ref)^2 + (imag(z\_rx)-y\_ref)^2 ); % inches

dr = dr1 + dr2;

c=3e8;

t\_los = 0.0254\*abs(z\_tx-z\_rx)/c

t\_r = 0.0254\*dr/c % seconds

%%\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_

**E.3.2 Line.m**

classdef Line < handle

properties (SetAccess = private)

m = 0 % slope

c = 0 % y-intercept

x\_min = NaN % x of left-bottom point

x\_max = NaN % x of right top point

alpha = 0 % angle from x-axis

d = 0 % x-intercept

ejalpha = 1 % exp(1j \* alpha)

ej2alpha = 1 % exp(1j \* 2 \* alpha)

z\_strt = NaN % starting point

z\_end = NaN % ending point

z\_min = NaN % left-bottom point

z\_max = NaN % right top point

is\_vertical = 0 % flag to indicate that the line is vertical

end

properties (Constant, Hidden)

EPS = 1e-3

end

methods

% define with y = m x + c

% strt\_in, end\_in : starting and ending points of the line.

% also used to get x(y)\_min and x(y)\_max

function obj = Line(m\_in, c\_in, strt\_in, end\_in)

if ( (nargin >= 2) && isreal(m\_in) && isreal(c\_in) ) % input is m and c

obj.m = m\_in;

if (abs(obj.m) > tan(pi/2 - obj.EPS) ) % vertical

obj.m = Inf;

obj.is\_vertical = 1;

obj.c = NaN;

obj.d = c\_in; % input corresponds to x intercept

else % not vertical

obj.is\_vertical = 0;

obj.c = c\_in;

obj.d = obj.c/obj.m;

end

% dependent varaibles

obj.alpha = atan(obj.m); % will possibly be updated later!

obj.ejalpha = exp(1j\*obj.alpha);

obj.ej2alpha = exp(1j\*2\*obj.alpha);

% the edge points

if ( (nargin == 4) && isreal(strt\_in) && isreal(end\_in) ) % input also has x\_min and x\_max

% store the starting and ending points

if (obj.is\_vertical == 0) % not vertical

obj.z\_strt = strt\_in + 1j\*(obj.m\*strt\_in + obj.c);

obj.z\_end = end\_in + 1j\*(obj.m\*end\_in + obj.c);

else

obj.z\_strt = obj.d + 1j\*(strt\_in);

obj.z\_end = obj.d + 1j\*(end\_in);

end

% update alpha, since atan only has (-pi/2, pi/2)

if (strt\_in > end\_in) % the starting point is on the right!

if (obj.m>0)

obj.alpha = -pi + obj.alpha;

end

if (obj.m<0)

obj.alpha = pi + obj.alpha;

end

end

% store the min and max along x and z

if (obj.is\_vertical == 0) % not vertical

obj.x\_min = min(strt\_in, end\_in);

obj.x\_max = max(strt\_in, end\_in);

obj.z\_min = obj.x\_min + 1j \* (obj.m\*obj.x\_min + obj.c);

obj.z\_max = obj.x\_max + 1j \* (obj.m\*obj.x\_max + obj.c);

else % input is actually y\_min and y\_max and will use x-intercept

obj.z\_min = obj.d + 1j\*min(strt\_in, end\_in);

obj.z\_max = obj.d + 1j\*max(strt\_in, end\_in);

end

else

warning('Line:construct', ' start and end are not defined!\n');

end

else

error('Line:construct', 'invalid number/type of inputs (m, c)\n');

end

end

% draw the line for the ROOM

function h = draw(this, plt\_clr, Npts)

if (nargin <= 1)

plt\_clr = struct('Color', 'b', 'LineWidth', 4, 'LineStyle', '-');

end

if ( ~isnan(this.z\_strt) && ~isnan(this.z\_end) ) % start and end known

h = plot( real([this.z\_strt this.z\_end]), imag([this.z\_strt this.z\_end]), plt\_clr);

elseif ( ~isnan(this.z\_min) && ~isnan(this.z\_max) ) % use min and max

h = plot( real([this.z\_min this.z\_max]), imag([this.z\_min this.z\_max]), plt\_clr);

else % many points

if (nargin <= 2)

Npts = 1024;

end

tmp = (0:Npts-1)/Npts \* (this.z\_max - this.z\_min) + this.z\_min;

h = plot(real(tmp), imag(tmp), plt\_clr);

end

end

% intersection with a line L2

function [z\_intersect, within\_limits] = intersect(this, L2)

% 11=both vertical, 10=this is vertical, 01=L2 is vertical, 00=neither

tmp = this.is\_vertical\*10 + L2.is\_vertical ;

if ( tmp == 0 ) % neither

if ( abs(this.m-L2.m) < (this.EPS+L2.EPS)/2) % parallel or almost parallel

z\_intersect = NaN + 1j\*NaN; % no intersect

else

tmp = [-this.m 1; -L2.m 1]\[this.c; L2.c]; %??

z\_intersect = tmp(1) + 1j\* tmp(2); % old tmp with a new imag part

end

elseif (tmp == 1) % only L2 vertical

% x intercept of L2 + imag of (y = m\*xint + c) for L2

z\_intersect = L2.d + 1j\*(this.m\*L2.d+this.c);

elseif (tmp == 10) % only this vertical

% x intercept of this + imag of (y = m\*xint + c) for L2

z\_intersect = this.d + 1j\*(L2.m\*this.d+L2.c);

else % both vertical

% no reflection

z\_intersect = NaN + 1j\*NaN;

end

clear tmp

if (nargout > 1) %number of outputs specified

if ( abs(this.m-L2.m) < (this.EPS+L2.EPS)/2) % parallel or almost parallel

within\_limits(1:2) = 0;

warning('Line:intersect', 'input lines are almost parallel! need to code this part.\n');

else

if (this.is\_vertical==0)

tmp\_test = (real(z\_intersect) >= this.x\_min) && (real(z\_intersect) <= this.x\_max);

else

tmp\_test = (imag(z\_intersect) >= min(imag(this.z\_min), imag(this.z\_max))) && (imag(z\_intersect) <= max( imag(this.z\_min), imag(this.z\_max)));

end

if ( tmp\_test )

within\_limits(1) = 1;

else

within\_limits(1) = 0;

end

if (L2.is\_vertical==0)

tmp\_test = (real(z\_intersect) >= L2.x\_min) && (real(z\_intersect) <= L2.x\_max);

else

tmp\_test = (imag(z\_intersect) >= min( imag(L2.z\_min), imag(L2.z\_max))) && (imag(z\_intersect) <= max( imag(L2.z\_min), imag(L2.z\_max)));

end

if ( tmp\_test )

within\_limits(2) = 1;

else

within\_limits(2) = 0;

end

end

end

end

%% reflection of a point z\_in

function [z\_refl, is\_valid] = reflect(this, z\_in)

if (this.is\_vertical == 0)

z\_refl = this.ej2alpha \* conj(z\_in) + 1j\*this.c \* (1 + this.ej2alpha);

else

z\_refl = 2\*this.d-real(z\_in) + 1j\*imag(z\_in);

end

if (nargout > 1)

tmp\_r = real((z\_in+z\_refl))/2;

if (this.is\_vertical == 0)

if ( (tmp\_r>=this.x\_min) && (tmp\_r<=this.x\_max) )

is\_valid = 1;

else

is\_valid = 0;

end

else

if ( (tmp\_r>=imag(this.z\_min)) && (tmp\_r<=imag(this.z\_max)) )

is\_valid = 1;

else

is\_valid = 0;

end

end

end

end

%% angles subtended

function end\_angles = view(this, z\_in)

end\_angles(1) = angle(this.z\_strt - z\_in);

end\_angles(2) = angle(this.z\_end - z\_in);

end

%% perpendiclar distance

function [d, d2] = perpendicular\_distance(this, z\_in)

% create a line of perp slope

if (this.m< this.EPS) % horizontal

tmp\_l = create\_line(z\_in, z\_in + (0+1j));

elseif (this.is\_vertical) % vertical

tmp\_l = create\_line(z\_in, z\_in + (1+0j));

else % all else

tmp\_m = -1/this.m;

tmp\_l = create\_line(z\_in, z\_in + (1+1j\*tmp\_m));

end

%% intersection

[tmp\_int, tmp\_vld] = this.intersect(tmp\_l);

% within limits of line?

if (tmp\_vld(1) == 1)

d = abs(z\_in - tmp\_int);

d2 = NaN;

else

d = NaN;

d2 = min( abs(z\_in - this.z\_min), abs(z\_in - this.z\_max) );

end

end

end

end

**E.3.3 create\_line.m**

function L = create\_line(z\_strt, z\_end)

%% create a line with two complex numbers as end points

EPS = 1e-3;

tmp = z\_end - z\_strt;

m = imag(tmp)/real(tmp); %m=y/x

if ( abs(m) <= tan(pi/2 - EPS) ) % not vertical

c = imag(z\_strt) - m\*real(z\_strt); % c = y - mx

x\_min = real(z\_strt); %x1

x\_max = real(z\_end); %x2

else % vertical

c = real( (z\_strt+z\_end)/2); % c = (x1+x2)/ 2

x\_min = imag(z\_strt); %y1

x\_max = imag(z\_end); %y2

end

L = Line(m, c, x\_min, x\_max); % return m,c,x1,x2, enough to draw line

return

**E.3.3 multiple\_reflections.m**

function [AoA, AoD, z\_reflection] = multiple\_reflections(L, reflectors, z\_tx, z\_rx)

% reflectors are number of walls

EARLY\_STOP = 1;

%initialize

AoA = struct('r', NaN, 'theta', NaN);

AoD = struct('r', NaN, 'theta', NaN);

z\_reflection = NaN(length(reflectors), 1);

% if same reflectors exist print error

if ( ~isempty(find(diff(reflectors) == 0, 1)) )

error('multiple\_reflections:reflectors', 'consecutive reflectors cannot be the same!\n');

end

z\_tx\_refl = NaN(length(reflectors), 1);

% recursively reflect the Tx towards the Rx

z\_tx\_refl(1) = L{reflectors(1)}.reflect(z\_tx);

for i=2:length(reflectors)

% sequentially reflect Tx

z\_tx\_refl(i) = L{reflectors(i)}.reflect(z\_tx\_refl(i-1));

end

%reflection may not be "valid" but, there might still be a path.

%only ray traced check is useful

reflection\_valid = NaN(length(reflectors), 1);

% join the last Tx-image to the Rx to get the last intersection point

tmp\_L = create\_line(z\_tx\_refl(end), z\_rx);

[z\_reflection(end), tmp] = L{reflectors(end)}.intersect(tmp\_L);

if (sum(tmp) == 2) % How many reflections to keep

reflection\_valid(end) = 1;

else

reflection\_valid(end) = 0; %#ok<NASGU>

if (EARLY\_STOP), return; end % DONE if we want speed!

end

%will come here only if the reflection is valid

for i=length(reflectors)-1:-1:1

% line from current reflection point to previuos tx-reflection

tmp\_L = create\_line(z\_tx\_refl(i), z\_reflection(i+1));

[z\_reflection(i), tmp] = L{reflectors(i)}.intersect(tmp\_L);

if (sum(tmp) == 2)

reflection\_valid(i) = 1;

else

reflection\_valid(i) = 0;

if (EARLY\_STOP), return; end % DONE if we want speed!

end

end

%let the ray tracing begin

no\_intersections = NaN(length(reflectors)+1, 1);

%tx->1st reflector

tmp\_L = create\_line(z\_tx, z\_reflection(1));

no\_intersections(1) = check\_intersections(tmp\_L, L, reflectors(1));

if ( (no\_intersections(1) == 0) && EARLY\_STOP), return; end

for i=2:length(reflectors)

% one reflection to the next

tmp\_L = create\_line(z\_reflection(i-1), z\_reflection(i));

no\_intersections(i) = check\_intersections(tmp\_L, L, reflectors(i-1:i));

if ( (no\_intersections(i) == 0) && EARLY\_STOP), return; end

end

%last reflector->rx

tmp\_L = create\_line(z\_reflection(end), z\_rx);

no\_intersections(end) = check\_intersections(tmp\_L, L, reflectors(end));

if ( (no\_intersections(end) == 0) && EARLY\_STOP), return; end

%finally!

%angles

tmp\_L = create\_line(z\_tx, z\_reflection(1)); % tx -> reflection

AoD.theta = tmp\_L.alpha;

tmp\_L = create\_line(z\_rx, z\_reflection(end)); % reflection -> rx, note : needs coded reverse, to get the angle right

AoA.theta = tmp\_L.alpha;

%distance

tmp\_r = abs(z\_reflection(1) - z\_tx);

for i=2:length(reflectors)

tmp\_r = tmp\_r + abs(z\_reflection(i) - z\_reflection(i-1));

end

tmp\_r = tmp\_r + abs(z\_rx - z\_reflection(end));

AoA.r = tmp\_r;

AoD.r = tmp\_r;

return

function valid = check\_intersections(L, other\_L, ignore\_indicies)

L2check = setdiff(1:length(other\_L), ignore\_indicies);

tmp\_v = NaN(length(other\_L),1);

tmp\_v(ignore\_indicies) = 0;

for i=L2check

[~, tmp] = L.intersect(other\_L{i});

tmp\_v(i) = tmp(1) & tmp(2);

end

%no intersections

if (sum(tmp\_v) == 0)

valid = 1;

else

valid = 0;

end

return

**E.4 Reflector Prediction with Ray Tracing**

%% Create impulse train

clear;clc;close all;

% Define path arrival times from PDPs

c = 3e8;

my\_expected\_max\_dist\_elevator = sqrt(500^2 + 550^2)\*0.0254; % meters

% These dimensions use ray tracer inches, also used in plotting

rx = 165+100j;

tx1 = 300+240j;

tx3 = 25+240j;

tx5 = 165+435j;

tx7 = 300+630j;

tx9 = 25+630j;

tx = [tx1;tx3;tx5;tx7;tx9];

dimag = imag(tx-rx);

dreal = real(tx-rx);

% angles of tx's relative to rx

phi = atan2d(dimag,dreal);

% MUST BE TO THREE DECIMAL POINTS

% delay time observations

t = {}; % [ LOS | MP1 ]

t{1,1} = 0.019;

t{1,2} = NaN;

t{3,1} = 0.019;

t{3,2} = NaN;

t{5,1} = 0.029;

t{5,2} = 0.063;

t{7,1} = 0.049;

t{7,2} = 0.069;

t{9,1} = 0.049;

t{9,2} = 0.068;

% d = c\*t % these dimensions are in meters, convert to inches at end!

d = cellfun(@(x) c.\*(x.\*(1e-6)), t, 'un', 0);

d = cell2mat(d);

d1 = d(:,1); % direct LoS path distance

d2 = d(:,2); % distance travelled by first reflection MP

delta\_d = d2 - d1; % difference in distance travelled

% d2 = a - b

% -> a = distance from Rx to reflector

% -> b = distance from Tx to reflector

% knowing delta\_d, here are all combinations for a,b

% locus

steps = 0.1;

% step time of 0.1

% generate all possible vals up to d2, for all positions

Combos\_tmp = allcomb(steps:steps:max(d2),steps:steps:max(d2));

a=zeros(1000,5);

b=zeros(1000,5);

for tmp = 1:length(d1) % for each Tx position

count\_tmp = 1;

for i = 1:length(Combos\_tmp) % for each a b combo

cmb\_d2 = Combos\_tmp(i,2) + Combos\_tmp(i,1); % d2 = a + b

cmb\_delta\_d = cmb\_d2 - d1(tmp); % delta\_d = d2 - d1

if (delta\_d(tmp)==cmb\_delta\_d && Combos\_tmp(i,1)~=0 && Combos\_tmp(i,2)~=0)

a(count\_tmp,tmp) = Combos\_tmp(i,2);

b(count\_tmp,tmp)= Combos\_tmp(i,1);

count\_tmp = count\_tmp + 1;

end

end

end

% theta from Rx

d1m = repmat(d1',size(a,1),1); % duplicate rows of array

cosTheta = (a.^2 + d1m.^2 - b.^2)./(2.\*a.\*d1m);

theta = real(acosd((a.^2 + d1m.^2 - b.^2)./(2.\*a.\*d1m))); % all theta values for valid setups

ind1 = find(theta(:,1)~=0);

ind3 = find(theta(:,2)~=0);

ind5 = find(theta(:,3)~=0);

ind7 = find(theta(:,4)~=0);

ind9 = find(theta(:,5)~= 0);

% angle to draw line a to reflector

ang1 = phi(1) - theta(ind1,1);

ang3 = phi(2) - theta(ind3,2);

ang5 = phi(3) - theta(ind5,3);

ang7 = phi(4) - theta(ind7,4);

ang9 = phi(5) - theta(ind9,5);

% x2 = x1 + r\*Cos(theta)...

ref1x = real(rx) + a(ind1,1) .\* 39.3701 .\* cosd(ang1);

ref1y = imag(rx) + a(ind1,1) .\* 39.3701 .\* sind(ang1);

ref3x = real(rx) + a(ind3,2) .\* 39.3701 .\* cosd(ang3);

ref3y = imag(rx) + a(ind3,2) .\* 39.3701 .\* sind(ang3);

ref5x = real(rx) + a(ind5,3) .\* 39.3701 .\* cosd(ang5); % from meters to inches

ref5y = imag(rx) + a(ind5,3) .\* 39.3701 .\* sind(ang5);

ref7x = real(rx) + a(ind7,4) .\* 39.3701 .\* cosd(ang7);

ref7y = imag(rx) + a(ind7,4) .\* 39.3701 .\* sind(ang7);

ref9x = real(rx) + a(ind9,5) .\* 39.3701 .\* cosd(ang9);

ref9y = imag(rx) + a(ind9,5) .\* 39.3701 .\* sind(ang9);

% draw Tx, Rx

zall\_tx = [300+240j,165+240j,25+240j,300+435j,165+435j,25+435j,300+630j,165+630j,25+630j];

%plot(real(z\_tx), imag(z\_tx), 'r\*');

figure(1)

hold on;

lbl = 1;

for i=1:length(tx)

plot(real(tx(i)), imag(tx(i)), 'r\*');

text(real(tx(i))+3, imag(tx(i))-1, strcat('Tx',int2str(lbl)), 'Color', 'r');

lbl = lbl+2;

end

%plot Rx

plot(real(rx),imag(rx),'rx','Linewidth',3);

%plot locus

plot(ref1x,ref1y,'bx');

plot(ref3x,ref3y,'vx');

plot(ref5x,ref5y,'gx');

plot(ref7x,ref7y,'kx');

plot(ref9x,ref9y,'yx');

%plot walls

plot([525 525], [0 760],'b--');

plot([-800 525], [0 0],'b--');

plot([-800 525], [760 760],'b--');

plot([0 0], [0 760],'b--');

plot([-800 -800], [0 760],'b--')

xlim([-1000 800])

hold off;

1. [↑](#footnote-ref-1)