Improving Bluetooth-based Indoor Positioning Using Vision and Artificial Networks

Naghdi, Sharareh

doctoral thesis

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Improving Bluetooth-based Indoor Positioning Using Vision and Artificial Networks

by

Sharareh Naghdi

A THESIS
SUBMITTED TO THE FACULTY OF GRADUATE STUDIES
IN PARTIAL FULFILMENT OF THE REQUIREMENTS FOR THE
DEGREE OF DOCTOR OF PHILOSOPHY

GRADUATE PROGRAM IN GEOMATICS ENGINEERING

CALGARY, ALBERTA

JULY, 2020

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Abstract

The demands for accurate positioning and navigation applications in complex indoor environments such as emergency call positioning, fire-fighting services, and rescue operations are increasing continuously. Global Navigation Satellite Systems (GNSS) receivers, while ubiquitous in outdoor positioning, are not effective indoors. One of the best solutions to solve this problem and increase the accuracy of the user's position in indoor areas is to apply other sensors.

This research takes advantage of Bluetooth Low Energy (BLE) technology, vision systems, and Artificial Neural Networks (ANNs) to improve the accuracy of the position solutions in indoor environments for pedestrian applications. BLE technology faces challenges related to the Received Signal Strength Indicator (RSSI) fluctuations caused by human body shadowing. This thesis presents methods to compensate for losses in the RSSI values by applying ANN algorithms to RSSI measurements from three BLE advertising channels. The resulting improved RSSI values are then converted into ranges using path loss models and trilateration is applied to obtain indoor positions.

Two neural network algorithms were implemented. The first used only the RSSI values while the second incorporated a wearable camera as an additional source of information about the presence or absence of human obstacles. The results showed that the two proposed artificial-based systems could enhance RSSI due to human body shadowing and provide significantly better ranging and positioning solutions than fingerprinting and trilateration techniques with uncorrected RSSI values. Two proposed systems provided 3.7 m and 6.7 m positioning accuracy in 90% of the time in a complex environment with the presence of the human body, nevertheless, the fingerprinting
and the classic algorithms offered 8.7 m and 12.3 m position accuracy in the same situation, respectively.
Acknowledgments

I would like to acknowledge all who have been supporting me throughout my doctoral studies. The completion of this long journey would not have been possible without their help. My sincere gratitude goes to my supervisor, Dr. Kyle O’Keefe, for his valuable guidance and advice. I appreciate his professional supervision, strong support, encouragement, and patience over the past four years.

I would like to extend my appreciation to my supervising committee: Dr. Aboelmagd Noureldin, and Dr. Derek Lichti. Thank you both for providing me with your constructive suggestions and valuable discussions. Meanwhile, I appreciate Dr. Emmanuel Stefanakis, Dr. Steve Liang, and Dr. Paolo Barsocchi for taking their time to attend my final thesis exam. Special thanks to Dr. Gérard Lachapelle to inspire me with his dedication and passion for research. I would also like to thank Dr. Adel M. Moussa for his helpful discussions.

My sincere thanks go to all current and past PLAN group and staff members of the Geomatics Engineering department for their help. Special thanks to Rakesh, Niranjan, Paul V. G., Chandra, Cheng, Paul G., Dongyu, Rene, Andreas, and Maliha for all the good times that we have had together. I would like to express my sincere thanks to my best friend Zahra Abbaszadeh, for her care and attention during my difficult times.

Finally, I would like to thank my family for their unconditional love and support. Special thanks to my sister, Shamim, who always supports and encourages me in my life.

Last but not the least, this research would not have been possible without the endless love, full support, and warm encouragement of my love, Ehsan.
Dedication

To

My parents: Feri & Behrouz

My siblings: Sirous, Soheila, and Shamim

And

My beloved Ehsan
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<th>Definition</th>
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<tr>
<td>$C_r$</td>
<td>Variance-covariance matrix of the residual vector</td>
</tr>
<tr>
<td>$c$</td>
<td>Speed of light = 299792458 m/s</td>
</tr>
<tr>
<td>$f$</td>
<td>Signal frequency (Hz)</td>
</tr>
<tr>
<td>$G_t$</td>
<td>Transmitter Antenna gain</td>
</tr>
<tr>
<td>$G_r$</td>
<td>Receiver Antenna gain</td>
</tr>
<tr>
<td>$H$</td>
<td>Design matrix</td>
</tr>
<tr>
<td>$J$</td>
<td>Jacobian matrix</td>
</tr>
<tr>
<td>$m$</td>
<td>Number of Transmitters</td>
</tr>
<tr>
<td>$\mu$</td>
<td>Center of Gaussian function</td>
</tr>
<tr>
<td>$n$</td>
<td>Path loss exponent</td>
</tr>
<tr>
<td>$P_t$</td>
<td>Transmitted power (mW)</td>
</tr>
<tr>
<td>$P_r$</td>
<td>Received power (mW)</td>
</tr>
<tr>
<td>$\varphi(x)$</td>
<td>Activation function</td>
</tr>
<tr>
<td>$R$</td>
<td>Observation variance-covariance matrix</td>
</tr>
<tr>
<td>$v$</td>
<td>Measurement error</td>
</tr>
<tr>
<td>$w_k$</td>
<td>Neural networks weight</td>
</tr>
<tr>
<td>$X$</td>
<td>State vector</td>
</tr>
<tr>
<td>$X_o$</td>
<td>Observation error</td>
</tr>
<tr>
<td>$\hat{x}$</td>
<td>Estimate of the state vector</td>
</tr>
<tr>
<td>$x_{RX}$</td>
<td>Receiver position components in the East direction</td>
</tr>
<tr>
<td>$x_{TX}$</td>
<td>Transmitter position components in the East direction</td>
</tr>
<tr>
<td>$y_{RX}$</td>
<td>Receiver position components in the North direction</td>
</tr>
<tr>
<td>$y_{TX}$</td>
<td>Transmitter position components in the North direction</td>
</tr>
<tr>
<td>$Z$</td>
<td>Measurement/observation vector</td>
</tr>
<tr>
<td>$\delta z$</td>
<td>Misclosure vector</td>
</tr>
<tr>
<td>$\Theta$</td>
<td>Neural network bias</td>
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<tr>
<td>AA</td>
<td>Access Address</td>
</tr>
<tr>
<td>AFH</td>
<td>Adaptive Frequency Hopping</td>
</tr>
<tr>
<td>AI</td>
<td>Artificial Intelligence</td>
</tr>
<tr>
<td>ANN</td>
<td>Artificial Neural Network</td>
</tr>
<tr>
<td>AOA</td>
<td>Angle Of Arrival</td>
</tr>
<tr>
<td>AP</td>
<td>Access Point</td>
</tr>
<tr>
<td>BLE</td>
<td>Bluetooth Low Energy</td>
</tr>
<tr>
<td>CDF</td>
<td>Cumulative Distribution Function</td>
</tr>
<tr>
<td>CNN</td>
<td>Convolutional Neural Network</td>
</tr>
<tr>
<td>CRC</td>
<td>Cyclic Redundancy Check</td>
</tr>
<tr>
<td>EKF</td>
<td>Extended Kalman Filtering</td>
</tr>
<tr>
<td>FA</td>
<td>False Alarm</td>
</tr>
<tr>
<td>FHSS</td>
<td>Frequency Hopping Spread Spectrum</td>
</tr>
<tr>
<td>FOV</td>
<td>Field Of View</td>
</tr>
<tr>
<td>FPN</td>
<td>Feature Pyramid Network</td>
</tr>
<tr>
<td>FSFM</td>
<td>Free Space Friis Model</td>
</tr>
<tr>
<td>GNSS</td>
<td>Global Navigation Satellite Systems</td>
</tr>
<tr>
<td>GPIO</td>
<td>General Purpose Input/Output</td>
</tr>
<tr>
<td>GPS</td>
<td>Global Positioning Systems</td>
</tr>
<tr>
<td>HOG</td>
<td>Histogram of Orientated Gradients</td>
</tr>
<tr>
<td>INS</td>
<td>Inertial Navigation Systems</td>
</tr>
<tr>
<td>IPS</td>
<td>Indoor Positioning Systems</td>
</tr>
<tr>
<td>ISM</td>
<td>Industrial, Scientific, and Medical</td>
</tr>
<tr>
<td>KNN</td>
<td>K-Nearest Neighbor</td>
</tr>
<tr>
<td>LBP</td>
<td>Local Binary Pattern</td>
</tr>
<tr>
<td>LOS</td>
<td>Line-of-Sight</td>
</tr>
<tr>
<td>MAC</td>
<td>Media Access Control</td>
</tr>
<tr>
<td>MD</td>
<td>Missed Detection</td>
</tr>
<tr>
<td>MLP</td>
<td>Multi-Layer Perceptron</td>
</tr>
<tr>
<td>MSE</td>
<td>Mean Square Error</td>
</tr>
<tr>
<td>NFC</td>
<td>Near Field Communication</td>
</tr>
<tr>
<td>NLOS</td>
<td>Non-Line-of-Sight</td>
</tr>
<tr>
<td>PDU</td>
<td>Protocol Data Unit</td>
</tr>
<tr>
<td>PHY</td>
<td>Physical Layer</td>
</tr>
<tr>
<td>PSO</td>
<td>Particle Swarm Optimization</td>
</tr>
<tr>
<td>RGB-D</td>
<td>Red Green Blue-Depth</td>
</tr>
<tr>
<td>RBF</td>
<td>Radial Basis Function</td>
</tr>
<tr>
<td>RF</td>
<td>Radio Frequency</td>
</tr>
<tr>
<td>RFID</td>
<td>Radio Frequency Identification</td>
</tr>
<tr>
<td>RP</td>
<td>Reference Point</td>
</tr>
<tr>
<td>RSSI</td>
<td>Received Signal Strength Indicator</td>
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<tr>
<td>Abbreviation</td>
<td>Definition</td>
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<tr>
<td>--------------</td>
<td>------------------------------------------</td>
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<tr>
<td>SIFT</td>
<td>Scale-Invariant Feature Transform</td>
</tr>
<tr>
<td>SOM</td>
<td>Self-Organizing Map</td>
</tr>
<tr>
<td>STD</td>
<td>Standard Deviation</td>
</tr>
<tr>
<td>SIG</td>
<td>Special Interest Group</td>
</tr>
<tr>
<td>SoC</td>
<td>System on Chip</td>
</tr>
<tr>
<td>SVM</td>
<td>State Vector Machine</td>
</tr>
<tr>
<td>2D</td>
<td>Two Dimensional</td>
</tr>
<tr>
<td>3D</td>
<td>Three Dimensional</td>
</tr>
<tr>
<td>TOF</td>
<td>Time Of Flight</td>
</tr>
<tr>
<td>UART</td>
<td>Universal Asynchronous Receiver-Transmitter</td>
</tr>
<tr>
<td>USB</td>
<td>Universal Serial Bus</td>
</tr>
<tr>
<td>UWB</td>
<td>Ultra-Wideband</td>
</tr>
<tr>
<td>WCL</td>
<td>Weighted Centroid Localization</td>
</tr>
<tr>
<td>WKNN</td>
<td>Weighted K-Nearest Neighbor</td>
</tr>
<tr>
<td>WLAN</td>
<td>Wireless Local Area Network</td>
</tr>
<tr>
<td>YOLO</td>
<td>You Only Look Once</td>
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Chapter 1

INTRODUCTION

One of the popular candidates in wireless technology for indoor positioning is the Bluetooth Low Energy (BLE). However, this technology faces challenges related to the Received Signal Strength Indicator (RSSI) fluctuations due to the behavior of the different advertising channels and the effect of human body shadowing among other effects. To mitigate these effects, this thesis proposes and implements a dynamic Artificial Intelligence (AI) model that uses the three different BLE advertising channels and vision information to detect human body shadowing and compensate the RSSI values accordingly. This chapter begins with an introduction to indoor positioning and a brief description of the available technologies and models used in this field in Section 1.1. Section 1.2 describes some of the limitations of these technologies and models. The motivations and contributions of this thesis are summarized in Section 1.3. The thesis outline and the list of related publications are presented in Sections 1.4 and 1.5, respectively.
1.1 Indoor Positioning

The position estimation of a target in outdoor environments is widely solved by employing Global Navigation Satellite Systems (GNSSs). Considering the fact that people spend most of their time in indoor environments, the demand for reliable indoor localization applications has rapidly increased. In the case of indoor positioning, GNSS signals are not usable in a satisfactory manner. Numerous studies have been investigating Indoor Positioning Systems (IPSs), based on a wide range of different technologies (Mainetti et al., 2014). The most famous and well-investigated technologies for indoor positioning are Radio Frequency (RF) technologies (Abdat et al., 2010), Inertial Navigation Systems (INSs) (Harle, 2013), and vision sensors (Elloumi et al., 2013). However, inertial sensors suffer from fast-growing errors and frequent updating is necessary to control these errors. Moreover, vision-based techniques are sensitive to the illumination and distribution of features. Vision techniques can be affected by the absence of features in some parts of the building like corridors and the bad feature distribution (geometry) that will make it difficult to derive accurate orientation in given axes.

Different performance parameters such as cost, accuracy, scalability, robustness, etc. should be taken into consideration to choose the best technology for IPS. While many studies focus on high precision indoor positioning solutions, these systems are often costly, complex to install, and not adjustable to the real environment. For instance, an INS-assisted system was developed by Retscher (2006) with a positioning accuracy under 0.3 m in a multi-floor building, though, the system was expensive. An electrode-based indoor positioning introduced by Valtonen et al. (2009) was accurate (15 cm positioning accuracy) but complex to install. To reduce the cost and complexity, the current trend is to use technology such as RF with the already existing
infrastructure in the indoor area or the available standard communication systems on the user’s smart devices such as smartphones, laptops, etc.

RF-based localization includes Wireless Local Area Networks (WLANs), Bluetooth, Zigbee, Radio Frequency Identification (RFID), Ultra-Wideband (UWB), etc. Examples of each technology can be found in the prior work of Prasithsangaree et al. (2002); Bargh and de Groote (2008); Amer and Noureldin (2016); Ruiz et al. (2012); and Chiu and O’Keefe (2008). Most of these technologies are prevalent, freely available in the indoor areas, and in most cases, supported by current mobile devices. However, each technology has limitations, including vulnerability to signal interference, multipath and signal attenuation, requirements for clock synchronization between transmitters and receivers, requirements for calibration, or suffer from unbounded systematic errors.

Radio communication systems have the ability to provide location information based on three different specific physical characteristics of radio signals: (i) the power of the propagated signal, (ii) the propagation time, and (iii) the direction of the propagation wave. Regarding those physical characteristics, Liu et al. (2007) divided RF-based indoor positioning into three broad categories: (i) Received Signal Strength Indicator (RSSI)-based methods, (ii) Time of Flight (TOF) measurements, and (iii) Angle of Arrival (AOA)-based methods.

The TOF method considers the elapsed time between the transmission of a signal and the reception at the receiver. This method either requires accurate time synchronization between the transmitter and receiver or a two-way transmission. Alternatively, with synchronized infrastructure and sufficient measurements, the user’s clock offset can be estimated with the user’s position as is the case in GNSS. The AOA method uses the angle of the arrived signal at a receiver to calculate
localization. Measuring the angle of the arrival usually demands special hardware (Iliev & Paprotny, 2015) and/or multiple antennas, and thus is rarely implemented on mobile devices. Approaches that employ the RSSI measurements are considered the simplest since they do not necessitate any hardware modifications, system timing coordination, or synchronization between transmitters and receivers. Although the RSSI method is one of the most widespread approaches, there are still some challenges that need to be addressed. In general, the position accuracy, when using the RSSI approach, is poor because the signal strength can be affected by multipath, interference, and shadowing caused by various factors such as the presence of obstacles, the number of reflective surfaces, and the overall dynamics of the environment.

RSSI-based ranging and fingerprinting are two common methods that rely on the RSSI measurements for positioning. Positioning that utilizes fingerprinting has the potential to achieve high accuracy, provided sufficiently dense training data are available, however, this process is time-consuming and does not adapt well to environmental changes. RSSI-based ranging needs a path loss model to estimate ranges from the RSSI values and then applies trilateration to compute a position.

Among all these technologies, WiFi (the trade name for WLAN) and Bluetooth are the two most common choices in the context of indoor wireless location. Both of these technologies have widespread applications and relatively lower costs. The availability of the existing WiFi infrastructure in indoor environments makes it one of the best options for indoor localization. Nevertheless, the placement of Access Points (APs) is determined by communication requirements and it not necessarily optimal for localization. In recent years, the smart device market has increasingly relied on Bluetooth for short-range device-to-device communication, which makes
this technology a viable alternative solution to the WiFi technology for indoor localization (Kriz et al., 2016; Contreras, Castro, & de la Torre, 2017).

Bluetooth technology has received more attention since 2010 when the Bluetooth Special Interest Group (SIG) introduced the BLE standard with the Bluetooth core specification version 4.0. BLE (Bluetooth, S.I.G, 2010) is a very low power, low cost, low complexity, and low maintenance technology. Depending on the connection interval, battery-powered BLE modules are able to last for 1-2 years (Kamath & Lindh, 2010).

BLE beacons were originally developed as replacements for cables to connect devices and transmit wireless data in addition to the localization information. The transmission power of BLE beacons is adjustable, which can usually be varied between –30 to 0 dBm, and they reliably transmit data up to 30 m (Townsend et al., 2014). BLE operates at a frequency band of 2.4 GHz, which is divided into 40 channels with 2 MHz spacing (Heydon, 2012). Out of these 40 channels, 3 advertising channels (labeled 37, 38, and 39) are reserved to continuously broadcast advertising messages. Initially, the proposed application for the BLE beacons was proximity marketing, which advertises marketing messages to mobile devices close to a particular location in shopping centers, museums, hotels, stadiums, exhibition halls, etc. Examples of these marketing messages include relevant information, related news, and special offers.

The RSSI values can be obtained from these 3 channels by users in the range of the BLE beacons. Since each channel has a different channel gain and multipath, the RSSI values from each of the advertising channels differ (Faragher & Harle, 2015). Most existing research (Bargh & de Groote, 2008; Contreras et al., 2017; Kriz et al., 2016) has considered the RSSI values from all 3
channels together to achieve the aggregate signal, which contains more fluctuations when compared to each of the individual channels.

In wireless propagation, fading may either be due to the interference from multipath propagation or shadowing from obstacles. Due to the difficulty of the signal attenuation modeling caused by obstacles, this effect is often neglected in the available models. However, to properly model radio propagation for the RSSI-based ranging, all the obstacles between the transmitter and receiver should be considered. A common signal attenuation source is the human body, which can shadow or fully obscure the signal path. A human body can be detected by many different approaches and technologies such as vision, distortion, and irregularities in the signal, etc. The three BLE advertising channels follow the same pattern during a human body blockage. When a human body blocks the signal, all three channels drop, and when a human body leaves the area, all three channels return to their former values. Human body obstacles cause attenuation on all three channels simultaneously while multipath affects the channels individually.

The RSSI values can be mathematically related to the distance by empirical or AI algorithms. The AI models have been considered as a powerful tool to learn from the observed data in real environments and model the complex relationships between the input and output values. Empirical models perform well in terms of processing time and memory efficiency, although they are less compatible with sudden changes in the propagation environment (Isabona & Srivastava, 2016; Wolfle & Landstorfer, 1997).

More details and studies about separate advertising BLE channels, human body shadowing, vision sensors, and Arterial Neural Networks (ANNs) are provided in Chapter 2.
1.2 Limitation of Previous Work

The radio propagation models to estimate the behavior of the radio signals in indoor environments have been well studied in recent years. However, much of the work done so far has focused on the use of empirical path loss propagation models. These systems predict the loss in the received signal, and cannot properly estimate the radio signal fading based on the real environment. To decrease fluctuations in the measured RSSI values, many improvements have been proposed for various BLE propagation models (Altini et al., 2010; Baronti et al., 2018; Mendoza-Silva et al., 2019; Schmalenstroeer & Haeb-Umbach, 2016), however, the resulting path loss models still only provide ranges with about 6 m of accuracy in 90% of the time. All these studies used the aggregate BLE RSSI values, which have been shown to have larger fluctuations in the RSSI values compared to the individual advertising channels. To achieve more accurate results, some other groups have considered the BLE RSSI values from separate channels, although, these studies have used complicated algorithms (Zhuang et al., 2016) or extra hardware (Cantón Paterna et al., 2017; Huang et al., 2019).

The AI techniques such as fuzzy logic and neural networks can be utilized as effective methods to achieve high computational efficiency and robustness against noise and interference. Thus, it is possible to reduce the error margin of radio propagation models by taking advantage of AI networks and predicting the propagation behavior of radio signals more accurately. Flexible neural network solutions can be used to model the relationship between the predicted and measured RSSI values and have been demonstrated in Gong et al. (2016); Schloter and Aghajan (2006); Takenga et al. (2006). This is because intelligent networks are adaptive and dependent on the observed data rather than on analytical and theoretical models of a system (Hu & Hwang, 2002;
Wu et al., 2007). For example, an AI network presented in Amer and Noureldin (2017), was able to predict the WiFi path loss in the indoor areas. When compared to the empirical models, log-normal, and COST 321 (multiple walls), their AI results achieved less error and could deal with dynamic environment changes.

Moreover, previous studies (Cantón Paterna et al., 2017; Huang et al., 2019; Zhuang et al., 2016) did not investigate the AI approach using separate BLE channels. Besides, other available sensors on mobile devices provide the opportunity to collect more information about the propagation environment. This information can prepare more accurate input parameters with proper weight for AI networks. It would be interesting to use the additional sensor information to improve the radio propagation model based on intelligent networks.

1.3 Motivation and Objectives

The possible application of this thesis can be the support of firefighter movements or tracking of emergency staff which needs 3 m to 4 m of accuracy, however, human body shadowing can significantly affect this value. Then in this thesis, the main objective is to design and implement an AI network for a radio propagation model to improve the RSSI-based ranging and account for the effect of human body obstacles. This main objective is fulfilled with two sub-objectives: i) Investigating the benefits of using the three BLE advertising channels separately, and ii) applying vision sensors as an additional source of information about the presence or absence of human obstacles. In this AI model, sequential patterns of the RSSI values and the number of blocking bodies captured by a camera image can be used to characterize the body shadowing effect. The outputs of AI are the compensated RSSI values which can then be evaluated in terms of a trilateration positioning solution. To accomplish the objectives, the following tasks are pursued:
1. **Applying separate BLE advertising channels**: Experimental data collection and characterization of the RSS sensitivity to fading and uncertainty caused by human body obstacles for separate BLE advertising channels in indoor environments.

2. **Modeling RSSI based on ANN**: Proposing a mathematical model for the BLE signals based on the different AI networks, designing the architecture, training, and tuning the parameters on each model. To evaluate the performance of the AI models both the validation and testing processes are designed.

3. **Detecting human blockages by signal**: Using the advantage of uniform reaction of the three BLE advertising channels to the human body shadowing allows the ANN algorithms to detect this blockage.

4. **Compensation of human blockages effect**: the attenuation of the signal due to the human body is detected and compensated based on artificial intelligence through the training data.

5. **Adding vision information form environment**: Employing other sensor information such as cameras to permit the AI network to model a radio propagation based on more accurate input parameters.

This project resulted in the following contributions to the field:

1. The first detailed comparison of using individual BLE advertising channels rather than aggregate RSSI for detection of obstacles when applying a path loss model and trilateration for RSSI ranged-based positioning.
2. The first application of a thresholding method to detect the uniform reaction of three BLE advertising channels to detect human body obstructions and a detailed comparison with prior methods.

3. The first use of ANN as a method to detect and correct for human body obstructions using a sliding window of RSSI on multiple advertising channels.

4. The first demonstration of the combination of BLE RSSI, wearable camera, and ANN to detect and correct RSSI values for human body obstructions.

The thesis is organized to present the details of each task, document the contributions, and finally, explain how the objectives were met.

1.4 Thesis Outline

The remainder of the thesis is structured as follows:

- Chapter 2 provides a background and literature review about recent research for the BLE technologies in indoor environments, the RSSI-based techniques, the AI applications in indoor positioning and the vision algorithms to detect human bodies.
- Chapter 3 presents the fundamentals of the models and algorithms used in this thesis for the BLE signals, human body effect, artificial networks, and image object detection.
- Chapter 4 presents the proposed system design based on three methods: threshold-based, artificial-based, and artificial-based augmented by vision information. In this chapter, block diagrams for all proposed algorithms and implementation details are discussed.
• Chapter 5 introduces the experimental setup, data collection system, test areas, and verification of the proposed hypothesis. The sensitivity analysis and tuning of the parameters in different algorithms and networks, which are adapted in this study, are also discussed.

• Chapter 6 presents the results of the proposed methods and compares the solutions with the fingerprinting and non-empirical models as well as with aggregate RSSI signals to allow comparison with prior works.

• Chapter 7 provides conclusions and suggestions future work.

1.5 Publications

The contributions of this thesis have also been published in the following research papers:


Chapter 2

BACKGROUND

This chapter provides the background and literature review on the work done related to the radio-based indoor positioning systems, Artificial Neural Network (ANN) systems, and vision sensors. The chapter begins with the background on the radio-based indoor positioning systems in Section 2.1, including the radio technologies and mathematical models, as well as their applications and challenges in human body shadowing. For the sake of brevity, only an overview of the Bluetooth theories and signals, as applied in this work, are presented and compared to other well-known radio technologies. In Section 2.2, basic explanations and the most recent studies of the neural network algorithms in addition to the comparison between the ANN algorithms and traditional path loss models for the radio positioning systems are presented. In Section 2.3, a brief introduction to the vision sensor research and development, as it relates to this thesis, is presented along with a review of the studies proposing the integration of the vision sensors and object detection systems.
2.1 Radio-based Indoor Positioning

RF signals are electromagnetic waves in the range of 3 kHz to 300 GHz. Most RF technologies have been developed primarily for the communication systems, however, Radio-based technologies were developed for navigation in parallel. Currently, the most common method for indoor localization involves using IEEE 802.11 WiFi due to the wide-spread adoption of WiFi in mobile devices and the existing infrastructure deployed to support these users.

The IEEE 802.11 standard consists of several sub-standards such as IEEE 802.11a/b/g/n/ac/ax to enhance the communication speed, and IEEE 802.11e/i/v/s/p to focus on the quality of service, security, network management, mesh networking and vehicular environments, respectively. The mentioned sub-standards operate in the 2.4 or 5 GHz Industrial, Scientific, and Medical (ISM) bands, and provide different coverage areas (50-100 m), and a typical gross bit rate of 11, 54, or 108 Mbps (Mathiesen et al., 2005; Sendra et al., 2011). For location estimation services, researchers have focused more on IEEE 802.11a/b/g (Maglogiannis & Hadjieftymiades, 2007; Makki et al., 2015) and the application of fingerprinting approaches, though future standards promise more accurate timing, and thus the potential for the accurate TOF positioning (IEEE 802.11az, 2018).

The WiFi systems were not originally designed for the positioning purposes and the WiFi networks are usually designed to optimize the communication service area. The number and placement of the APs need to be reconsidered if providing accurate localization is also desirable (Huszák et al., 2013). The accuracy of the WiFi positioning systems is on the order of 3 to 30 m, with an update rate in a few seconds range (Liu et al., 2007). Although WiFi technology for
positioning is popular and accurate, Bluetooth has advantages in terms of cost, energy consumption, and deployment simplicity.

In contrast to the WiFi, which is a wideband with wireless internet protocol connectivity, the Bluetooth technology (IEEE 802.15.1) is more concerned with small area networks which are called piconets or personal area networks. The Bluetooth technology is designed for short-range wireless communications and developed to provide an alternative to wired connections for personal peripheral devices such as audio headphones, keyboards, and mice. This technology has since been widely adopted in mobile phones, personal computers, and gaming consoles. Like WiFi, Bluetooth also operates in the 2.4 GHz ISM radio band. The ISM band is a very crowded frequency band, and sharing the same frequency band used by the Bluetooth and WiFi technology makes both vulnerable to interference. To end this, Bluetooth uses Frequency Hopping Spread Spectrum (FHSS) to improve performance and diminish the impact of the interference. The Bluetooth FHSS involves switching between frequency channels in a pseudorandom pattern up to 1600 times per second (Hallberg et al., 2003). Figure 2.1 shows the main WiFi channels in comparison to the Bluetooth channels. It should be noted that the WiFi channels 1, 6, and 11 do not overlap with each other; thus, these channels are most commonly used. At the same time, Bluetooth was originally designed to randomly hop across all of its 79 channels. To choose the best frequency for hopping in order to avoid WiFi interference, Bluetooth now uses an adaptive sort of FHSS which is called Adaptive Frequency Hopping (AFH).

The main idea of the AFH is to permit the Bluetooth device to measure the quality of the wireless signal in the propagation environment to determine whether the channel has been interfered with or intentionally attacked so that the Bluetooth can adjust the hopping pattern to
avoid those channels. Frequency hopping also provides security for transmitted signals that unauthorized receivers are not able to detect and monitor the communication because it occurs only for brief periods on any given channel and changes rapidly in a pseudorandom way.

**Figure 2.1:** The WiFi and classic Bluetooth channels in the 2.4 GHz ISM band.

BLE is a low power version of the classic Bluetooth technology in which its low power consumption makes this technology able to run on a small battery for years. The BLE technology also applies the frequency hopping mechanism for communication, however, 3 channels out of 40 have been reserved for advertising. The AFH technique is used in BLE, similar to the classic Bluetooth technology. Nevertheless, to minimize the energy consumption of applying the AFH technique, the number of channels has been reduced to 40 (with 2 MHz width) compared to the classic Bluetooth that has 79, 1 MHz channels. More details about the BLE technology will be presented in Section 3.1.

The ubiquity of the Bluetooth technology on mobile devices such as smart-phones, the availability of its low-cost hardware, simple deployment, and low power consumption make it an excellent attractive technology for indoor localization.
2.1.1 Radio Math Models

The BLE communications can provide positioning solutions based on the RSSI values which are strongly correlated to the distance between transmitters and receivers. Proximity, fingerprinting, and trilateration are different types of RSSI-based positioning algorithms. In the next few paragraphs, these are briefly described as they apply to the BLE technology.

2.1.1.1 Proximity

The first category of the RSSI-based location models is the proximity algorithms which suggests if an access point (AP) or beacon can be connected to a user, then the user's position is located in the region of the AP. The regions can be considered as cell areas and identified based on threshold approaches. Yin et al. (2015) proposed a triggering threshold optimization method for the BLE proximity-based positioning. The placement of beacons was an important task in the cell-based method that determined the region of the intersection of the visible beacon ranges (Chawathe, 2008). The limited range of the Bluetooth was used as an advantage in a cell-based method in Chawathe (2009). Indeed, the method consisted of making a binary test (true or false) of the signal reception state based on the visibility of the Bluetooth beacons. Moreover, the method did not rely on the RSSI or other indicators of the signal strength. Some studies emphasized the geometry of the rooms where the beacons were installed (Kyritsis et al., 2016).

In Kystinsis et al. (2016) a threshold-based approach was used to identify between the same room and the adjacent room. Localization at room resolution with just one BLE node and one BLE sensor located approximately at the center of each room was presented in Verhaevert and Van Baalen (2016). Their results showed a correct localization more than 90% of the time and even more accurate results when the doors were closed. Smartphone-based indoor navigation systems
could take advantage of its embedded sensors to improve position accuracy. Kindt et al. (2020) presented a comprehensive energy model for a BLE infrastructure that pushed notifications to offer some actions on the user’s smartphone or tablet when the user was close to a particular BLE beacon. Proximity algorithms are satisfactory for some applications, especially in short-range communication systems, however, proximity methods do not give the exact position of the user.

2.1.1.2 Fingerprinting

Scene analysis is the second category, also known as fingerprint matching, which includes two phases: (i) off-line learning and (ii) on-line positioning. During the off-line phase, a site survey is accomplished by collecting the RSS measurements from the nearby APs and storing the measurements in a database. In the on-line phase, the current signal strengths of the APs are compared with the recorded information from the database to determine the user's position. The fingerprinting approach has seen a widespread application for WiFi signals since the WiFi APs are widely deployed in many indoor environments and positioning services using fingerprinting have been implemented by many service providers including telecommunications companies and mobile phone operating systems providers. More recently, BLE based fingerprinting has been added to some of these services (V. Chandel et al., 2016; De Schepper et al., 2017; Faragher & Harle, 2015a). The quantity and placement of the APs have a significant influence on the positioning performance. To identify each AP, a Media Access Control (MAC) address is used. The wireless radio signal database information is commonly recorded as a part of deployment for maintenance purposes in massive organizations such as airports, malls, stadiums universities, and office buildings. Pioneering companies in positioning technology such as Google, Apple, etc., have already developed massive worldwide databases to support precise indoor positioning. There are
also many public databases available containing the RSSI values from a variety of technologies (He et al., 2017; Xia et al., 2017).

For some applications, the proximity alone may also provide a sufficiently accurate position solution. One example would be to determine whether a particular device is in a particular building. Proximity can also be applied to limit the search area and decrease the computation time in the fingerprint matching (Hile & Borriello, 2008; La Delfa & Catania, 2014).

Davidson and Piché (2017) divided the fingerprinting localization techniques into three groups:

1. Deterministic algorithms such as the K-Nearest Neighbor (KNN) presented by Feng et al. (2012) and Weighted K-Nearest Neighbor (WKNN), described by Peng et al. (2016). These algorithms minimize the Euclidean distance of the RSSI measurements to calculate the position in the on-line phase deterministic algorithms that are simple, robust, and accurate.

2. Probabilistic algorithms such as a coverage area (Koski et al., 2010) and path loss (Viswanathan & Srinivasan, 2015) in which the user’s position was computed based on the probability distribution of the measured RSSI values. The most likely user’s location maximized the posterior probability.

3. Machine learning techniques such as State Vector Machines (SVM) (Farjow et al., 2011), deep learning (Dai et al., 2016), etc.

In the fingerprinting method, some studies focused on reducing the computation efforts, by using the server-side BLE fingerprint technique (An & Choi, 2016). An effective way for dealing with dynamic changes is to combine sensors (for instance RFID, and optical sensors) to adapt the
localization BLE fingerprinting method to the dynamic changes (Belmonte-Hernández et al., 2017; Zhu et al., 2018). De Schepper et al. (2017) presented another dynamic BLE fingerprinting approach used for location-aware applications in smart homes. Luo and Hsiao (2019) used this approach and they were able to reduce the position error by 2.5 m as compared to non-adaptive localization methods. The combination of other sensors with BLE fingerprinting was also helpful to diminish the calibration efforts (Kolakowski, 2019). A study by Bargh and de Groote (2008) presented a fingerprinting localization method that relied only on the response rate of the Bluetooth inquiries. This method showed the measured response rate decreased as a function of the distance between the user and the beacon. Their approach showed a 98% accuracy to localize a device in a full Bluetooth sensor coverage room when the target was static for 3 minutes.

The above-motioned studies utilized fingerprinting for the aggregate BLE signals, whereas a small number of other studies have considered the separate BLE channels in the fingerprinting method. Separate-channel proposed BLE fingerprinting methods showed that the data from separate channels provided better results than the aggregate signal fingerprinting. Faragher and Harle (2015 and 2015), for example, concluded that the separate channel BLE fingerprinting method achieved an accuracy better than 2.6 m 95% of the time when walking in a room, much better compared to the WiFi accuracy, which was about 8.5 m, 95% of the time (Faragher & Harle, 2015, 2014). The results from Powar et al. (2017) and Ishida et al. (2016) studies showed great improvements in positioning accuracy using the individual channel signal compared to an aggregate signal method. Their results indicated that the separate the BLE fingerprinting method had an accuracy of 2.56 m 90% of the time with one beacon each 9 m (Ishida et al., 2016).
Leu et al. (2015) presented improved results of the fingerprinting accuracy by adding extra APs to the fingerprinting database. Zhao et al. (2010) proposed an effective preprocessing scheme to select Reference Points (RPs) and APs to reduce redundancy. The proposed scheme could improve the accuracy of both the Kernel-based and KNN matching algorithms by 25%. Moreover, the results emphasized that the dense APs distribution improved the performance but at considerable cost.

Nevertheless, fingerprinting techniques face challenges in scalability and manual calibration efforts. The off-line phase in the fingerprinting is tedious and time-consuming, especially in a large mapping area that requires longer site surveys to build the RSS database. If any dynamic changes happen in the decoration of the furniture or reconstruction in the building, then the stored radio maps will have to be recalibrated and updated again. During the on-line phase, a subset of the RSS measurements should be selected since not all measurements provide beneficial information. Usually, the measurements are distorted by shadowing and Non-Line-of-Sight (NLOS) propagation.

2.1.1.3 RSSI-based Ranging

In the final category, a path loss model is used to estimate ranges from the RSSI values. Trilateration is then used to compute a position. Position accuracy was shown to significantly improve by Amer and Noureldin (2016) by adding a Kalman filter to an RSSI path loss modeling. A comparison between their proposed system and the fingerprinting approach reduced the position error from 4.5 m to 2.8 m with an 80% probability. Rida et al. (2015) proposed a localization system based on RSSI of BLE and an ultrasound speaker in which their results showed the average localization error about 1 m. Subhan et al. (2011) also showed significant position accuracy
improvement, using Bluetooth for indoor positioning. They used the standard radio propagation model with the RSSI and trilateration approaches. The average position error decreased from 5.87 m to 2.67 m using a gradient filter. Another approach to improve accuracy was proposed by Chai et al. (2016). They were able to obtain accuracy at the centimetre level by utilizing a pre-processed algorithm to remove outliers in BLE RSSI values, the Kalman filtering to calculate the distance, and the triangulation algorithm to calculate the position.

Jianyong et al. (2014) designed a Gaussian filter and distance weighted filter to pre-process BLE RSSI in different sampling points. Their location error was less than 1.5 m in 80% of the time during their tests. The localization performance of the RSSI-based BLE technology was evaluated in Contreras et al. (2017); and Neburka et al. (2016). The viability of the BLE for indoor positioning scenarios was evaluated in Contreras et al. (2017). Their results showed a linear relationship between energy consumption and discovery time. Another investigation of the performance of the RSSI-based BLE technology for indoor positioning was presented in Neburka et al. (2016) and was tested in an anechoic chamber and real environments. The experimental results demonstrated that the BLE technology behaved similarly in ideal (no signal reflection) and real (multipath propagation) transmission environments.

Many proposed BLE RSSI-based ranging systems often use the RSSI values from all three advertising channels together to obtain an aggregate signal (Kao et al., 2017; Tabata et al., 2015). However, the signals have been shown to exhibit different overall path loss models and are affected by the multipath fading and attenuation differently. As a result, considering all channels together (aggregate), they could give the appearance of the large fluctuations in power level (from channel to channel) even when the individual channels’ power levels are stable.
Zhuang et al. (2016) applied the variety of the BLE channels in an algorithm, combining a polynomial regression model, fingerprinting, two levels of outlier detection, and Extended Kalman Filtering (EKF). However, the investigated scenario was an empty corridor and the effect of the obstacles was not investigated. Another recent study was presented in Canton Paterna et al. (2017), where channel information, a Kalman filter, and a trilateration method were applied to improve the precision of the BLE RSSI-based trilateration. In this case, one or more mobile users were transmitting and several stationary receivers were deployed where each receiver was equipped with separate hardware to monitor each of the three advertising channels in parallel and then only the single channel with the least variation on each link was used for the trilateration. A robust positioning system based on separate channels was investigated by Huang et al. (2019). Unlike Zhuang et al. (2016) and Canton Paterna et al. (2017), Huang et al. (2019) applied a trained dataset to fit a path loss model to each channel. Later in the operational stage, the RSSI observations were taken and the median values were used to estimate ranges for each channel. For each link, a weighted average range was then assembled from the ranges obtained from the available channels. This average range was used for the trilateration. The BLE RSSI-based ranging system will be further investigated in Sections 4.1 and 4.2.

2.1.2 Comparison and Integration of Bluetooth and WiFi Positioning Techniques

The WiFi and Bluetooth technologies are well-studied subjects and the comparison has been explored by many groups. Pei et al. (2012) investigated the WiFi positioning in coexistence with Bluetooth. The study showed how WiFi suffered from the interference problems when coexisting with other high-frequency wireless networks while the frequency hopping mechanism decreased the Bluetooth interference to the WiFi RSSI scanning. Zhao et al. (2014) compared the BLE-based
localization to the WiFi localization. Their results showed that BLE was more accurate than WiFi with the same spots where the WiFi APs were placed. Zhao et al. showed that the Root Mean Squared (RMS) localization error of BLE (3.8 m) compared to WiFi (5.2 m) was improved by 27%. Another comparison between the BLE and WiFi fingerprinting was presented by Faragher and Harle (2015). They showed that the BLE fingerprinting technique had a tracking accuracy of less than 2.6 m in 95% of the time by using a dense distribution (1 beacon per 30 m²) and less than 4.8 m using a lower density distribution (1 beacon per 100 m²) whereas WiFi could achieve about 8.5 m, 95% of the time in the same environment. They concluded that increasing the number of beacons decreased the positioning error, but there was no further improvement after 8-10 beacons.

Another comparison study between the Bluetooth and WiFi signal propagation for indoor localization was performed by Dimitrova et al. (2012). They investigated factors such as the technical characteristics, manufacturing differences of sensor nodes and multipath signals directions that could affect the signal propagation for both Bluetooth and WiFi. Their results demonstrated that there were no major differences between Bluetooth and WiFi, but the WiFi signals had higher transmit power than the Bluetooth signals, which caused stronger multipath components and subsequently, WiFi was less robust to the deviation of the RSSI values. The BLE energy consumption was measured, modeled, and compared to the ZigBee (IEEE 802.15.4) in Siekkinen et al. (2012). Their results indicated that BLE was more energy-efficient than Zigbee and had a very advantageous ratio of energy per bit transmitted. Moreover, BLE had a higher scan rate than WiFi that helped to average out the occasional outlier’s effect. The channel hopping mechanism was also shown to reduce noise in RSSI. Davidson and Piché (2017) proposed a
comprehensive survey of the BLE-based indoor positioning mechanisms for smartphones and concluded that BLE was superior for indoor localization.

Some research investigated the integration of Bluetooth and WiFi technologies. A Bluetooth propagation model based on RSSI was implemented by Galván-Tejada et al. (2013) which could estimate about 0.87 m of position errors by combining the proposed system with WiFi. A Weighted Centroid Localization (WCL) method was presented in Subedi et al. (2016) to enhance the location accuracy and reduce the computation load. An iterative WKNN localization method based on RSSI of the BLE was proposed by Peng et al. (2016). They were able to improve the position accuracy from 5.19 m to 2.52 m compared to the traditional KNN.

2.1.3 Human Body Shadowing

Some studies investigated the effect of human bodies on fingerprinting-based and range-based positioning (Bultitude, 1987; Fet et al., 2013; Kashiwagi et al., 2010). Early studies approximated the attenuation due to the body shadowing with a Rician distribution (Bultitude, 1987). A range-based indoor localization system based on RSSI BLE sensors and an on-line probability map was presented by Palumbo et al. (2015) that could reduce the effects of the multipath, fading, and shadowing. Also, a weighting scheme was proposed by Xu et al. (2015) to leverage the credibility of the measured RSSI values to overcome multipath and shadowing for the range-based and range-free algorithms.

A path loss shadowing model for the RSSI-based ranging based on a Markov process was introduced by Kashiwagi (2010), where shadowing effects on each propagation path were generated individually using a transition probability. In RSSI-based fingerprinting, trained data is typically collected for multiple orientations to compensate for attenuation due to the person
holding the mapping device. Fet et al. (2013) showed that the signal distribution with distance would employ an elliptical shape due to the presence of a human body. Later, a signal attenuation model was proposed based on the properties of the ellipse to generate an orientation-independent fingerprinting database. Although the above-mentioned studies did not provide a comprehensive analysis of the effects of the body shadowing and body orientation on the RSSI-based positioning, none of the studies introduced a dependency of the shadowing on the distance of a body from a transceiver, nor did they consider the influence of the number of bodies. However, some studies considered the number of people or their distances from the transmitters, accounting for the shadowing effects on the propagation model (Wang et al., 2015; Woyach et al., 2006; Youssef et al., 2007). A twin-cylinder model was presented by Wang et al. (2015) for moving the human body shadowing at 60 GHz, in which the geometrical position of a human body was considered. Woyach et al. (2006) presented the indoor radio channel characterization to detect and characterize the motion of the network nodes and moving objects in a network environment using the changes in RSSI values. The RSSI mean and variance values can be useful indicators in signal-based human detection techniques. There are many algorithms to monitor the mean and variance of RSSI for detecting the presence of human bodies and other obstacles (Youssef et al., 2007). A flexible queuing system was presented by Brockmann et al. (2018) which worked based on the BLE channel diversity. In Chapter 4, radio propagation models for the RSSI measurements is designed that is able to automatically detect and compensate the body shadowing effect by using the three BLE advertising channels.
2.2 Artificial Neural Networks

ANNs are the mathematical models inspired by the human brain architecture. Initial studies in this area mainly focused on achieving human-like performance, such as information retrieval, voice, and image recognition. Neural network models can indicate the intricate relationships between the input and output of a complex system. The ANN structures include three main layers: input, output, and hidden layers. Input and output layers are responsible to take information from surrounding areas and transfer the answer to the outside, respectively. The hidden layers have no contact with the surroundings and only receive and transmit information between the input and output layers. The system may have a single or multiple layers (Mitchell, 1997).

In the signal processing perspective (Hu & Hwang, 2002), several models of artificial neural networks exist, e.g., Multi-Layer Perceptron (MLP) model, Radial Basis Function (RBF), and Support Vector Machines (SVMs). SVMs outperform MLP and RBF in the classification problems, though, for regression-based problems, SVM generally achieves lower accuracy (Munaye et al., 2019). A comparison was presented between MLP, RBF, and SVM models to predict a time series model by Ghorbani et al. (2016) where it was concluded that the MLP and RBF models performed better than SVM in time series problems.

In the 1950s, the perceptron model was presented by Rosenblatt (1958). Their model used a linear weighted function from a single neuron. It was one of the first implementations of ANNs and after that time, many single layer (Föckler et al., 2005) and multilayer (Dai, Ying, et al., 2016) perceptron models have been implemented and used for the positioning applications. Multilayer perceptron models have at least one hidden layer and can handle non-linear terms. Since the relationship between RSSI and distance is non-linear and a single layer cannot model non-linear

RBF neural networks use a radial basis activation function (Bishop, 1995). The activation of a hidden unit is identified by the distance between the input vector and a prototype vector. Each neuron in the hidden layer consists of an RBF and the output layer has a weighted sum of the outputs from the hidden layer. The hidden and output layers apply a non-linear and linear transformation, respectively. Hidden neurons are dynamically generated during the training procedure to achieve the desired performance. The number of basis functions is equal to or less than the number of input data sets. RBF models have been implemented and applied for positioning applications (Guo et al., 2014; Salim & Mohammed, 2019). Figure 2.2 illustrates the basic concept of MLP and RBF.

![Figure 2.2: The MLP and RBF initial block diagrams.](image)

The training procedures in the RBF networks can be significantly faster than the training procedures in the MLP networks. There are two stages of the training procedure for training radial basis function networks. The first stage involves the determination of the mean value and distance
from the center of the activation function of the input data by unsupervised training methods. In
the second stage, the output layer weight vector is found (Bishop, 1995).

A comparison between the performance of the MLP, RBF, and Kalman filter was presented
by Shareef et al. (2008) for noisy distance measurements in localization with wireless sensor
networks, however, their results contradicted those of Bishop (1995). Bishop, concluded that MLP
generally performed better than RBF but at the cost of MLP training being much slower than RBF,
whereas the experimental results in Shareef et al. (2008) indicated that in terms of accuracy, the
RBF neural network provided better performance than MLP. Nevertheless, regarding
computational and memory requirements, they found MLP to be superior. Gong et al. (2016)
presented an indoor localization system based on the RSSI and RBF neural network which was
optimized by Particle Swarm Optimization (PSO). Their results showed that the improved
localization algorithm had higher positioning accuracy than using only the PSO algorithm.

The above-mentioned ANNs are usually categorized as traditional neural networks, while
deep learning represents the cutting edge of the neural network technology. The main difference
between traditional neural networks and deep learning is the ability of deep learning to train itself
to process and learn from data using multiple hidden layers. The abundance of the layers enables
the deep learning algorithm to learn in multi-step levels. Deep learning algorithms are quite
beneficial when dealing with massive unstructured and unsupervised data to extract complex and
non-linear patterns (Goodfellow et al., 2016; Najafabadi et al., 2015).

All of the empirical positioning models (mentioned in Section 2.1) are computationally
efficient and easy to implement, although less able to tackle the sudden changes in the real
environment. Unlike analytical or empirical models, AI networks can learn from observed data
(Alshami et al., 2017; Jiao et al., 2017a; Wu et al., 2007) in real environments and identify patterns that might not be captured by rule-based thresholding techniques. AI is particularly useful when the correlation between the input and output values of a system is ambiguous or subject to noise (Hu and Hwang, 2002).

The majority of the prior studies used AI models as tools to determine sensor locations based on the general parameter information such as RSSI (Powar et al., 2017) and transmitter identification in advance (Mok & Cheung, 2013). Other AI studies determined the BLE RSSI values for the indoor environments (Amer & Noureldin, 2017) using more specific information such as direct distance between transmitters and receivers to optimize the RSSI values. Li et al. (2018) proposed an RSSI real-time correction method based on the PSO back propagation neural network, however, the method needed a gateway to collect RSSI in real-time on top of the receiver measurements.

In this thesis, AI models are proposed to detect and compensate for the obstacle shadowing effect in a dynamic indoor environment using the three BLE advertising channels and vision information.

2.2.1 Learning Processes

Artificial networks can improve their performance through the learning process from a set of training data. The learning process is divided into two types:

1. Supervised Learning: Past values or available information for training a data set are called labels (Mohri et al., 2018). A necessary assumption for the supervised learning techniques is the availability of a labeled set of training data. There are many studies in the radio-based indoor positioning systems that utilized supervised neural network
(Alhamoud et al., 2014; Altini et al., 2010; Behmann et al., 2016; Chen & Lin, 2010; Dai, Ying, et al., 2016; Dakkak et al., 2014; Fang & Lin, 2008; Lin & Lin, 2005). The most common supervised neural network approach is the MLP with K-nearest neighbor mixture algorithms (Lippmann, 1987). Dakkak et al. (2014) made a performance comparison between different RSS fingerprints methods based on the supervised MLP neural networks and KNN. The authors believed that the advantage of the proposed MLP neural network technique was in its robustness against the external disturbances that might have affected the received RSS signal. A backpropagation neural network is one of the supervised learning algorithms that improve the performance of the neural network by tuning the weight values. The backpropagation technique was presented by Farid et al. (2016) in which fingerprinting approaches in WiFi were adopted. The proposed method was shown to be beneficial and improve the accuracy of the solution. Their method reduced the position solution error from 1.36 m to an average of 1.05 m. Altini et al. (2010) used a multi neural network with Bluetooth RSSI for indoor navigation. Their system was able to localize the user correctly 90% of the times with an accuracy of 0.5 m along a corridor. Furthermore, a backpropagation multilayer neural network was studied by Dai et al. (2016) for the RSS-based indoor localization to compute the unknown node location directly without using a radio path loss model or radio map. The huge number of variables in the construction of the backpropagation MLP was the main disadvantage of this technique. Alhamoud et al. (2014) applied the Bluetooth technology for user identification and tracking based on supervised learning MLP and SVMs. Both techniques achieved good performances by classifying all the test instances correctly.
Zhang et al. (2013) investigated the comparison between SVM and a backpropagation MLP for the localization with the Bluetooth fingerprinting-based algorithms. It was shown that in terms of accuracy and precision, SVM was slightly better, but its training time was too long (about 3 hours).

2. Unsupervised Learning: Unsupervised learning methods do not require labeled training samples in order to learn to classify. Instead, they model the input data based on their statistical properties. To obtain better localization accuracy for the multi-floor indoor positioning problem, Campos et al. (2014) combined two supervised and unsupervised techniques based on RSSI. Since the hardware variance could significantly decrease the position accuracy of the RSS-based WiFi localization systems, Tsui et al. (2009) presented an unsupervised learning method to automatically solve the hardware variance problem and they improved the position accuracy within 100 s of learning time. Self-Organizing Maps (SOMs), a well-known unsupervised learning technique, was implemented by Szabo et al. (2011), and Parodi et al. (2006). Szabo et al. (2011) proposed the time of arrival fingerprinting system with the SOM unsupervised learning technique, which reduced the calibration and measurement effort and simultaneously improved the position error distance of 1.47 m in 90% Cumulative Distribution Function (CDF). Parodi et al. (2006) used the SOM unsupervised learning techniques to improve the quality of an RSS on the radio map that started with an initial propagation model with low complexity.
2.3 Vision Systems

Vision-based navigation arises as an attractive solution for indoor navigation and positioning in recent years. In general, vision-based positioning based on the two dimensional (2D) cameras consists of capturing images, detecting features, and matching the detected features frame to frame or with prior information (stored landmarks information for instance). Since monocular cameras are passive sensors that only capture a 2D projection of the three dimensional (3D) world, many approaches were designed to cope with this issue such as using stereo cameras (Zabih & Woodfill, 1994), a monocular camera with multiple viewpoints (Andriluka et al., 2010) or a monocular camera with a fusion of information from the environment such as a map (Hile & Borriello, 2008).

Recently, novel Red Green Blue-Depth (RGB-D) sensors like the Microsoft Kinect or the Asus Xtion sensor that would provide both color and dense depth images have become rapidly available. The collection of the 3D data resolved the scale factor problem. The RGB-D sensors are used in various contexts such as robot navigation (Jia et al., 2016) or 3D mapping (Henry et al., 2012). RGB-D are active sensors that provide images based on RGB along with the per-pixel depth information. Roberto et al. (2016) introduced an evaluation of motion tracking and depth-sensing functionalities of the Tango tablet. The geometric quality of the Kinect system as a function of the scene was evaluated by Chow et al. (2012). Gonzalez-Jorge et al. (2013) reported the results of the accuracy and precision assessment of the Xtion system and Kinect sensors. Yeh et al. (2016) proposed a system to improve the performance of the RSSI survey by using an RGB-D sensor. This work reduced manpower, time, and cost to build the radio map for the pattern matching approaches in an indoor positioning system. They used RSSI information from a smart-phone and depth information from an Asus Xtion.
Over the last decades, object detection, feature detection, segmentation, and classification have become popular techniques in computer vision technology. Feature detection is the process where an image is examined by unique objects. It is divided into three main groups: (i) edge detection, (ii) corner detection, and (iii) region detection (Y. Li et al., 2015). A combination of the corner and edge feature detector was implemented by Harris and Stephens (1988) who used normalized cross-correlation for feature detection and tracking. In the indoor area, the more complex structure could exist, requiring more robust methods to extract the other common feature (Montalvo et al., 2014; Srigul et al., 2016). Many studies are also done in the object detection area based on the 2D and 3D sensors (Gupta et al., 2014; Lim et al., 2013; Tieng & Boles, 1997; Ye & Malik, 2013).

Vision can be the main sensor for indoor positioning (Bonin-Font et al., 2008; K. Guan et al., 2016) or integrated with other technologies (Beauregard et al., 2008; T. Guan et al., 2017). In the integration case, the camera provides valuable information to the system. Lo et al. (2010) proposed an augmented reality by using mobile device cameras to help navigate users to their destinations. The user of the system could take a picture from the environment and indicate the destination while the positioning system would add some auxiliary descriptions (such as arrows and texts) on the picture to help the user navigate. In some previous research, sequence images were used to find the relative position and orientation information of a moving platform. More details about this technique are presented in Bonin-Font et al. (2008). Lu et al. (2014) proposed a multi-view image localization framework for predicting the image location and orientation, which is commonly used for daily activity recognition and pose estimation. A learned multi-view
regression model can retrieve the location information by avoiding large scale correspondences search.

Other studies have applied fusing map information with a camera to improve the positioning system. However, to reduce the amount of image processing calculation in the corresponding match between the image and floor point, it is required to reduce the ambiguous cases and search space positioning information in the database. Some researchers have also focused on the reduction in the number of ambiguous cases and search area localization information in the database such as Hile and Borriello (2008); Chandel et al. (2016); Bejuri et al. (2012), and Mohamad et al. (2013).

Human body detection is playing a critical role in calculating the human body shadowing effect. In computer vision research, objects such as human bodies can be detected in two main categories: (i) hand-crafted features (Mikolov, Karafiat´, et al., 2010) and (ii) learning-based methods (Simonyan & Zisserman, 2014). The first category relies more on pre-designing descriptors including Haar (Viola & Jones, 2001), Local Binary Pattern (LBP) (Ahonen et al., 2006), Histogram of Orientated Gradients (HOG) (Dalal & Triggs, 2005), Scale-Invariant Feature Transform (SIFT) (Chen & Hauptmann, 2009), etc.. The drawback of the hand-crafted methods is the requirement to extract features manually from the raw data by using specialized algorithms. In contrast, learning-based methods can automatically learn from the raw data within less computational time and more reliable performance. Deep learning-based methods are one of the most powerful object detection algorithms (Howard et al., 2017). Convolutional Neural Network (CNN) is a type of deep learning technique that has been widely used in human body detection in challenging indoor environments (Jiao et al., 2017). Among all deep learning approaches, the highest accuracy of human detection belongs to the RetinaNet method (Lin et al., 2017).
Chapter 3

FUNDAMENTALS OF THE SYSTEM MODELING

This chapter provides more details about the BLE technology and signals. Moreover, it explains how BLE RSSI can be used in an indoor positioning system. The human body shadowing effects on the path loss model, as well as the trilateration positioning algorithms, are discussed. Two well-known neural network algorithms, their mathematical models, and the learning algorithms are presented. Also, the fundamental theory of the image object detection based on two different methods are described. Finally, the general overview of the proposed systems is illustrated.

3.1 Bluetooth Technology

BLE is a recent wireless communication technology that is emerging as a standard for indoor positioning based on a 40-channel frequency hopping scheme. A wide range of BLE-based indoor positioning solutions are provided commercially by several companies such as Beaconstac,

For discovery services, BLE uses three advertising channels: 37 (2402 MHz), 38 (2426 MHz), and 39 (2480 MHz). Figure 3.1 depicts how the BLE channels are positioned in the frequency band. The first channel, 37, is centered at the frequency of 2402 MHz, while the last one, the 39th, is centered at 2480 MHz. Channels from 0-36 are assigned for data transmission. It should be noted that the three-channel numbers are not sequential and the three advertising channels, in fact, include the lowest and highest center frequency channels.

![Figure 3.1: The BLE frequency channels with 37 data transmission channels (orange) and the three advertising channels (green).](image)

3.1.1 BLE Connection

BLE technologies can operate in two modes. The first communication mode is the traditional connection-based mode which needs to pair the transceivers with the connection interval. This
connection mode is known as “master-slave”, in which the connection-initiating device employs the master role over the other devices. This connection creates a bond that enables the master and slave to transmit and receive data. In the case of the indoor positioning, no data is needed to be transferred between devices; thus, a connection might not be always necessary. Reference devices with the ability to broadcast the wireless information would be enough for positioning purposes.

The second communication mode is connectionless mode, in which the transmitter is broadcasting to a receiver and the transmitters are unaware of the number of the advertising packets received by the receiver. Recently, BLE sensors designed to work in a connectionless-mode, which only broadcasts data, have become very popular for positioning purposes, especially in healthcare, first aid, firefighting, and sports applications.

Figure 3.2 illustrates the two possible applications of BLE in firefighting and emergency services, in which BLE can support firefighter movements or track emergency staff. For the user of localization applications, connectionless communication is an ideal choice because of its simplicity, seamless handover, energy efficiency, and low overhead.

The BLE broadcasting process includes a transmitter (broadcaster) and receiver (scanner). The transmitter periodically broadcasts the advertising packets to any devices that can receive them. The receiver continuously scans to receive available advertising packets from a broadcaster at periodic intervals.
Figure 3.2: The BLE connectionless applications.

One of the most important features in the broadcaster is the advertising interval or the rate that the advertising packets are sent. On the other hand, scan intervals and scan windows represent the rate that the scanner turns on and the time it keeps on scanning per each scanning interval, respectively. Scan interval and scan window sizes have a deep impact on power consumption. Together, they determine the amount of time the scanner must be turned on. Figure 3.3 shows a simple example of a BLE advertisement and scan event with a transmitter in advertising mode and the receiver in scanning mode. Most importantly, the transmitter sends advertising packets on all three channels sequentially at a relatively high rate while the receiver scans one channel at a time at a lower rate.
The duration of the advertising interval and scanning windows can cause multiple measurements of one channel in some periods of the scanning time. In Figure 3.3, for instance, at the beginning of scanning, channel 37 has been scanned twice while channel 38 is only scanned once. Yet, for the next scan at 140 ms (not illustrated here), channel 37 is measured only once. Remaining asleep during broadcast intervals helps the BLE system to achieve an optimal power consumption, however, a shorter broadcast interval increases the number of broadcasted packages and the accuracy of their readings at the expense of additional power consumption.

### 3.1.2 BLE Packet Structure

The main structure of the BLE packet typology for both types of communication is similar and includes the following components: Preamble (PRE), Access Address (AA), Protocol Data Unit (PDU) (2-257 bytes) and Cyclic Redundancy Check (CRC) code (Bluetooth, S.I.G, 2010). The PRE is used to perform frequency synchronization and timing estimation. The AA provides the physical address. The data channel PDU includes a 16-bit header and a variable size payload, from 0 to 255 bytes. The advertising channel PDU includes a 16-bit header and a payload, from 0
to 37 bytes. The header comprises the PDU type, reserved for future use, channel selection, transmitter address, receiver address, and length of the payload. The payload includes 6 bytes of the broadcast address and a maximum of 31 bytes of the broadcasting data. Figure 3.4 describes the BLE advertising packet structure for the connectionless-mode. CRC is also used to detect the communication errors.

Transmitters can send advertising packets, including an estimate of the transmitted power level which is identified by the MAC address of the senders. When a BLE receiver node obtains the advertisement packets, it calculates the RSSI by comparing the received signal strength of the advertising message and the value of the transmitted power in the message. Each transmitter advertises frequently on all three channels, however, sometimes the RSSI measurements are only recorded on one or two channels on the receiver side since the transmitters and receivers are neither synchronized nor transmitting and scanning at the same rates.
3.1.3 BLE Channel Diversity

As each channel has a slightly different carrier frequency, each BLE advertising channel will have distinct propagation characteristics such as a different power level owing to varying channel gain and multipath fading. Furthermore, one or more channels may experience multipath fading while others do not. An example of this is shown in Figure 3.5, in which the first 100 samples of each channel are used to compute different means with small standard deviations, whereas the next 100 samples are plotted in aggregate mode resulting in a single mean value with a large standard deviation. When the channels are considered separately, small fluctuations are visible in each, while the fluctuations are larger when considering them in the aggregate mode. Using the advantage of separate BLE advertising channels is one of the fundamental principles of this thesis.

Figure 3.4: The BLE advertising packet structure (Bluetooth, S.I.G, 2010).
The RSSI value is a relative number that measures how strong a signal is when it is received by a device. For a fixed transmitter and receiver, the antenna gain and power are constant values, then the RSSI can indicate the relative distance of the transmitter from the receiver.

\[
\text{RSSI} = \text{Transmit power} + \text{Antenna gain} - \text{Path loss}
\]  

(3.1)
dBm (dB- milliwatts) is a logarithmic measurement of the signal strength and the mathematical relationship between the power in mW (milliwatts) and dBm is:

\[
dBm = 10\log(\text{mW})
\]  

(3.2)

More explanation about the integer nature of the RSSI value is presented in Bardwell (2002).

![Figure 3.5: Received Signal Strength Indicator (RSSI) samples received from the three advertising channels compared to the combination (aggregate).](image)

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3.2 Human Body Shadowing Effect

The human body is one of the non-negligible sources of the propagation loss. The human body shadowing effect can be caused by the user of the device as well as other people close to the device (Figure 3.6). Two parameters were taken into account to address a body shadowing effect caused by people who obstruct the Line-of-Sight (LOS). The first one is the number of obstacles and the second one is the distance between the device and the obstacle. Moreover, the gesture and heading of the user can be used to characterize the shadowing effect caused by the user of the device. To quantify the body shadowing in the RSSI values in both cases (caused by the user or other people), the difference between the RSSI values in the shadowing case and the one in the no-shadowing case was considered and trained to the system. The relationship between the RSS body shadowing loss, the number of people, and the blocking angle will be described in Chapter 5 using experimental data.

Figure 3.6: The body shadowing effect caused by the user of the device or other people.
To find the number of people blocking signals in this thesis, the vision information and simple features like moving variance on RSSI values are used to detect human presence. Human motions and activities directly affect signals propagation and RSSI values. Consequently, the moving variance is a reliable indicator to detect the human body. Three BLE advertising channels provide the opportunity to have a reliable response and uniform fluctuation of the RSSI values due to human body obstacles. In this thesis, a similar response of the three BLE advertising channels to obstruction by a human body is applied to detect and compensate the RSSI values for this effect. In particular, Figure 3.7 displays an obvious example of this kind of detection based on three channels.

To detect the attenuation caused by the human body obstruction and compensate for this effect, two main approaches of threshold-based and artificial-based have been investigated in this thesis with the help of sliding window techniques on the RSSI values. In the threshold-based approach, a new sample of RSSI was compared to the mean and variance of the former samples of the sliding window. If the new sample is significantly different from the mean and variance of the previous samples, a detection event will be considered. Another approach is the artificial-based, which repeats the same scenario of the threshold-based with the difference of avoiding to set thresholding rules. The artificial-based approach learns automatically from the trained data to find the fluctuation as a result of the human body obstacles. Furthermore, in the next step of the system design, the artificial-based approach has become further completed by integrating the visual information to make the detection system more robust. All proposed approaches for the human body detection based on the RSSI fluctuation, threshold-based, artificial-based, and artificial-based integrated by vision approaches will be discussed more in-depth in Chapter 4.
Figure 3.7: The effect of blockage on the RSSI samples received from the three advertising channels.

3.3 Distance Model

The power density of the signal is attenuated as it propagates through space as well as objects. The ratio of the transmitted power $P_t$ to the received power $P_r$ is defined as a linear path loss, although expressing the path loss in dB is more common. The path loss is a function of the distance which helps to estimate the distance between the transmitter and the receiver. As discussed in the previous section, to model the signal based on the distance, several factors must be taken into account such as shadowing and fading. To calculate distances from RSSI, one of the basic propagation models, known as the Free Space Friis Model (FSFM) is used. This model (3.3) is applicable in free space that is an environment with no obstacles to interfere with the signals, as the name suggests (Figure 3.8).
\[ d = \frac{P_t}{P_r} \left( \sqrt{G_t \cdot G_r} \right) \cdot \left( \frac{c}{4\pi f} \right) \]  

(3.3)

where \( G_t \) and \( G_r \) are the antenna gain values of the transmitter and receiver, \( c \) represents the speed of light, and \( f \) is the signal frequency.

\[ RSSI = RSSI(d_0) - 10n \log_{10}\left( \frac{d}{d_0} \right) + X_\sigma \]  

(3.4)

where \( RSSI(d_0) \) represents the RSSI value at the reference distance \( d_0 \), \( X_\sigma \) and \( n \) represent the observation error and path loss exponent value, respectively, and \( d \) is the distance between the transmitter and the receiver. In free space, \( n \) is 2 while it is often greater because of the other sources of attenuation and can be less than 2 in wave-guideres. Usually, parameter \( d_0 \) is fixed to 1 m, and \( RSSI(d_0) \) becomes the average measured RSSI when the receiver is 1 m away from the
transmitter. The path loss exponent $n$, which is related to the wireless environment along with $RSSI(d_0)$ can both be determined either by fitting a line to the training measurements or by choosing the standard values. Theoretically, $n$ should be constant, however, in reality, the BLE transmit power has time-varying characteristics, and the path loss exponent is dependent on the environment. In Figure 3.9, the general relationship between the received power and distance is illustrated. The horizontal axis represents the distance in both logarithmic and linear scales. The received power decreases as the distance between the transmitter and receiver increases. As Figure 3.9 shows, the received power is decreasing linearly with the distance in the logarithmic scale and logarithmically in the linear scale.

![Figure 3.9: Trend of power over distance.](image)

As a result, it is difficult to identify the relationship between RSSI and the distance accurately when applying the log-distance model. Researchers have used different techniques to fit the RSSI
distance model more precisely such as additional gateway corrections (G. Li et al., 2018), or adding random noise (Zhuang et al., 2016).

The log-distance parameters for each channel were determined empirically from the trained data in an environment without any obstructions, but the performance will also be evaluated using standard (non-empirical) values with and without the observation error.

3.4 Positioning Algorithm

The BLE localization applications aim to find the position of an object based on the physical characteristics of the BLE signals such as RSSI, TOF, and AOA. As discussed in Section 2.1, the localization based on each signal physical feature has its own pros and cons, even though the RSSI values were concluded to be the best option for the localization for the BLE technology. BLE can be used in proximity mode with dense beacons, although in this thesis the main focus is given to the trilateration with redundant observation. To have a proper comparison of the trilateration performance and other RSSI-based techniques, the fingerprinting technique is implemented as well.

3.4.1 Trilateration

The trilateration algorithm is the way of getting the location of a target by measuring the distances between the target and at least three anchor nodes whose positions are already known. In 2D positioning, two measurements can provide positioning solutions as long as one of the possible solutions can be eliminated through some kind of restriction on possible locations. When additional measurements are available, an ideal situation of the trilateration technique can be illustrated as in Figure 3.10, where the three circles have a single intersection point. The trilateration algorithm uses the distance $d_m$, estimated from the received RSSI values from all
three transmitter nodes to compute the position of the single intersection. For overdetermined trilateration with errors, non-linear least squares are the standard method used to find a solution that minimized the mean squared error of the residuals.

![Ideal trilateration diagram](image)

**Figure 3.10: Ideal trilateration.**

Herein, the corresponding direct distance from each transmitter to the receiver is calculated from RSSI values with the corrected human body effect to calculate a 2D position. This direct distance is computed for each BLE advertising channel by using the corresponding log-distance model. All available ranges are then used in the trilateration using non-linear parametric least-squares. If \( m \) transmitters with known coordinates
\((x_{TX_1}, y_{TX_1}, z_{TX_1}), (x_{TX_2}, y_{TX_2}, z_{TX_2}), \ldots, (x_{TX_m}, y_{TX_m}, z_{TX_m})\) are deployed, and the receiver has an unknown location \((x_{RX}, y_{RX}, z_{RX})\), the \(m\) distances are related to the unknown positions as:

\[
d_m = \sqrt{(x_{TX_m} - x_{RX})^2 + (y_{TX_m} - y_{RX})^2 + (z_{TX_m} - z_{RX})^2}
\]

Since the height of the receiver is constrained, the state vector of the position estimator \((x)\) is given by:

\[
x = [x_{RX} \ y_{RX}]^T
\]

where \(x_{RX}\) and \(y_{RX}\) are the 2D position components in the horizontal plane of the East and North directions. Parametric least-squares employs the following observation model:

\[
z = h(x) + v
\]

where \(z = [d_1, \ldots, d_m]^T\) uses the distance estimates from the propagation model as the measurements vector, \(v\) is the vector of measurement error which is modeled as a Gaussian distribution, with a covariance matrix is \(R = E(v, v^T)\) and \(h(x)\) is a vector where each element is an instance of equation (3.5). To linearize the non-linear measurement model a Taylor series is applied:

\[
H_m = \left[ \frac{- (x_{TX_m} - x_{RX})}{d_m} \quad \frac{- (y_{TX_m} - y_{RX})}{d_m} \right]_{x=x_0}
\]

where \(x_0\) is the point of expansion. The result is the design matrix \(H\) that contains information regarding the geometry of the measurements. The misclosure vector \((\delta z)\) is the difference between the true measurements \((z)\) and the measurements estimated from the current states \((x_0)\):

\[
\delta z = H. \delta x + v
\]
The least-squares solution for the error in $x_0$, which is applied to the original state vector to correct it to the next solution $x_1$, is given by:

$$\delta x = (H^T R^{-1} H)^{-1} H^T R^{-1} \delta z$$

(3.10)

To make this distinction more explicit, the initial state estimations are then updated as follows:

$$x_1 = x_0 + \delta x$$

(3.11)

since the model is non-linear, the iteration is used to converge to a final solution ($\hat{x}$) which yields no further improvement with additional iteration.

3.5 Neural Networks Theory

ANNs consist of several simple and highly interconnected processing neurons set up into layers. MLP and RBF neural networks are two of the basic and well-known types in a neural network with a wide range of applications in many areas of estimation and decision making, including indoor positioning.

3.5.1 Multilayer Perceptron (MLP) Neural Network Techniques

MLP networks consist of a single input layer, at least one hidden layer, and a single output layer. The output of each neuron is described by the following:

$$y = \varphi \left( \sum_{k=0}^{n} w_k x_k \right)$$

(3.12)

where $n \in \mathbb{N}$ is the number of neuron inputs, $x_k, w_k \in \mathbb{R}$ are the input value and its weight, respectively, at $k^{th}$ neuron, $y$ is the neuron output and $\varphi(x)$ is an activation function. Figure 3.11 illustrates the structure of an MLP neuron network and a single neuron model inside an MLP. Each activation function receives the sum of the weighted inputs plus a bias term ($\Theta$).
The activation function is a mathematical gate in between the inputs and outputs of a neuron which can be a step function (i.e. output is active if the input value is greater than a threshold value), a linear function (i.e. the output is the input times some constant factor) or a non-linear function.

Figure 3.11: Structure of an MLP neuron network.

The non-linear functions allow the model to map the complex relationships between the inputs and outputs, which are essential for the learning and modeling the complicated real data. The two most common non-linear activation functions are: (i) Logistic (also known as the Logistic Sigmoid) and (ii) Hyperbolic Tangent which are represented in Equation (3.13) and Equation (3.14), respectively.
$$\varphi_{\log}(U_k) = \frac{1}{1 + \exp(-U_k)}$$ (3.13)

$$\varphi_{\tanh}(U_k) = \tanh(U_k) = \frac{e^{u_k} - e^{-u_k}}{e^{u_k} + e^{-u_k}} = \frac{1 - \exp(-2U_k)}{1 + \exp(-2U_k)}$$ (3.14)

3.5.2 Radial Basis Function (RBF) Neural Network Techniques

RBF is an ANN technique that identifies the activation of a hidden unit by the distance between the input vector and a prototype vector during the training (Figure 3.12). Each neuron in the hidden layer consists of a radial basis function and the output layer is a weighted sum of the outputs from the hidden layer. The hidden and output layers apply a non-linear and a linear transformation, respectively. The training procedures in the RBF networks can be significantly faster than the training procedures in the MLP networks.

Figure 3.12: The structure of an RBF neuron network.
There are two stages in the training procedure of an RBF network. The first stage involves the determination of the mean value and distance from the center of the activation function using the input data by unsupervised training methods. In the second stage, the output layer weight vector is determined. In RBF, the hidden layer uses a set of Gaussian functions, known as radial basis functions, given by:

\[
\varphi(x, \mu) = \exp\left(-\frac{(x - \mu)^2}{2d^2}\right)
\]  

(3.15)

where \( \mu \) is the center of the Gaussian function (i.e., the mean value of \( x \)), and \( d \) is the distance from the center of the Gaussian function. The output of each hidden unit is based on the distance of the input from the center of the Gaussian radial function \( \varphi(x, \mu) \). Subsequently, data points closer to the center of the radial basis function have more effect on the results. This effect can be adjusted by controlling the distance \( d \). Parameters \( d \) and \( \mu \) are defined and adjusted separately at each RBF unit during the training procedure. Layer 3 or the output layer is a weighted linear combination of the outputs from the hidden layer:

\[
\text{output} = \sum_i (\varphi_i W_i)
\]  

(3.16)

3.5.3 Training Algorithm

Once the neural network is established, the input data from the input layers are propagated to the hidden neurons and finally to the output neuron. If the number of neurons and layers are decided, the only unknown parameter will be the weight which is normally initialized with random values. The data training algorithm includes feed-forward, to calculate the neural network outputs, and backpropagation computation, to adjust outputs and hidden neuron weights. More than one
sample is required to obtain accurate results for training neural networks. In Figure 3.13, the general overview of the training process is illustrated where the training data is defined by an input matrix $\tilde{x}$, an expected output matrix $\tilde{y}$, and weight matrix $w$ which includes all weights and biases. The objective of the optimization is to minimize the error $E(w)$ between the expected and the neural network output $\tilde{x}w$ in each step. The cost function can be equal to the Mean Square Error (MSE), cross-entropy, or any other cost function and the backpropagation algorithm can be adaptive gradient descent, Levenberg–Marquardt algorithm, and Bayesian algorithm, etc.

![Figure 3.13: Neural network training flowchart.](image)

The standard backpropagation algorithm is a gradient descent in which the network weights are moved along the negative of the gradient of the performance function. However, gradient descent is too slow for practical problems. Levenberg–Marquardt algorithm is way faster than the
standard backpropagation algorithm and more effective in converging to an optimal solution. The Levenberg–Marquardt algorithm using the following equation is:

$$
\Delta w_\mu = -[J^T J + \mu I]^{-1} J^T (\tilde{y} - \tilde{x}w)
$$

(3.17)

where $\mu$ is a variable small scalar that controls the learning process, $J$ shows the Jacobian matrix which is $J = \Delta E$, and $E$ represents the cost function. When $\mu$ is large, the adjustment method shown above becomes the gradient descent method with $\frac{1}{\mu}$ step.

### 3.6 Image Object Detection Theory

To effectively characterize an image for object detection, two main categories have been discussed in Section 2.3: Hand-crafted features and learning-based methods. Two methods from each category are explained in this section and followed by being tested for human detection in Section 5.6.

#### 3.6.1 Hand-crafted Features Approach

These approaches refer to the application of the features that are hand-crafted manually by data scientists. This method is conventional which is divided into two parts: (i) image feature extraction, and (ii) image feature classification, as shown in Figure 3.14.

![Figure 3.14: Conventional object detection.](image)
Haar cascade and HOG are the two different types of hand-crafted approaches. Harr cascade method uses a classifier based on a weighted majority vote of weak learners. A Haar feature is obtained by subtracting the sum of the pixels under the adjacent rectangular regions at a specific location in a detection window. During the detection phase, the final detector with different sizes is moved over the image, to extract features using integral images and applies the trained cascade classifier.

The HOG is another type of hand-crafted approach which works based on the histogram of the image to count the occurrence of the gradient orientation in the localized image regions. By dividing the image into the small squares (cells), the gradient orientation of each pixel can be calculated in each cell, and based on the contribution of each pixel in the cell, a histogram will be constructed. The range of the orientation angle can be from 0 to 180 degrees or 0 to 360 degrees. The histogram can be normalized over the large regions to improve the robustness of the features against variations in illumination. Finally, the final HOG feature vector is obtained based on all the normalized histograms.

3.6.2 Learning-based Approach

These approaches refer to the application of the features that are automatically obtained from a machine learning algorithm as shown in Figure 3.15. The learning-based approach is a system based on deep learning such as You Only Look Once (YOLO) (Redmon et al., 2016) or RetinaNet methods.
The architecture of the deep network, in general, is formed by the following:

\[
s(i, j) = \sum_{k=1}^{N} (X_k * W_k)(i, j) + b
\]  

(3.18)

where \( N \) is the number of input matrices, \( X_k \) is the \( K^{th} \) input matrix, \( W_k \) is the \( K^{th} \) weight matrix, \( b \) is the bias, and \( s(i, j) \) is the feature map at the location \((i, j)\) in the image. In this method, a region represents an expected object, in which the coordinate of each region can be found by:

\[
x = x_{\text{center}} + l_x \frac{W_{\text{img}}}{w_R * 2}
\]  

(3.19)

\[
y = y_{\text{center}} + l_y \frac{H_{\text{img}}}{h_R * 2}
\]  

(3.20)

where \((x, y)\) is the center of the region, \((x_{\text{center}}, y_{\text{center}})\) is the center of the initialized region, \((W_{\text{img}}, H_{\text{img}})\) the width and height of the image, and \((w_R, h_R)\) the width and height of the region. Finally, the number of detected objects is calculated by the number of output regions. More information is presented in Mikolov et al. (2010).

YOLO can detect real-time objects by applying a single neural network to the image and dividing the image into regions. This method predicts bounding boxes and probabilities for each
region. TinyYOLOv3 is an updated and fast version of YOLO. Another method is RetinaNet which includes the bottom-up pathway, top-down pathway, classification subnet, and regression subnetwork.

### 3.7 General Overview

The general overview of the proposed algorithm is illustrated in Figure 3.16. The proposed system consists of the \( m \) number of transmitters in fixed positions and a mobile receiver. This architecture mainly involves the human body detection, RSSI compensation model, RSSI propagation model, and positioning estimation which all have been generally discussed in the preceding sections of this chapter. The processed data for the proposed algorithm are the RSSI values from three advertising channels of the observed BLE transmitters. In this system, body detection can detect the human body based on the uniform reaction of all three channels due to blockage, however, in the following chapters this scenario will be more completed by adding the vision sensors information. In this thesis, the RSSI compensation is based on two models: (i) threshold-based and (ii) artificial-based. Both of the compensation models will be discussed in detail in Chapter 4, and their setup and performances will be examined in Chapter 5 and Chapter 6.

Chapter 4 focuses on the details of the RSSI correction models, and how the models work based on thresholding (expert knowledge) or machine learning algorithms. Chapter 5 provides all the details about the data collection on a microcontroller and how the data is used in the RSSI correction models that were developed on the windows operation system, and the last part of Chapter 5 discusses the verification of the developments. All the testing results of the proposed models are presented in Chapter 6.
The propagation model is a simple empirical log-normal in which its results are compared to non-empirical log-normal and non-empirical log-normal shadowing models. The positioning algorithm and distance model have been discussed in detail in the above sections.

Figure 3.16: The general architecture block diagram.
Chapter 4

SYSTEM DESIGN

This chapter provides the details of the proposed RSSI-based ranging systems using separate BLE advertising channels. As discussed in Chapter 3, the accuracy of the RSSI-based positioning system is highly affected by dynamic changes in environments such as a blockage. To find the blockage and compensate for this effect in the RSSI measurements, using the three BLE advertising channels or vision information is proposed. The objective of this system is to account for the human body shadowing effect dynamically to enhance the RSSI measurements. The corrected RSSI measurements are then evaluated in a ranging-based positioning algorithm.

As mentioned in Chapter 3, to correct the RSSI measurements for the effect of the body shadowing, two strategies are implemented and tested: (i) threshold-based (an expert) model and (ii) artificial intelligence-based model. After comparing the performance of the two approaches, the artificial-based approach is augmented by the vision information as an additional input. To elaborate more on these models, this chapter is divided into three sections to describe each strategy.
comprehensively. Section 4.1 provides more details about the threshold-based model to detect the human body blockages. Section 4.1 explains the proposed artificial intelligence-based model. Section 4.2 describes the combination of BLE and the vision information for the artificial intelligence model as well as the association of the visual information with separate BLE RSSI measurements to find the blockages and compensate for their effect.

4.1 Threshold-based System to Correct the RSSI Measurements

A thresholding-based system uses the knowledge of a human expert and represents it within a computer system. The expert knowledge is encoded as rules which allow the thresholding-based system to decide. The thresholding-based system can result in false-positives and false-negatives if the rules are not defined accurately or if they are specific to some samples. Next, finding the right threshold is a challenge in the threshold-based system. Finding the number of blockages plays a critical role in calculating the shadowing effects on the RSSI measurements in the proposed thresholding-based algorithm. This section is divided into two sections, in which the system search for finding the human body in the LOS direction is discussed in 4.1.1, and the compensation for the human body effect is presented in 4.1.2.

4.1.1 Blockage Detection

In the first step of searching for the existence of people in the thresholding-based algorithm, the system has to look for changes in three BLE channel signals followed by deciding if the changes are attributable to the human body. The human body causes signal attenuation, which affects the RSSI mean and variance values. So one of the best possible options for detecting the human body is monitoring the RSSI mean or variance (Brockmann et al., 2018).
Figure 4.1 illustrates the general block diagram of the thresholding-based algorithm for finding the human body blockage. As shown in the figure, a sliding window search algorithm is used to take a new sample of RSSI ($S$) and compare it with the mean and variance of the preceding window of samples ($L$) in each channel. If the new RSSI value is attenuated by a significant amount below the mean RSSI, a detection event can be assumed. If all channels show the same effect and Equation (4.1) is valid for all three channels, then the detection event will take place with high probability.

$$RSSI(S) < std-windows(L - 1)$$  \hspace{1cm} (4.1)

The goal of the $N$ samples in the sliding window technique is to detect the moments that the human body blocks the signal or leaves the LOS. To see this effect, the set of samples needs to be just long enough to detect the transition. If the sequence is too short, no pattern will be detectable whereas if it is too long, a sequence may require the system to deal with multiple transitions, which was required to be avoided. In order to choose the right size of the window and the threshold value, a sensitivity analysis was conducted which is described in Section 5.3.

4.1.2 Blockage Compensation

To model the losses due to the human body, Specific Absorption Rate (SAR) is applied. The SAR can characterize the electromagnetic power that is absorbed or consumed by the tissue in units of (W/kg) (Gosselin et al., 2011). By transforming (W) to (dBm):

$$Pathloss_{\text{human}} = 30 + 10 \log(w \ast n \ast SAR)$$  \hspace{1cm} (4.2)

where $w$ and $n$ represent human body mass and the number of detected human bodies in the area, respectively. The International Electrical Commission (IEC) guideline (IEC., 2010) reported the SAR maximum value 2 W/kg by doing a test on 10 g of a human tissue sample. The method and
IEC guidelines used by Gosselin et al. (2011) were adopted to a 60 kg human body mass and SAR 0.002 W/kg in which 20 dBm losses were obtained using Equation (4.2).

If the transmitter to receiver path involves a human body, then the RSSI is modeled as:

$$RSSI_{RX} = RSSI_{TX} - Pathloss_{human} - Pathloss_{Distance}$$ (4.3)

where $RSSI_{RX}$ represents the received strength of the signal and $RSSI_{TX}$ is the transmission power value. $Pathloss_{human}$ and $Pathloss_{Distance}$ represent attenuation of the signal caused by the human body and the space between antennas, respectively. The compensated RSSI value can provide accurate ranging and reliable positioning solutions.

In the proposed threshold-based method if a person is detected in the blockage detection algorithm, the power loss will be calculated by Equation (4.2) for a 60 kg of the human body, and if nobody is detected, the proposed method will skip the blockage compensation algorithm.
Figure 4.1: General architecture for threshold-based blockage detection.
4.2 Artificial-based System to Correct the RSSI

In this section, an artificial-based approach is presented to correct RSSI measurements. In thresholding-based systems, as already explained in Section 4.1, the method needs the human-made rules to decide deterministically. The thresholding-based systems are incapable of learning from the data. Designing the rules by experts in addition to the requirement for updates with changes, are time-consuming processes especially in huge and noisy data. In contrast to the thresholding-based method, the ANN techniques can be applied to process complicated and noisy inputs. This is because, with sufficient trained data, ANN can learn patterns that are not obvious to the conventional decision-making techniques. On the other hand, the artificial-based approach is a probabilistic method that demands the training data learn the relationship between the input and output data and utilizes statistical models rather than the deterministic rules.

The artificial-based approach provides the blockage status and corrected RSSI values as outputs in one algorithm. To convert the threshold-based to the artificial-based approach the system requires prior information of the measurements. A neural network can map complex static inputs, whereas the blockage effect is a procedure that seriously requires to consider the earlier states of the RSSI measurements. To create a memory of the previously-obtained values of the RSSI measurements, a common method is to use a sliding window of past sequence values as inputs to the ANN. Static memory is then provided for the network to map inputs to outputs, depending on the prior information. In general, the main shortcoming of sliding windows implementation in ANN in such a manner is that it increases the number of neurons in the input layer to the number of samples in the sliding window. Generally, the additional input neurons require additional neurons in the subsequent hidden layers and the amount of computation
increases rapidly as a function of the window size. Nevertheless, this drawback is not significant to the proposed approach since the number of inputs is not enormous. The process of choosing an optimum window size is explained and discussed in Section 5.3.

Another challenge in tuning the sliding window is to determine the amount of the data overlap between the window shifts since it could be a non-overlap or overlap with different percentages. Selecting a correct size and the overlapping amount of the sliding window is critical and affects the ANN accuracy. The validation of choosing the appropriate window overlapping is explained in Section 5.3.

The step-by-step algorithm for correcting the RSSI measurements is explained briefly for the ANN method in the following:

1. Obtain the RSSI values corresponding to each of the transmitters when there is no person around in each BLE channel.
2. Repeat Step 1 with a human body that blocks the signal.
3. The inputs can be samples from Steps 1 and 2 randomly, although, the outputs can be only selected from Step 1 since they represent the RSSI values with no blockages.
4. Take 70% of all measurements in Steps 1 and 2 to train the ANN system.
5. Evaluate and test the with 30% of all measurements in Steps 1 and 2.

Figure 4.3 is illustrated to explain the steps including the training and testing procedure in the artificial-based approach comprehensively.
In this approach, only the RSSI values are used as inputs to find the human body blockages and compensate for the effected RSSI values. These inputs may or may not be affected by the human body shadowing. The ANN outputs include three corrected RSSI values (one for each channel) and the blocking information state (regarding whether an obstacle is present or not). The output RSSI values represent those corrected RSSI values for the ideal situation with no shadowing. During the training phase, the RSSI values with and without human body obstruction were provided for the input, however, the corresponding outputs for training were only sampled from the set of RSSI values with no obstructions observed from the same receiver position.
Figure 4.3 demonstrates the concept of the sliding window technique in the artificial-based approach to provide the prior RSSI measurements for the system. For each transmitter, $N$ previous RSSI samples from each channel is fed as the input into the ANN structure. The output of the ANN system consists of the optimized RSSI values and the blockage state. The output RSSI values for training are obtained from an additional calibration data set with no obstructions, which were also used to determine the empirical path loss exponents for each transmitter. Two different ANN methods are implemented in this approach, MLP, and RBF.

### 4.2.1 Training the Artificial Neural Networks

In this thesis, a supervised learning method with an error backpropagation algorithm is employed. In the backpropagation algorithm, at first, the input vector is propagated with constant weights and biases through a forward pass and the output is produced. Then synaptic weights and biases are adjusted by using the error signal that propagates backward to minimize the cost function of the neurons in the output layer:

$$ C = \frac{1}{2m} \sum_{i=1}^{m} \left\| (\tilde{y}(x_i) - \hat{y}^l(x_i)) \right\|^2 $$

where $\tilde{y}(x_i)$ and $\hat{y}^l(x_i)$ represent the desired and the actual outputs, respectively. $x_i$ represents the $i$th trained example. $l$ and $m$ denote the number of layers and the number of trained examples, respectively.
Figure 4.3: General architecture of the sliding window in the artificial-based inputs.
In principle, both the threshold-based and artificial-based methods could be augmented to estimate more than one person after certain adjustments, such as updating the threshold value and training the ANN for more number of people.

4.3 Artificial-based System Augmented by Vision Information

In Section 4.2, the effect of the human body blockage on the BLE RSSI measurements are corrected by the artificial-based method. The ANN can learn from the BLE RSSI training dataset to detect the shadowing effect on the three advertising channels and the sliding window allows the ANN to consider the previous RSSI measurements on all channels to find the blockages. The ANN is able to learn the difference between the multipath fading and human body showing, though, it is not a perfect algorithm and may cause missed detections and false alarms during the test.

In order to reduce the possibility of the wrong classifications, the ANN requires more information to be fed. In this section, the number of people that cause the blockages is obtained from the vision sensor and is passed to the ANN as inputs. This number can be 0, 1, or 2 persons here. Although the combination of the vision and RSSI as inputs are supposed to mitigate the classifications errors, it is still difficult to eliminate these errors completely since the vision-based human body detection algorithms contain errors.

The proposed RSSI correction method by the ANN algorithm, in this section, is different from Section 4.2, but the distance model and positioning algorithm are the same. The general overview of the proposed algorithm is demonstrated in Figure 4.4. In this figure, the number of blockages fed to the ANN in addition to the RSSI measurements in three advertising channels is depicted.
Figure 4.4: The general overview of the artificial-based system augmented by the vision information.

In the proposed algorithm, the RSSI measurements are collected in all RPs in the three advertising channels while the number of the extracted blockages from images interacts with the ANN inputs. More details of the system, data collection, and database are presented in Figure 4.5.

The objective of the proposed method is to identify the RSSI patterns corresponding to shadowing due to the human bodies in the three BLE advertising channels, using an artificial neural network and the vision information. This neural network method is trained to notice the sudden simultaneous fluctuation of all three channels as an obstacle. However, a sudden fluctuation of only two advertising channels would not be considered as an obstacle. Moreover, a deep learning algorithm is used for estimating the population density of the captured images by an expert user’s camera (here it is assumed an expert user is, for example, a first responder with a wearable camera...
as opposed to a normal user who would likely not have a wearable camera and would have to rely on RSSI measurements only).

As shown in Figure 4.4, the deep learning algorithm runs on the image processing block, which is not a part of the main AI system that has its training and testing separately.

![Diagram](image)

**Figure 4.5: Schematic diagram of the artificial-based approach augmented by the image information.**

The ANN model outputs are the BLE RSSI values from all \( m \) number of transmitters which are compensated and corrected for applying in a path loss trilateration positioning algorithm. The detailed scheme of the sliding window of the proposed algorithm is shown in Figure 4.6. The
proposed system utilizes the overlapping moving windows in the separate channels of the RSSI measurements and consecutive images. The sliding window and overlapping size are similar to the ones described in Section 4.2 with the details explained in 5.3.

Figure 4.6 illustrates the schematical difference between the sampling rate in the RSSI values in three channels and the captured images. More details of the wearable camera specification are discussed in Chapter 5. As the window started to move, the system was trained by repeating the sampling RSSI values process until the new image was sampled.

Once the wearable camera captures images in sequence, an algorithm based on the image analysis performs the image processing to extract and detect the human bodies inside the images. Therefore, the image processing unit stores the latest status of the number of the human body so that the unit receives a new image to calculate the new status. The ANN algorithm combines the latest status from the image processing unit into the RSSI sliding window and inputs to the trained model to receive the compensated RSSI results.
Figure 4.6: General architecture of the artificial-based approach augmented by the vision.
Chapter 5

SYSTEM VERIFICATION AND DEVELOPMENT

This chapter describes all the experimental work. It begins with the development of a BLE data collection system in Section 5.1. The indoor test environments are explained in Section 5.2. Section 5.3 presents a sensitivity analysis of the thresholding-based system which was described in Section 4.1 followed by an analysis of the sliding window in the artificial-based system (described in Section 4.2) in Section 5.3. Section 5.4 justifies the uniform effect of the human body obstacle in three advertising channels based on the hypothesis described in Section 3.2. The design details of the two ANN systems are described in Section 5.5 in terms of designing the number of layers and neurons and training performance. Finally, several image processing methods are introduced in Section 5.6 to detect a human body, out of which some are applied in Section 6.3.

5.1 Prototype BLE Data Collection System

A large variety of the BLE development kits and open-source hardware are available. This section will discuss the various hardware components used as BLE transmitters and the receiver.
Section 5.1.1 describes the selected transceivers and Section 5.1.2 provides details about the used BLE channels and applied filtering.

5.1.1 Hardware Component

Two different BLE development kits were selected: (i) The DWM1001-DEV (Decawave Ltd, Dublin, Ireland) module that includes an nRF-52832 (Nordic Semiconductor, Trondheim, Norway) BLE radio, a LIS2DH12 (STMicroelectronics NV, Amsterdam, Netherlands) accelerometer, and a DW1000 UWB chip (Decawave Ltd, Dublin, Ireland). The DWM1001-DEV was chosen as the transmitter because of its low power consumption, small size, very low cost, battery-operated power, and easy deployment on walls. The development kit has been also used in other projects since it is a UWB transceiver. Each transmitter was configured to send the BLE advertising information with an interval of 20 ms.

(ii) The nRF52840 development kit (Nordic Semiconductor, Trondheim, Norway) which includes the nRF-52840 (Nordic Semiconductor, Trondheim, Norway) BLE radio, 4 buttons and 4 LEDs for the user interaction, a flash memory, PCA10056 chip, and a Near Field Communication (NFC) antenna. Development board PCA10056 is used as a development platform for the nRF52840 System on Chip (SoC) and provides onboard debugging as well as the programming solution. The nRF52840 development kit was selected as the receiver because it could provide full chip-level access to BLE and debug interfaces to develop and configure a data logging application. The receiver was configured to measure the RSSI values on all advertising channels with a scan-interval of 50 ms (Figure 5.1).
5.1.2 Embedded Software Development

Custom data collection software for the receiver was written using the Arm Mbed C++ development environment since this environment provides a user-friendly method to load programs to microcontrollers and direct access to the system clock. Arm Mbed provides the basics of communication with peripheral sensors though a library of C++ objects that supports serial communications such as Universal Asynchronous Receiver-Transmitter (UART), General Purpose Input/Output (GPIO) pins, and various bus standards (I2C, SPI, etc). The microcontroller is connected to a computer via serial over a Universal Serial Bus (USB) interface. The BLE protocol stack includes controller, host, and application level. In the controller part of the BLE protocol stack, the Physical Layer (PHY) contains the analog communications circuitry responsible for the translation of the received digital symbols to the link-layer which is responsible for advertising and scanning connections in the protocol stack. The data logging software is forced
to scan a single advertisement channel and report the RSSI values, channel index, and MAC address of the received advertisements via the serial interface for 25 ms and sleep for 25 ms, then move to the next channel. The scanner will only receive the advertising packet on one channel per advertising interval. For the next channel, the scanner will change the scanning channel and mask other channels on each scan window. The separate BLE advertising channels measurements are read by a microcontroller and logged by an Intel Core i7 laptop. Figure 5.2, shows the general flow of data from the control layer (link-layer and PHY) of the BLE stack to the data logger.

![Diagram](image)

**Figure 5.2: Flowing the data.**

The DWM1001-DEV transmitters merely run their stock firmware and broadcast the data frequently on 20 ms.
5.2 Experimental Setup

To evaluate the performance and accuracy of the proposed algorithms, two different indoor environments were selected, an empty room, and a lab area. In each of the environments (empty room and lab area), two different scenarios were investigated. Details of these scenarios are explained in Sections 5.2.1 and 5.2.2. In Chapter 4, three different methods were proposed for the human body blockage detection and compensation of this effect based on the RSSI measurements made on the separate BLE advertising channels. These three systems were: (i) The thresholding-based system, (ii) the artificial-based system, and (iii) the artificial-based system augmented by the vision information. Both systems of (i) and (ii) are tested in the empty room environment whereas (ii) and (iii) are tested in the more complicated lab environments.

In both the artificial-based proposed systems (ii, iii), 70% of the collected data was selected randomly for training, and the remaining data was used for testing.

5.2.1 Empty Room Environment

An indoor test space consisting of a medium-size lab room on the 3rd floor of a 3-story university building with very little furniture was used. The room was L-shaped with approximate dimensions of 6 m by 11 m (Figure 5.3). A 2D plan of this room is illustrated in Figure 5.4.
As shown in Figure 5.4, the inside corner near the top left of the room was considered as the origin of a local coordinate system. Four DWM1001-DEV modules served as the BLE AP transmitters, one on each wall with known locations. RPs for the receiver with 1 m spacing were marked on the floor.

In the first test scenario, shown in Figure 5.5 (left side), the test subject held an nRF52840 DK BLE module in front of her body to measure the RSSI values on all advertising channels. In order to create radio maps for comparison purposes, the BLE RSSI values were collected at each of the 41 RPs with known locations (Figure 5.4). In the first scenario, the RSSI values were collected in a line as the receiver was moved away from transmitter number 2 within 1 m to 10 m in steps of 1 m. Also, the RSSI values were collected with a human body blocking the signal at 1.5
m distance from the receiver which mostly blocked the received signals from transmitter 2 and partially blocked the received signals from transmitters 1 and 3.

Figure 5.4: The plan view of the room.

In test case #2, the RSSI values were measured while a closed-loop trajectory was walked continuously with the operator holding the receiver on her head as shown in Figure 5.5 (right side). The loop was repeated twice: once with no obstructions, and once with a second test subject walking the same trajectory 1 m ahead of the test subject.
5.2.2 Lab Environment

To test the system in a more complicated and slightly larger environment, experiments were carried out in a larger electronics lab on the 3rd floor of a different multi-story university building. The dimensions of this room were approximately 8 m by 16 m (Figure 5.6). Unlike the empty test room, this lab contained numerous work-benches, shelves, and storage cabinets.
The 2D plan of the lab area is illustrated in Figure 5.7, in which 34 RPs with the known locations were established. Similarly to the empty room, four DWM1001-DEV modules with known locations were served as the BLE AP transmitters. The advertisement interval and scan interval were exactly the same as the empty room case. A GOPRO HERO 7 high-resolution digital camera and the receiver were carried by the test subject in the lab area while both (camera and receiver) were kept on the same height. The initial parameters of the camera are shown in Table 5.1.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Camera model</td>
<td>GOPRO HERO 7</td>
</tr>
<tr>
<td>Focal length</td>
<td>17 mm</td>
</tr>
<tr>
<td>Sampling period</td>
<td>1.0 sec.</td>
</tr>
<tr>
<td>Image resolution</td>
<td>4000*3000 Pixels</td>
</tr>
</tbody>
</table>
In order to evaluate the proposed system (iii) in the lab, two scenarios were planned. The goal was to evaluate the system (iii) in the complicated lab and compare it with the proposed system (ii) as well as assessing the system (iii) in non-trained locations in the lab (blind points). During the first scenario, the neural network was trained and tested over 34 RPs and compared with the proposed system (ii), however, in the second scenario, the trained network from the first scenario was used to test the proposed system (iii) in additional locations in the same lab that were not occupied during the training phase.

In the first scenario, the receiver and camera were moved through the 34 RPs to collect 215 RSSI samples at each RP in the absence of a human body as an obstacle, 70 RSSI samples were collected with one human body obstacle and 70 more RSSI samples with two human bodies obstructing at least one signal at each RP. 70% of the collected data were randomly selected for training the system and 30% for testing. The training output was the RSSI values on each RPs with no person in the room, even the user. Based on the dynamics of the lab environment, the image sampling rate was one image per second and 16 images were captured in each point for testing data. In this research, the information from these low rate images is used to detect people, not for target tracking purposes.

The second scenario was intended to evaluate the already-trained network from the first scenario in some unknown and untrained location points referred to as “blind test points”. 5 blind test points were randomly selected in the same lab, and 200 RSSI measurements were collected at each with random appearances of people during each occupation. All gathered data in the second scenario was used for testing without a training phase for these blind points. 150 images were collected for the second scenario (30 images at each point).
Figure 5.7: The blueprint of the lab area scenario #1.

The results of testing the three proposed systems in all test cases and scenarios will be presented and discussed in Chapter 6.
5.3 Sensitivity Analysis

Two BLE RSSI-based methods were proposed in Chapter 4 to detect the blockages and correct the RSSI values: (i) the thresholding-based system, and (ii) the artificial-based system.

5.3.1 Threshold-based

As discussed in Section 4.1, the threshold system works based on the human-made rules. To discover if these rules are set up properly, the number of false alarms and missed detections can be examined. The parameters can be varied (the rules) in the proposed threshold-based system, including the threshold value and the size of the sliding window.

Suitable rules can be determined initially based on some preliminary investigation of the deployment environment. To set rules to find the attenuation due to the human body obstruction, the RSSI measurements were made over a 6 m distance between one transmitter and one receiver, and a test subject was made to periodically obstruct the signal. During 240 RSSI measurements, the test subject blocked the line-of-sight 7 times periodically. Different window sizes and threshold (value of standard deviation) are presented in Table 5.2.

<table>
<thead>
<tr>
<th>Window size</th>
<th>1 STD\textsuperscript{1}</th>
<th>1.5 STD</th>
<th>2 STD</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Missed Detection &amp; False Alarm</td>
<td>Missed Detection &amp; False Alarm</td>
<td>Missed Detection &amp; False Alarm</td>
</tr>
<tr>
<td>2</td>
<td>3 &amp; 64</td>
<td>4 &amp; 56</td>
<td>5 &amp; 50</td>
</tr>
<tr>
<td>5</td>
<td>3 &amp; 40</td>
<td>5 &amp; 36</td>
<td>6 &amp; 24</td>
</tr>
<tr>
<td>10</td>
<td>3 &amp; 25</td>
<td>5 &amp; 22</td>
<td>6 &amp; 18</td>
</tr>
<tr>
<td>15</td>
<td>4 &amp; 32</td>
<td>6 &amp; 20</td>
<td>7 &amp; 17</td>
</tr>
<tr>
<td>20</td>
<td>4 &amp; 33</td>
<td>6 &amp; 20</td>
<td>6 &amp; 17</td>
</tr>
<tr>
<td>30</td>
<td>4 &amp; 33</td>
<td>6 &amp; 22</td>
<td>5 &amp; 21</td>
</tr>
</tbody>
</table>

\textsuperscript{1} Standard Deviation, \textsuperscript{2} Missed Detection, \textsuperscript{3} False Alarm.
It should be noted that increasing the window size reduces the number of false alarms with very little impact on the number of missed detections. However, increasing the threshold also reduces the number of false alarms but at the expense of increasing the number of missed detection. Based on these results, a window size of 10 samples and a threshold of one standard deviation were selected.

5.3.2 Artificial-based

The process of identifying the threshold is simple but time-consuming and unable of learning and improving without given explicit instructions. AI can simulate human intelligence for making a decision. Although a computer is unable to think for itself, statistical functions can allow the AI system to model and decide from any given data. The ability to learn in AI systems makes the proposed artificial-based model (introduced in Section 4.2) a decision-maker that is dependent on the observed data rather than on analytical and theoretical models. The Mean Square Error (MSE) of training (system output and desired response) was compared in 120 epochs, using different window sizes, to choose the optimum window size in the artificial-based model. The results are summarized in Table 5.3. Although the processing time increases, the training error decreases as the window size is increased. The training errors are stable around the window size of 10 and 20, however, the timing for 20 samples is large.
Table 5.3. The artificial-based window size in terms of training MSE and time.

<table>
<thead>
<tr>
<th>Window size</th>
<th>MSE(^1) (dBm)</th>
<th>Time (ms)</th>
</tr>
</thead>
<tbody>
<tr>
<td>5</td>
<td>0.0115</td>
<td>28.39</td>
</tr>
<tr>
<td>8</td>
<td>0.0078</td>
<td>37.93</td>
</tr>
<tr>
<td>10</td>
<td>0.0057</td>
<td>46.61</td>
</tr>
<tr>
<td>20</td>
<td>0.005</td>
<td>57.77</td>
</tr>
</tbody>
</table>

\(^1\)Mean Square Error.

To compare between both the artificial-based and thresholding-based approaches, 10 samples of past BLE RSSI values were used as inputs with 90% overlapping. The optimum overlapping amount between sliding windows could be defined empirically, however, the ideal amount of the overlapping could be investigated with more reliable algorithms in future work.

5.4 BLE Signal and Impact of Human Body Assessments

To verify the influence of the human body on the BLE signals, the following tests were conducted.

5.4.1 Repeatability of the Blockage

To ensure the repeatability of the attenuation due to the human body obstruction, the RSSI measurements were made over a 6 m distance between a transmitter and receiver, and a test subject was made to periodically obstruct the signal. During 450 RSSI measurement epochs, the test subject blocked the line-of-sight 2 m from the receiver 5 times and then moved and blocked the line-of-sight another 4 additional times; this time 4 m from the receiver. The RSSI time series of this test is shown in Figure 5.8.

All nine obstruction events are evident, however, the magnitude of the effect is smaller when the obstacle is farther away from the receiver. Based on these results, there is an assumption that the human obstacle will be detectable using this method when it is close enough to the receiver to
affect the RSSI. This test, as well as the various test scenarios described in Sections 5.3, were all conducted in relatively simple indoor environments. Obviously, real indoor environments will be more complicated and require additional testing.

![Figure 5.8: Repeatable response of the three BLE advertising channels due to the human body.](image)

### 5.4.2 Impact of the Blockage Direction

The test scenarios (i) and (ii) included both LOS and NLOS blockages but only LOS blockages were included in the training. In this section, two initial tests are considered to show how NLOS blockages could affect the RSSI values in a different angle of the receiver. The first test shows the effect of the human body on three BLE advertising channels, even if the body may not obstruct the direct visibility of the nodes. To verify the influence of the different angles of the human body shadowing on RSSI, 5 different angles between 0° and 180° were selected in this experiment, which was conducted in the lab area. The RSSI values were transmitted by
DWM1001-DEV and received by nRF-52840 DK for one minute on each angle. In this test, the transmitter and receiver were separated by 2 m and the blocking human was located 1 m from the transmitter; the first angle in the LOS and the remaining 4 angles were at NLOS positions, as shown in Figure 5.9. The maximum effect to the body shadowing was observed at 0° but an effect could also be observed at 45° while 90°, 135°, and 180° showed very little effect, if any variation could be detected. As was expected, the standard deviation of the aggregate signal is larger than the separate channels, however, the mean values are in the same range. The mean values are small within 0° to 90°, and they remain are similar between 90° and 180°.

The maximum effects of body shadowing were represented at 0° on each channel and the aggregate mode in which the human body blocked the signals completely, yet, channels were partially affected at 45°. The histograms of the signals at 90° and 135° did not show the huge difference with 180° in which the body shadowing did not affect the signals. The mean and standard deviations of all histograms of Figure 5.9 are summarized in Table 5.4.
Figure 5.9 The RSSI samples received from the three advertising channels and aggregate signals compared with different blockage angles.
Table 5.4. Mean and standard deviation values of the RSSI measurements.

<table>
<thead>
<tr>
<th>Degree</th>
<th>Channel</th>
<th>Mean(dB)</th>
<th>STD(dB)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>Aggregate</td>
<td>-55.9</td>
<td>2.7</td>
</tr>
<tr>
<td></td>
<td>Channel 37</td>
<td>-52.7</td>
<td>0.4</td>
</tr>
<tr>
<td></td>
<td>Channel 38</td>
<td>-56.2</td>
<td>0.6</td>
</tr>
<tr>
<td></td>
<td>Channel 39</td>
<td>-58.7</td>
<td>1.7</td>
</tr>
<tr>
<td>45</td>
<td>Aggregate</td>
<td>-55</td>
<td>3.6</td>
</tr>
<tr>
<td></td>
<td>Channel 37</td>
<td>-46.8</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>Channel 38</td>
<td>-55</td>
<td>0.4</td>
</tr>
<tr>
<td></td>
<td>Channel 39</td>
<td>-49.8</td>
<td>1.9</td>
</tr>
<tr>
<td>90</td>
<td>Aggregate</td>
<td>-49.9</td>
<td>2.7</td>
</tr>
<tr>
<td></td>
<td>Channel 37</td>
<td>-47.1</td>
<td>1.1</td>
</tr>
<tr>
<td></td>
<td>Channel 38</td>
<td>-53</td>
<td>0.3</td>
</tr>
<tr>
<td></td>
<td>Channel 39</td>
<td>-49.7</td>
<td>1.8</td>
</tr>
<tr>
<td>135</td>
<td>Aggregate</td>
<td>-50.5</td>
<td>2.5</td>
</tr>
<tr>
<td></td>
<td>Channel 37</td>
<td>-47.2</td>
<td>0.86</td>
</tr>
<tr>
<td></td>
<td>Channel 38</td>
<td>-53.4</td>
<td>0.5</td>
</tr>
<tr>
<td></td>
<td>Channel 39</td>
<td>-50.8</td>
<td>0.5</td>
</tr>
<tr>
<td>180</td>
<td>Aggregate</td>
<td>-50.3</td>
<td>2.7</td>
</tr>
<tr>
<td></td>
<td>Channel 37</td>
<td>-48.2</td>
<td>1.1</td>
</tr>
<tr>
<td></td>
<td>Channel 38</td>
<td>-53.7</td>
<td>0.5</td>
</tr>
<tr>
<td></td>
<td>Channel 39</td>
<td>-48.8</td>
<td>1.2</td>
</tr>
</tbody>
</table>

As a result, the body shadowing had a significant effect when a human body blocked LOS or any angles of about less than 45° from LOS.

A second RSSI experiment was conducted to verify the influence of the shadowing effect on the RSSI signals of the user and a second person when the user (and receiver) was not facing the transmitter (NLOS). In this experiment, results were presented in terms of the RSSI values on channels and aggregate mode. Figure 5.10 shows two scenarios in which the transmitter and receiver are 2 m apart. In the first scenario (Figure 5.10a) the user (and receiver) was facing sideways with respect to the transmitter. A second human body was then present for 30 seconds in front of the receiver (but not in the line of sight). This second human left the path for one minute
and then returned to the same spot for 30 s. The second scenario (Figure 5.10b) represents the first scenario with the receiver having a 180° rotation of the transmitter and facing the opposite direction. The information in Figure 5.10 is summarized in Table 5.5. The results demonstrate a significant body shadowing effect on all channels of the RSSI measurements even when the receiver does not face the transmitter. However, this effect is less on the 180° rotation scenario.

As a conclusion here, the body shadowing has significantly affected the RSSI values in the receiver direction.

![Figure 5.10](image)

**Figure 5.10.** RSSI samples received from the three advertising channels in receiver facing (a) 90° and (b) 180° rotation from the transmitter.
Table 5.5. Mean and standard deviation values of RSSI with and without the shadowing effect.

<table>
<thead>
<tr>
<th>Degree</th>
<th>Channel</th>
<th>Mean(dB) With people</th>
<th>Mean(dB) With no people</th>
<th>STD(dB) With people</th>
<th>STD(dB) With no people</th>
</tr>
</thead>
<tbody>
<tr>
<td>90</td>
<td>Aggregate</td>
<td>-62.7</td>
<td>-56.2</td>
<td>5.3</td>
<td>5.6</td>
</tr>
<tr>
<td></td>
<td>Channel 37</td>
<td>-68.2</td>
<td>-62.5</td>
<td>3.5</td>
<td>3.2</td>
</tr>
<tr>
<td></td>
<td>Channel 38</td>
<td>-61.6</td>
<td>-53.1</td>
<td>3.9</td>
<td>1.8</td>
</tr>
<tr>
<td></td>
<td>Channel 39</td>
<td>-58.1</td>
<td>-52.9</td>
<td>1.9</td>
<td>4.5</td>
</tr>
<tr>
<td>180</td>
<td>Aggregate</td>
<td>-69.1</td>
<td>-61.9</td>
<td>6.7</td>
<td>6</td>
</tr>
<tr>
<td></td>
<td>Channel 37</td>
<td>-76.6</td>
<td>-67.8</td>
<td>4.6</td>
<td>4.7</td>
</tr>
<tr>
<td></td>
<td>Channel 38</td>
<td>-66</td>
<td>-59.9</td>
<td>3.5</td>
<td>3.4</td>
</tr>
<tr>
<td></td>
<td>Channel 39</td>
<td>-64.5</td>
<td>-58.1</td>
<td>3.5</td>
<td>4.2</td>
</tr>
</tbody>
</table>

5.5 Artificial Algorithm Assessments

As mentioned in Sections 4.2 and 4.3, the two artificial-based systems are proposed to detect and compensate for the human body shadowing effects: (i) the artificial-based system (Section 4.2) and (ii) the artificial-based system augmented by the vision information (Section 4.3). To design the artificial-based system in both proposed methods, different numbers of layers with various numbers of neurons were investigated in Section 5.5.1.

5.5.1 Numbers of Layers and Neurons

The AI algorithm includes three important layers which were discussed in Section 3.5; input, hidden, and output layers. The neurons in inputs and outputs layers are dependent on the configuration of the proposed system design (Section 4.2 and 4.3). For example in Section 4.2, in both AI methods (MLP and RBF) of the proposed system, the number of input nodes is designed according to the sliding window length (30 nodes).

The artificial-based system proposed in Section 4.2, was investigated with 1 and 2 hidden layers, each tested by 1 to 50 neurons. Figure 5.11 shows the relationship between the total number
of neurons and the standard deviation ($\sigma_{RSSI}$) of the compensated RSSI errors (the output). In general, 2 hidden layers provided more accurate prediction solutions than 1. There was also no improvement in the prediction accuracy beyond 20 neurons per layer. As a result, an architecture with 2 hidden layers with 20 neurons per layer was adopted for MPL and a hidden layer with 20 neurons was adopted for RBF.

![Figure 5.11: Standard deviation of output errors of Multi-layer Perceptron (MLP) in various layers and neurons.](image)

The artificial-based system proposed in Section 4.3, augmented by the vision information, was investigated for 1 and 2 hidden layers with 1 to 100 neurons per layer. The optimal number of the hidden neurons for the MPL version of the system proposed in Section 4.3 could be determined by observing Figure 5.12 in which the standard deviation of the output is plotted as a function of both the number of layers and the number of neurons per layer. Two hidden layers provided more accurate prediction solutions than one. There is also no improvement in the accuracy beyond 30 neurons.
neurons per layer. As a result, an architecture with 2 hidden layers and 30 neurons was adopted for MPL and the same number of neurons for RBF.

![Standard deviation of the output errors of MLP in various layers and neurons.](image)

**Figure 5.12:** Standard deviation of the output errors of MLP in various layers and neurons.

### 5.5.2 Artificial Neural Network Assessments

To evaluate the performance of an artificial network, one can evaluate loss function per iteration for training, test, and validation datasets. In this case, the loss function is the MSE as a function of the number of trained epochs. This shows that the network has arrived in the best learning and the lowest error after a certain number of iterations.

To validate the performance of the proposed artificial-based system in Section 4.2, 1500 samples of RSSI were collected from each transmitter on each of the three channels. This dataset included 750 line-of-sight epochs and 750 epochs in which one of the four lines-of-sight was
obstructed by a second test subject who blocked the line-of-sight between transmitter #4 (presented in Figure 5.4) and the receiver at a random distance between 1 and 3 m from the receiver. Ten reference points with approximately 1 m spacing in a line between transmitters #2 and #4 were occupied (Figure 5.4). The receiver was moved to each reference point to collect 150 RSSI measurements (75 with obstruction and 75 line-of-sight). It should be noted that in “unobstructed” samples, the line-of-sight from transmitter #2 to the receiver was always obstructed by the test subject holding the receiver.

From the 750 measurements in the obstructed case, 525 have been employed to train the network, 75 for validation purposes, and the remaining 150 non-training observations were used to test its performance. The same breakdown of the 750 line-of-sight measurements was to use for the training, validation, and testing. Figure 5.13 shows the training, validation, and testing performance for observations from transmitter #4 in terms of the mean squared error (in RSSI) as a function of the number of iterations. The training stop criteria were chosen from the point where the validation data reached a minimum error. The model was able to converge within 8 iterations and model weights were chosen based on this epoch.
Figure 5.13. Training, validation, and testing performance for transmitter number 4. The best validation performance is 0.038404 at epoch number 8.

To validate the performance of the proposed artificial-based system augmented by the vision information system in Section 4.3, 12070 samples of RSSI were collected from each transmitter on each of the three channels (7310 line-of-sight, 4760 obstructed).

From 12070 measurements in this scenario (presented in Section 5.2.2), 8449 were employed to train the network, 1810 were reserved for validation purposes, and the remaining 1811 non-training observations were used to test the system performance. Figure 5.14 shows the training, validation, and testing performance for observations from transmitter #1 (presented in Figure 5.7) in terms of the mean squared error (in RSSI) as a function of the number of iterations. The model could converge within 39 iterations and model weights were chosen based on this epoch.
Figure 5.14. Training, validation, and testing performance for transmitter number 1. The best validation performance is 0.15207 at epoch number 39.

5.6 Image Processing Algorithms Assessments

Human body detection is a computer vision technology that deals with the detection of a human body in a digital image. Haar cascade, HOG, TinyYOLOv3, and RetinaNet models were carried out to evaluate the best algorithm in this research for human body detection. 25 images were tested using each model. The results showed the RetinaNet model had a minimum false alarm and missed detection.

5.6.1 Assessments of Hand-crafted Features Approach

Haar and HOG models, require the selection of the features of an image (Figure 5.15). The cascade classifier is the decision tree, which eliminates the non-object regions and detects the objects of interest in each stage. The HOG model evaluates a dense grid of normalized local
histograms of image gradient orientations over the image windows. In HOG, the human must be within a perfect area in the image. If the human is too close or too far, they will not be detected.

5.6.2 Assessments of Learning-based Approach

Deep learning algorithms have become popular due to their powerful ability in the detection tasks. Deep learning frameworks could work based on the one-stage detector or two. In two-stage detectors (Jiao et al., 2017b), a proposal generator generates potential objects as a set of rectangle bounding boxes to extract features from each proposal. Moreover, the region classifiers predict the category of the proposed region. However, one-stage detectors (T.-Y. Lin et al., 2017) make the objects prediction directly on each location of the feature maps.

The one-stage detectors are more time-efficient and significantly applicable to a real-time object. Figure 5.16 represents the correct detection (a) and missed detection (b), using the one-stage detector Tiny YOLOv3 algorithm.

![Figure 5.15: (a) Haar cascade and (b) HOG models.](image-url)
Figure 5.16: (a) Correct and (b) missed detections in TinyYOLOv3 algorithm.

In order to estimate the number of people in the environments from an image, a robust one-stage object detector RetinaNet was employed and adapted (T.-Y. Lin et al., 2017).

In this method, a combination of Feature Pyramid Network (FPN) and ResNet was used as the backbone architecture (Figure 5.17). Two subnets of classification and box regression were used. These two subnets are used for the classification and bounding box regression to perform convolution, respectively. The backbone’s responsibility is to compute a convolutional feature map over an entire input image.
Figure 5.17: RetinaNet: the deep learning architecture adapted in the proposed framework.
Chapter 6

EXPERIMENTAL RESULTS AND ANALYSES

This chapter presents the evaluation of the three proposed systems: (i) The thresholding-based system (Section 4.1), (ii) the artificial-based system (Section 4.2), and (iii) the artificial-based system augmented by the vision information (Section 4.3), using the experimental scenarios described in Section 5.2. All three proposed systems are similar in that they apply the three separate BLE advertising channels to detect human body blockages and compensate for this effect on the RSSI measurements. Each proposed system is assessed in terms of its ability to detect blockages and compensate for the RSSI on separate channels. The resulting improvements in the range and position domains are also presented. The assessment of the range and position error results of the thresholding-based, artificial-based, and artificial-based augmented by the vision information systems are presented in Sections 6.1, 6.2, and 6.3, respectively.
6.1 Threshold-based System Evaluation

This section starts with the evaluation of the threshold-based system ability in the detection of the human body, followed by a comparison between the RSSI values from separate channels and all channels together (aggregate) using the empirical distance model (Section 6.1.1). In Sections 6.1.2 and 6.1.3, the threshold-based system is evaluated in terms of distance and positioning accuracy in test scenarios which were introduced in Sections 5.2.1 and 5.2.2, respectively. Finally, this section ends with a discussion part in Section 6.1.4.

6.1.1 Human Body Detection Performance

The ability of the threshold-based system to correctly detect a human body was evaluated based on the number of missed detections and false alarms. Table 6.1 represents the numbers of corrected and uncorrected RSSI samples processed by the threshold-based system. As discussed earlier in Section 3, 300 test epochs were collected in test cast #1 (150 obstructed and 150 unobstructed). Each epoch contained the RSSI measurement from the four transmitters for a total of 1200 observations (600 obstructed and 600 unobstructed samples for all the testing data).

<table>
<thead>
<tr>
<th>Status</th>
<th>Samples</th>
<th>Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td>Correct detection (obstruction)</td>
<td>474</td>
<td>79%</td>
</tr>
<tr>
<td>Missed detection</td>
<td>126</td>
<td>21%</td>
</tr>
<tr>
<td>False alarm</td>
<td>162</td>
<td>27%</td>
</tr>
<tr>
<td>No detection (no obstruction)</td>
<td>438</td>
<td>73%</td>
</tr>
</tbody>
</table>

The threshold-based approach was able to correctly classify 79% of the epochs in the data where human body shadowing was present as opposed to the 21% missed detections. When
shadowing was not present, only 27% of these epochs were false alarms and the remaining 73% were correctly classified as the line-of-sight situations.

To evaluate the advantage of using separate RSSI measurements in contrast with the aggregate signal, the range and position error of the trilateration method are shown in Figure 6.1 and Figure 6.2. Herein, the RSSI values are not corrected for the human body shadowing, however, the impact of separate BLE RSSI measurements in the range and position solutions is investigated.

The performance of the distance estimation using the separate empirical path loss model for each advertisement channel and the aggregate empirical path loss model for all advertisement channels are illustrated in Figure 6.1. To calculate the range error, the BLE transmitter #1 (presented in Section 5.2.1 and Figure 5.4) was used, and several RSSI measurements were collected at various RPs. Figure 6.1 depicts the Cumulative Distribution Functions (CDFs) of the distance estimation errors using an empirical path loss model for the separate and aggregate BLE signals. 90% of the distance estimation errors of the separate method in channels 37, 38, and 39 were better than 4.8 m, 5.1 m, and 5.9 m, respectively, an improvement of 26.15%, 21.54%, and 9.23% over the aggregate method (6.5 m). This test shows that separate channels can provide a more accurate distance estimation than the aggregate mode.

The performance of the RSSI ranging location estimation based on the trilateration method for each advertisement channel is compared in Figure 6.2. In general, the RSSI ranging method applied per channel has better performance than the aggregate RSSI ranging. 90% of the 2D horizontal location estimation errors using individual channels are better than 6.6 m, 4.7 m, and 5.9 m, respectively, however, the aggregate mode shows 10 m error.
Figure 6.1. CDFs of the distance estimation errors for transmitter #1 using separate and aggregate signals.

Figure 6.2. CDFs of the location estimation errors using separate trilateration and aggregate signals.
For comparison purposes, the performance of the fingerprinting-based location estimation for separate databases in each advertisement channel is compared with the aggregate database in Figure 6.3. The RSSI training values were collected at 41 points (Figure 5.4) in an empty experimental room area (Section 5.2.1) and tested using the two linear trajectories shown in Figure 5.5. Generally, the separate databases have better performance than the aggregate one. The 90% 2-D horizontal location errors of the fingerprinting method, using separate databases, were 3.71 m, 3.78 m, and 3.78 m for the three channels. This shows a reduction of 11.9%, 10%, and 10% over the usage of the aggregate database (4.2 m). The results, presented in Figure 6.1, Figure 6.2 and Figure 6.3 are comparable with the literature (Faragher & Harle, 2015c; Zhuang et al., 2016a).

Figure 6.3. CDFs of the location estimation errors using separate and aggregate fingerprinting (FP) databases.
6.1.2 Range and Position Estimation of Scenario #1 in the Empty Room

As mentioned in Section 5.2.1, two scenarios were created in the empty room environment. To evaluate the impact of the thresholding-based system in the correction of the RSSI values in terms of ranging and position errors, the first scenario of the empty room (Section 5.2.1 and Figure 5.4) was selected. As mentioned in Section 5.2.1, in the first scenario, the RSSI values (blocked and non-blocked) were collected in a line as the receiver was moved forward to transmitter number 4 within 1 m to 10 m.

In this scenario, the performance of four different approaches is evaluated and compared with each other. The methods include: (i) the conventional trilateration based on fitting a path loss exponent (empirical classic approach), (ii) the conventional trilateration based on a fixed path loss exponent (non-empirical classic approach), (iii) the threshold-based trilateration based on fitting a path loss exponent (empirical proposed approach), and (iv), the threshold-based trilateration based on a fixed path loss exponent (non-empirical proposed approach). For (iii) and (iv) the RSSI values were corrected in the proposed threshold-based system by applying Equation (4.2) which was described in Section 4.1.2. For (ii) and (iv) the fixed path loss exponent was set to $n = 2.5$ for all channels and this value was selected based on other studies for indoor areas that used path loss exponents between 2.4 to 2.6 (Andersen et al., 1995; Rappaport, et al., 1997). Table 6.2 shows the empirical path loss exponent for all three channels and aggregate.

<table>
<thead>
<tr>
<th>Channel</th>
<th>Path loss exponent value</th>
</tr>
</thead>
<tbody>
<tr>
<td>37</td>
<td>2.6</td>
</tr>
<tr>
<td>38</td>
<td>2.3</td>
</tr>
<tr>
<td>39</td>
<td>2.9</td>
</tr>
<tr>
<td>Aggregate</td>
<td>2.6</td>
</tr>
</tbody>
</table>
Figure 6.4 displays the range error distribution by histograms for different BLE channels, using four different methods (empirical classic, non-empirical classic, empirical proposed and, non-empirical proposed), and four different transmitters. When the classic log-distance algorithm with empirical and non-empirical path loss was used, the majority of the absolute range errors were widely spread in less than 8.8 m and 11 m, respectively. However, in the threshold-based method with the empirical and non-empirical path loss model, the range error distribution was concentrated around 0 with the spread of less than 2.9 m and 3.6 m, respectively. Applying the empirical path loss exponent improved the classic and thresholding results. All the histogram standard deviations in Figure 4.6 are summarized in Table 6.3. The results show that the thresholding-based system was able to correct the effect of the blockage and improve the ranging error, especially in transmitter number 4 which was subject to the largest number of blockages.

Table 6.3. The standard deviation of the range error (all in metres).

<table>
<thead>
<tr>
<th>TX's</th>
<th>Algorithm</th>
<th>Channel 37</th>
<th>Channel 38</th>
<th>Channel 39</th>
</tr>
</thead>
<tbody>
<tr>
<td>TX1</td>
<td>Classic Emp²</td>
<td>2.1</td>
<td>1.2</td>
<td>4.6</td>
</tr>
<tr>
<td></td>
<td>Classic Non-Emp.</td>
<td>3</td>
<td>2</td>
<td>5</td>
</tr>
<tr>
<td></td>
<td>Proposed Emp.</td>
<td>1.6</td>
<td>1.2</td>
<td>2.9</td>
</tr>
<tr>
<td></td>
<td>Proposed Non-Emp.</td>
<td>1.8</td>
<td>2.9</td>
<td>3.3</td>
</tr>
<tr>
<td></td>
<td>Classic Emp.</td>
<td>3.9</td>
<td>6.5</td>
<td>4.4</td>
</tr>
<tr>
<td></td>
<td>Classic Non-Emp.</td>
<td>4.3</td>
<td>7</td>
<td>6.8</td>
</tr>
<tr>
<td></td>
<td>Proposed Emp.</td>
<td>2.7</td>
<td>2.5</td>
<td>2.8</td>
</tr>
<tr>
<td></td>
<td>Proposed Non-Emp.</td>
<td>3.5</td>
<td>2.5</td>
<td>2.8</td>
</tr>
<tr>
<td>TX2</td>
<td>Classic Emp.</td>
<td>4.6</td>
<td>3.2</td>
<td>4.4</td>
</tr>
<tr>
<td></td>
<td>Classic Non-Emp.</td>
<td>5.5</td>
<td>4</td>
<td>9</td>
</tr>
<tr>
<td></td>
<td>Proposed Emp.</td>
<td>1.4</td>
<td>1.3</td>
<td>1.7</td>
</tr>
<tr>
<td></td>
<td>Proposed Non-Emp.</td>
<td>3.4</td>
<td>3.6</td>
<td>3.5</td>
</tr>
<tr>
<td>TX3</td>
<td>Classic Emp.</td>
<td>5.7</td>
<td>2.5</td>
<td>8.8</td>
</tr>
<tr>
<td></td>
<td>Classic Non-Emp.</td>
<td>8.8</td>
<td>3.2</td>
<td>11</td>
</tr>
<tr>
<td></td>
<td>Proposed Emp.</td>
<td>1.4</td>
<td>1.5</td>
<td>1.4</td>
</tr>
<tr>
<td></td>
<td>Proposed Non-Emp.</td>
<td>2.7</td>
<td>2.6</td>
<td>2.7</td>
</tr>
<tr>
<td>TX4</td>
<td>Classic Emp.</td>
<td>5.7</td>
<td>2.5</td>
<td>8.8</td>
</tr>
<tr>
<td></td>
<td>Classic Non-Emp.</td>
<td>8.8</td>
<td>3.2</td>
<td>11</td>
</tr>
<tr>
<td></td>
<td>Proposed Emp.</td>
<td>1.4</td>
<td>1.5</td>
<td>1.4</td>
</tr>
<tr>
<td></td>
<td>Proposed Non-Emp.</td>
<td>2.7</td>
<td>2.6</td>
<td>2.7</td>
</tr>
</tbody>
</table>

¹ Transmitter (TX). ² Empirical (Emp).
Figure 6.4. The histogram of the distance estimation errors for all the transmitters (each transmitter presented in one row), using four different methods (empirical classic, non-empirical classic, empirical proposed and, non-empirical proposed) for each BLE advertising channel.

Figure 6.5 presents CDFs of the positioning errors of the classic and proposed threshold-based trilateration with the empirical and non-empirical path loss exponents. For comparison purposes, the fingerprinting technique is also presented in the results. Figure 6.5a depicts the CDF of the position error in the East direction in which the 90% location error of the classic log-distance algorithm with non-empirical path loss is 6.7 m which shows the maximum error compared with the proposed threshold-based trilateration and fingerprinting. The 90% location error of the
proposed threshold-based algorithm with an empirical path loss exponent is 2.8 m, which is reduced by 42% over the fingerprinting approach (3.2 m) and 33% over the classic trilateration with an empirical path loss (4.8 m).

The CDF of the positioning error in Figure 6.5b shows that the 90% location error of the proposed threshold-based algorithm with an empirical path loss exponent is 3.5 m, which is reduced by 34% over fingerprinting (4.8 m) and 10% over the classic trilateration with an empirical path loss (5.3 m).

Consequently, only the empirical path loss exponents are used in the following section.

6.1.3 Positioning Estimation of Scenario #2 in the Empty Room

The results of the first scenario in the empty room (Section 5.2.1) were presented in Section 6.1.2. Herein, the thresholding-based system positioning results in the second scenario of the
empty room environments are presented. The RSSI values in the second test set were measured by walking inside a closed-loop with an approximate size of 4 m × 5 m (Figure 5.5).

Figure 6.6a depicts the CDF of the position error in the East direction for the classic and proposed threshold-based trilateration with the empirical path loss exponent as well as the fingerprinting technique presented in contrast to the trilateration method. Comparing the proposed threshold-based model with the positioning error of about 3.3 m with the fingerprinting and classic log-distance methods with 5.4 m and 7.4 m in 90% of the data presents 39% and 55% error reduction, respectively. In Figure 6.6b, the positioning errors in the North direction are better than 4 m in 90% of the samples using the proposed threshold-based model. This is while the fingerprinting and uncorrected log-distance models, which use empirical path loss models obtained from empty room training data and do not account for the human body blockages, provided 4.5 m and 6 m errors, respectively.

![Figure 6.6. Test #2 CDFs of (a) the absolute East-West, and (b) North-South position errors; using the three different methods (Proposed threshold-based, fingerprinting (FP), and Classic).](image)
6.1.4 Discussion of Thresholding-based Proposed System

In the thresholding-based system, a separate channel advertising scheme to measure RSSI on each advertising channel was developed and evaluated with the experimental data. An algorithm to detect the presence of a human body based on the variance of the received RSSI values in the three advertisement channels was developed to detect and model the effect of human body shadowing. The proposed thresholding-based system was able to correctly classify 82% epochs in the data where the human body shadowing was present. Using separate channel information provided a significant improvement in the accuracy in the ranging and trilateration positioning. To provide a different baseline for comparison, the fingerprinting solutions were presented using the individual channels and the aggregate RSSI values.

The proposed algorithm not only can be easily implemented without extra hardware costs but also has the advantage of dynamic correction of the RSSI values, which minimizes the positioning error.

6.2 Artificial-based System Evaluation

The evaluation of the artificial-based system is presented in this section. The experiments to test the proposed system were conducted in an empty room area (Figure 5.4, and Figure 5.5) and are described in Section 5.2.1.

The ability of both MLP and RBF to correct the RSSI values for the human body shadowing was evaluated in the range domain by applying the log-distance model with empirical path loss exponent to convert the corrected RSSI values into the distance. The ANN-based results were compared to the uncorrected RSSI values with the same empirical path loss exponent used, referred to as the classic method.
On the other hand, to see the effect of the empirical model in the proposed method, all three methods (classic, MLP, and RBF) are tested with a fixed (non-empirical) path loss exponent set to \( n = 2.5 \) for all channels. This number was selected based on other studies for indoor areas that applied path loss exponents between 2.4 to 2.6 (Andersen et al., 1995; Rappaport, et al., 1997).

6.2.1 Human Body Detection Performance of Artificial-based Approach

The ability of the artificial-based system to correctly detect a human body is evaluated in this section for both MLP and RBF. The results of the MLP algorithm on the RSSI values for transmitter #4 (Figure 5.4) in the training and test data sets are presented in Figure 6.7. The RSSI values of all three advertising channels were compensated during the human body shadowing events that occurred around samples 20 and 80 in the test data. In these cases, the plus symbols, representing the observed RSSIs, were consistently low and the ANN was able to distinguish and compensate the shadowing effect in the output (Figure 6.7.d). However, MLP is not a perfect method and may generate both missed detections and false alarms. It occasionally misclassified fading on one or two channels as blocking and corrected the RSSI values, though this classification error was beneficial because the result was a corrected RSSI. In addition, in the first three samples of the test data, that were experiencing fading on all channels, MLP was unable to recognize this since there was no transition in the time series from full power to faded, resulting in an uncorrected RSSI that was interpreted as a much larger distance.

Table 6.4 represents the numbers of the corrected and uncorrected RSSI samples and how they were classified by both the MLP and RBF methods. As discussed earlier in Section 3, 300 test epochs were collected in test cast #1 (150 obstructed and 150 unobstructed). Each epoch
contained RSSI measurement from the four transmitters for a total of 1200 observations (600 obstructed and 600 unobstructed samples).

Table 6.4. Artificial Neural Network (ANN) performance in terms of the correct detection, missed detection, and false alarm.

<table>
<thead>
<tr>
<th>Status</th>
<th>Samples in MLP$^1$</th>
<th>Samples in RBF$^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Correct detection (obstruction)</td>
<td>534</td>
<td>522</td>
</tr>
<tr>
<td>Missed detection</td>
<td>66</td>
<td>78</td>
</tr>
<tr>
<td>False alarm</td>
<td>36</td>
<td>48</td>
</tr>
<tr>
<td>No detection (no obstruction)</td>
<td>564</td>
<td>552</td>
</tr>
</tbody>
</table>

$^1$ Multi-layer Perceptron (MLP). $^2$ Radial Basis Function (RBF).

Figure 6.7. The blocked and not blocked RSSI values in the MLP algorithm from transmitter #4 in channels 37, 38 and 39, for (a) input training, (c) output training, (b) input test, and (d) output test (All RSSI value are presented in dB).
MLP was able to correctly classify 89% of the epochs in the test data where human body shadowing was present as opposed to the 11% missed detections. When shadowing was not present, only 6% of these epochs were false alarms and the remaining 94% was correctly classified as the line-of-sight situations. RBF performed slightly worse with 13% missed detections and 8% false alarms.

The proposed artificial-based system results were compared in terms of the range and position errors in both test case scenarios (empty room shown in Figure 5.4 and electronics lab shown in Figure 5.5).

6.2.2 Range and Position Estimation of Scenario #1 in the Empty Room

Figure 6.8 exhibits the range error distribution by histograms for the different BLE channels, using three different methods (classic, MLP, and RBF), empirical path loss exponents, and four different transmitters, whereas Figure 6.9 represents the same results with using non-empirical (fixed) path loss exponent. When the classic log-distance algorithm with the empirical path loss was used, the majority of absolute range errors were widely spread in less than 10 m in all directions. However, in both ANN methods, MLP and RBF, with the empirical path loss model, the range error distribution tended to concentrate around 0 with the distribution of less than 2.5 m. Applying the empirical path loss exponent improved the classic results, but barely changed the MLP and RBF ranges. All the histogram standard deviations in both figures (Figure 6.8 and Figure 6.9) are summarized in Table 6.5.
Table 6.5. The standard deviations of the range error (all in metres).

<table>
<thead>
<tr>
<th>TX's</th>
<th>Algorithm</th>
<th>Channel 37</th>
<th>Channel 38</th>
<th>Channel 39</th>
</tr>
</thead>
<tbody>
<tr>
<td>TX1</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Classic</td>
<td>2.1</td>
<td>1.2</td>
<td>4.6</td>
</tr>
<tr>
<td></td>
<td>MLP</td>
<td>1</td>
<td>0.7</td>
<td>2.3</td>
</tr>
<tr>
<td></td>
<td>RBF</td>
<td>1.3</td>
<td>1</td>
<td>2.5</td>
</tr>
<tr>
<td></td>
<td>Classic-Non Emp(^2)</td>
<td>3</td>
<td>2</td>
<td>5</td>
</tr>
<tr>
<td></td>
<td>MLP-Non Emp.</td>
<td>1</td>
<td>0.8</td>
<td>2.3</td>
</tr>
<tr>
<td></td>
<td>RBF-Non Emp.</td>
<td>1.4</td>
<td>1</td>
<td>2.3</td>
</tr>
<tr>
<td>TX2</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Classic</td>
<td>3.9</td>
<td>6.5</td>
<td>4.4</td>
</tr>
<tr>
<td></td>
<td>MLP</td>
<td>1.7</td>
<td>2</td>
<td>1.7</td>
</tr>
<tr>
<td></td>
<td>RBF</td>
<td>2</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td>Classic-Non Emp.</td>
<td>4.3</td>
<td>7</td>
<td>6.8</td>
</tr>
<tr>
<td></td>
<td>MLP-Non Emp.</td>
<td>2.3</td>
<td>2</td>
<td>2.5</td>
</tr>
<tr>
<td></td>
<td>RBF-Non Emp.</td>
<td>2.1</td>
<td>2</td>
<td>2.2</td>
</tr>
<tr>
<td>TX3</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Classic</td>
<td>4.6</td>
<td>3.2</td>
<td>4.4</td>
</tr>
<tr>
<td></td>
<td>MLP</td>
<td>0.8</td>
<td>0.8</td>
<td>0.9</td>
</tr>
<tr>
<td></td>
<td>RBF</td>
<td>1.8</td>
<td>2</td>
<td>2.4</td>
</tr>
<tr>
<td></td>
<td>Classic-Non Emp.</td>
<td>5.5</td>
<td>4</td>
<td>9</td>
</tr>
<tr>
<td></td>
<td>MLP-Non Emp.</td>
<td>2.3</td>
<td>1.2</td>
<td>2.5</td>
</tr>
<tr>
<td></td>
<td>RBF-Non Emp.</td>
<td>1.9</td>
<td>2</td>
<td>2.3</td>
</tr>
<tr>
<td>TX4</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Classic</td>
<td>5.7</td>
<td>2.5</td>
<td>8.8</td>
</tr>
<tr>
<td></td>
<td>MLP</td>
<td>0.8</td>
<td>0.9</td>
<td>0.9</td>
</tr>
<tr>
<td></td>
<td>RBF</td>
<td>1.8</td>
<td>2</td>
<td>2.1</td>
</tr>
<tr>
<td></td>
<td>Classic-Non Emp.</td>
<td>8.8</td>
<td>3.2</td>
<td>11</td>
</tr>
<tr>
<td></td>
<td>MLP-Non Emp.</td>
<td>0.9</td>
<td>1.1</td>
<td>1.3</td>
</tr>
<tr>
<td></td>
<td>RBF-Non Emp.</td>
<td>2.1</td>
<td>2.1</td>
<td>2.1</td>
</tr>
</tbody>
</table>

\(^1\) Transmitter (TX). \(^2\) Empirical (Emp).
Figure 6.8. The histogram of the distance estimation errors for all the transmitters (each transmitter presented in one row), using three different methods (classic, MLP and Radial Basis Function (RBF)) for each BLE advertising channel with the empirical model.
Figure 6.9. The histogram of the distance estimation errors for all the transmitters (each transmitter presented in one row), using three different methods (classic, MLP, and RBF) for each BLE advertising channel with the non-empirical model.

Additionally, Figure 6.10 presents the CDFs of the absolute values of the horizontal position error components (East-West and North-South) for the three different methods with empirical and non-empirical path loss exponents. The East-West position error with an empirical path loss was better than 1.6 m for 90% of the samples when using the MLP method, which is a 67% improvement compared to the classic log-distance with a shadowing factor (4.8 m). The RBF method also showed acceptable position error (less than 2.4 m) or an improvement of 50%.
compared to the classic log-distance method. The position error in the North-South direction presented similar improvement with the 90% localization error for MLP at 1.7 m and for RBF at 3.5 m, which are 68% and 34% improvements over the log-distance method (5.3 m), respectively.

The position error using the non-empirical path loss in the East-West direction was better than 2.2 m in 90% of the time in MLP method, which is a 67% improvement compared to the non-empirical classic log-distance method (6.7 m). The RBF method also showed acceptable position error (less than 3.2 m) or an improvement of 52% compared to the non-empirical classic log-distance method. The AI-supported results were very close to those using the empirical path loss model. The position error in the North direction with non-empirical method also showed similar improvement with the 90% localization error for MLP at 2.3 m and for RBF at 4 m, which were 68% and 45% improvements over non-empirical log-distance method (7.3 m), respectively. It is worth noting that the classic method using the non-empirical path loss exponent suffered in the East-West direction compared to the classic results using the empirical path loss. This is because the classic method applied a shadowing loss to all observations and the observations to transmitters 1 and 3 were never obstructed in the test scenario.
Figure 6.10. Test #1 the cumulative distribution functions (CDFs) of (a) the absolute East-West, and (b) North-South position errors, using the three different methods (MLP, RBF, and Classic) with empirical path loss exponent (solid lines) and fixed path loss exponent = 2.5 (dashed lines).

6.2.3 Positioning Estimation of Scenario #2 in the Empty Room

The RSSI values were measured by walking inside a closed-loop with an approximate size of 4 m x 5 m (Figure 5.5).

Figure 6.11a depicts the CDF of the position error in the East direction. Both the ANN models (MLP and RBF) show positioning error about 2.7 m to 4 m compared with a classic log-distance method which shows 7.4 m in 90% of the data. The MLP method is decreased by 64% and the RBF method by 46% over the log-distance method. In Figure 6.11b, the positioning errors in the North direction are 2.8 m to 4 m in 90% of the data for both of the ANN models (MLP and RBF), while the log-distance model shows a higher error (6 m).
6.2.4 Discussion of The Artificial-based System

In the artificial-based method, a sliding window ANN method for detecting the human body attenuation in the BLE RSSI values using the three advertising channels has been proposed and implemented. The method uses a sliding window of the RSSI input from all three advertising channels to distinguish between the attenuation resulting from the sudden obstacle blockage and fading, caused by the multipath or a gradual signal level change due to changing the range. This will correct the RSSI level to match those for the unblocked cases. Both ANN methods are able to correctly identify sudden blockages more than 87% of the time. The corrected RSSI values are converted to the ranges, using a simple log-distance model with the empirical path loss exponents also obtained from the trained data. The ranges obtained from corrected and uncorrected RSSI values are used to compute the positions through the trilateration technique. The results demonstrate significant improvement in both the range and position accuracy compared to a
previously-proposed method where all the RSSI measurements were adjusted for shadowing, whether it would occur or not.

It is noteworthy to assess the results compared to those reviewed in the literature. Cantón Paterna et al. (2017) showed 1.82 m accuracy in 90% of the time in a 6 by 9 m^2 room and 4.6 m in a 16 by 17 m^2 room, which are close to the presented results (2.3 m in scenario #1 and 3.8 m in scenario #2, in 90% of the time). Zhuang et al. (2016a) achieved accuracies of less than 2.56 m in 90% of the time, (an average of two trajectories) with a dense deployment of the BLE beacons (one beacon per 9 m) but did not investigate the obstacles. Finally, Huang et al. (2019) offered a positioning accuracy of less than 2.4 m in 90% of the time, using a differential correction method that required a nearby reference receiver with known coordinates to experience the same obstruction.

6.3 Artificial-based System Augmented by Vision Information Evaluation

The assessment of the artificial-based system using the BLE signals and vision information is presented in this section. As explained in Section 4.3, an artificial-based system augmented by vision could calculate the number of the present human bodies based on image information. The GOPRO HERO 7 high-resolution digital camera was used here (GoPro, Inc., San Mateo, CA, USA) and the experiments for the proposed system were conducted in the lab area (Figure 5.6). As mentioned in Section 5.4.2, the body shadowing had a significant effect when a human body blocked LOS or an angle of about less than 45° from LOS, whereas the GOPRO HERO 7 has a 149° Field Of View (FOV) (GoPro, Inc., San Mateo, CA, USA) and was operated with a 1.0 sec sampling rate. Also, preliminary results in subsection 5.4.2 showed that the body shadowing significantly affected the RSSI values only when the blocking body was in the transmitter-receiver
line of sight. Capturing a photo was only capable of helping the system to decide people are present. It is unable to help the system if the people are present in the LOS but out of FOV.

6.3.1 Human Body Detection Performance of Artificial-based Approach Augmented by Vision

The ability of the vision system to correctly detect a human body in the image is evaluated in terms of the number of missed detections and false alarms. Table 6.6 shows the number of correctly or incorrectly detected people in the images using the deep learning RetinaNet system, discussed in Section 5.6.

As described in Section 5.2.2, 16 images were captured in each RP in test cast #1 for a total of 544 images (204 obstructed by one or two persons and 340 unobstructed).

Table 6.6. Vision performance in terms of the correct detection, missed detection, and false alarm.

<table>
<thead>
<tr>
<th>Status</th>
<th>Samples</th>
<th>Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td>Correct detection (obstruction)</td>
<td>188</td>
<td>92%</td>
</tr>
<tr>
<td>Missed detection</td>
<td>16</td>
<td>8%</td>
</tr>
<tr>
<td>False alarm</td>
<td>34</td>
<td>10%</td>
</tr>
<tr>
<td>No detection (no obstruction)</td>
<td>306</td>
<td>90%</td>
</tr>
</tbody>
</table>

The RetinaNet system was able to correctly classify 92% of the images in the data where the human body shadowing was present whereas 8% were missed detections. When the human body was not present, only 10% of these images were false alarms and the remaining 90% were correctly classified as unblocked situations.

To illustrate the ability of the artificial-based system augmented by the vision information (Section 4.3) for the correction of RSSI (Section 5.2), data from a reference point was selected. Figure 6.12 shows the corrected data on that point for the training and testing of the RSSI data in RP number 26, and transmitter number 1 (Figure 5.7). The inputs and outputs of MLP are shown
by dots and lines in three channels, respectively, in case of absence or presence of the human bodies. From the initial samples, with no obstructions, the advantage of considering the 3 advertising channels separately is obvious. With one and two obstructing people present, the uncorrected RSSI values are lower and more variable in all three channels. The output of the ANN (the corrected RSSI) clearly demonstrates its ability to detect and correct the effect of the human body.

![Graph showing RSSI values before and after ANN testing and training.]

**Figure 6.12.** Comparison of the collected RSSI values before and after the ANNs testing and training.

**6.3.2 Range and Position Estimation of Scenario #1 in the Lab Environment**

The ability of the artificial-based system augmented by the vision information system in the detection of the human body was investigated in Section 6.3.1. In this section, after the correction
of the RSSI values, the system is evaluated in terms of the range and positioning in the first scenarios of the lab environment (Section 5.2.2).

Figure 6.13 presents the distance errors of all the RPs for transmitter number 1 after the correction of RSSI on each channel, by applying Equation (3.4) and Equation (3.5).

![Figure 6.13. Mean of the distance error for each reference point for transmitter #1 in the lab environment.](image)

In comparison with the results in Section 6.2, Figure 6.14 illustrates the standard deviation of the distance error for all four transmitters before the RSSI correction (input channels and aggregate) and after the correction by the ANN algorithms augmented by the vision information (MLP and RBF), and without the vision information presented in Section 4.2 (MLP and RBF). Similar to Section 6.2, the empirical path loss models were used for their improved performance indoor environments as opposed to selecting a standard value for the path loss exponent. As
expected, less fluctuations in the RSSI values were observed after the correction, and the distance errors were smaller for cases and more precise for all the proposed artificial-based algorithms (Sections 4.2 and 4.3). However, the MLP and RBF algorithms augmented by the vision information offered even smaller errors than those with no vision information. The range accuracies were almost the same for MLP and RBF algorithms, although, the MLP showed slightly better results. The RBF has a simple architect and fast training procedure but it is responsive only to a limited section of inputs space.

The largest error belonged to the uncorrected input RSSI values in the aggregate mode, however, separating uncorrected RSSI values per channels reduced the distance error almost by half.

Figure 6.14. The standard deviation of the distance error before (input) and after the RSSI correction, using MLP and RBF with RSSI only (AI), and using MLP and RBF with RSSI and vision information (AI+ Vision).
The CDF of the positioning error in the East-West and North-South directions for the first test scenario of the lab environment (Figure 5.7) is plotted in Figure 6.15. The figure represents the localization errors for two methods of the trilateration and fingerprinting (FP), however, the fingerprinting solutions are presented for comparison purposes only. The trilateration method is used for the proposed artificial-based algorithms augmented by the vision information (MLP and RBF) and the artificial-based system presented in Section 4.2 (MLP and RBF). In addition, the positioning error of the trilateration for the uncorrected RSSI (called here classic) is evaluated.

As expected, the positioning error in the East and North direction presented a large error for the uncorrected RSSI, less than 10 m in East-West direction, and 7.2 m in North for 90% of the points. The fingerprinting algorithm produced better results in 90% of the points than the trilateration with the uncorrected RSSI values which was 6.8 m in the East direction and 5.5 m in the North direction.

In the East-West direction, the 90% location errors of the MLP and RBF with the corrected RSSI values by the artificial-based system (labeled AI) were 4.7 m and 5 m offering a reduction by 31% and 26% over the fingerprinting (6.8 m), and 53% and 50% over the classic trilateration (10 m) methods, respectively.

In the North-South direction, the 90% location errors of the MLP and RBF with the corrected RSSI values by the artificial-based system (labeled AI) were 4.9 m and 5.4 m, showing a reduction by 11% and 2% over the fingerprinting (5.5 m), and 32% and 25% over classic trilateration (7.2 m) methods, respectively.

In the East-West direction, the 90% location errors of the MLP and RBF with the corrected RSSI values by the artificial-based system augmented by the vision information (labeled
AI+Vision), were 2.9 m and 3.5 m, presenting a reduction by 57% and 48% over the fingerprinting (6.8 m), and 71% and 65% over the classic trilateration (10 m) methods, respectively.

In the North-South direction, the 90% location error of the MLP and RBF with the corrected RSSI values by the artificial-based system augmented by the vision information (labeled AI+Vision), were 2.4 m and 4.1 m, showing a reduction by 56% and 25% over the fingerprinting (5.5 m), and 67% and 43% over the classic trilateration (7.2 m) methods, respectively.

The results from MLP and RBF with the corrected RSSI values have less error, however, MLP shows the best results in both directions. Since the MLP algorithm in the artificial-based method augmented by the vision information has the best results compared with the RBF, the second scenario (Section 6.3.3) is executed only using the MLP algorithm.

![Figure 6.15. CDF of the positioning error for (a) East and (b) North directions.](image)

The results from this section confirmed that the two proposed artificial-based systems performed better than the fingerprinting method which required training steps, and significantly better trilateration using the uncorrected RSSI values. Fingerprinting methods are popular due to
their accuracy in the position domain compared to trilateration techniques using uncorrected data.

The proposed trilateration method with corrected RSSI values obtained by using AI has slightly better positioning accuracy than fingerprinting and the proposed trilateration method with corrected RSSI values by AI and the vision information has significantly better positioning accuracy than the fingerprinting technique.

6.3.3 Positioning Estimation of Scenario #2 in the Lab Area (Blind Test Case)

The results shown in Section 6.3.2 demonstrated the improvement obtained by adding vision to the ANN. In this section, the vision system is further tested in locations where no training data was collected. Similarly, since MLP outperformed RBF in the results shown in Section 6.3.2, only MLP will be used in this last test and will be compared with uncorrected trilateration (classic) and fingerprinting approaches.

To evaluate the proposed system in the untrained points, five unoccupied points during the training (Section 5.2.2) were selected randomly for testing in the lab environment (Figure 5.6). Figure 6.16 shows the success of the proposed algorithm in the correction of the human body shadowing in one blind point.
Figure 6.16. Comparison of the collected RSSI values in bind points before and after ANNs.

The results of the indoor localization experiment based on the fingerprinting method and trilateration method on the corrected RSSI (MLP) and uncorrected RSSI values (log-Normal) on the same blind point (Figure 6.16) are presented in Figure 6.17. The traditional methods (fingerprinting and log-Normal methods) suffer from positioning errors since the noise and attenuation caused by the RSSI fluctuations during the human body shadowing cannot be eliminated in these methods. By employing the proposed method to correct RSSI in three advertising channels, and further use of camera information to train the RSSI model, better positioning results were achieved. In 200 RSSI samples on each channel at one point, the proposed method showed more stable positioning.

In Figure 6.17, pink circles reference points were used for training both the MLP method and fingerprinting database. The test point location (red square) was chosen in the almost middle
of the lab and was not used for training. The positioning results show that the cluster of solutions based on (i) uncorrected RSSI values (log-Normal) contained huge errors (black circles), (ii) the fingerprinting solutions were slightly better and close to training data (red circles), and (iii) the proposed method was significantly better (blue circles).

![Figure 6.17. A comparison of the positioning results between the fingerprinting (FP) method, the proposed MLP algorithm with vision information, and the uncorrected log-normal method.](image)

Figure 6.18 shows the positioning results for the maximum and Root Mean Square Error (RMSE) from fingerprinting, and from trilateration with the corrected RSSI and uncorrected RSSI values. The RMSE was 6.11 m for the uncorrected RSSI values, 3.49 m for fingerprinting, and 2.41 m for the proposed method. The proposed method was able to effectively reduce the positioning error even in the untrained points with a maximum positioning error of 5.1 m.
6.3.4 Discussion of The Artificial-based System Augmented by Vision Information

The artificial-based system augmented by the vision information, have been proposed and implemented for detecting the human body blockages in the BLE RSSI values, using the separate advertising channels and vision information. To correct the RSSI values, the sliding window of RSSI from three advertising channels and the number of people who blocked the signal (can be 0, 1, or 2 persons) were used as inputs for the ANN algorithm. The system was trained based on the RSSI values obtained in the unattended lab environment.

Both the ANN methods could convert the corrected RSSI values to ranges using a simple log-distance model with the empirical path loss exponents found from the trained data. The obtained ranges from the corrected RSSI were used to compute position through the trilateration.
technique. The results showed significant improvement in the range and position accuracy compared with the AI-proposed method without the contribution of the vision information.
Chapter 7

CONCLUSIONS AND FUTURE WORK

This thesis presented and compared three systems that applied RSSI on separate BLE advertising channels to detect the obstructions caused by the human obstacles, correct the obstructed measurements, and improve the accuracy of ranging–based indoor positioning. Two of the proposed systems (the artificial-based and the artificial-based augmented by the vision) employed neural network algorithms to learn from training data in order to recognize the RSSI measurement patterns that would indicate the presence of human obstacles in indoor environments. In this chapter, the most important outcomes are summarized, some limitations of the work are discussed and possible future work is recommended.

7.1 Overview of Novelty

The main purpose of this research was to investigate the application of a simple BLE trilateration positioning algorithm in real indoor environments in which human bodies are present and can affect the signals. Both proposed neural network algorithms (the artificial-based and the
artificial-based augmented by the vision) were implemented to detect and correct for the presence of the human obstacles using observations from the three BLE advertising channels and vision information captured in indoor environments.

Most RSSI-based indoor positioning systems rely on the fingerprinting methods since fingerprinting is more accurate than the trilateration method in general, using RSSI-based ranges specifically because converting from RSSI to range depends heavily on the propagation environment. Fingerprinting is a time-consuming process that relies on the construction of the large databases and is not compatible with the propagation environment changes, particularly when the human body obstacles affect the signals. In this thesis, two systems that applied artificial intelligence to learn to identify and correct for human obstacles were proposed and compared to a thresholding-based approach. The first artificial-based method utilized the RSSI values only whereas the second incorporated a wearable camera as an additional source of information for the presence or absence of the human obstacles.

Following is the list of the contributions of this research:

Contribution 1: A detailed comparison of applying the individual BLE advertising channels as opposed to aggregate RSSI for (a) obstruction detection, (b) the correction of RSSI, and (c) ranging and trilateration positioning was conducted.

Contribution 2: The first (to the knowledge of the author) application of a thresholding method to detect the uniform reaction of three BLE advertising channels due to the human body obstructions, as well as a first detailed and thorough comparison of uncorrected RSSI ranging, fingerprinting, and corrected RSSI values in the thresholding-based in BLE technology.
Contribution 3: The first application of ANN as a method to detect and correct for human body obstructions using a sliding window of RSSI on multiple advertising channels including a detailed comparison of this method to the methods compared in Contribution 2.

Contribution 4: The first use of a combination of BLE RSSI, wearable camera, and ANN to better detect and correct for human obstacles including a detailed comparison of this method to the methods compared in Contribution 3.

7.2 Conclusions

The following conclusions could be obtained from this research:

- *The advantage of applying separate BLE advertising channels was demonstrated:* The RSSI measurements from three advertising channels are more accurate than considering all the channels together as the aggregate mode. The small fluctuations in the RSSI values are the outcome of considering the channels separately, however, the fluctuations will become larger when the aggregate mode is considered. The results (Figure 6.1, Figure 6.2) demonstrate that separate channels are able to achieve more accurate ranging and position solutions than the aggregate mode.

- *Detection of human body obstruction is shown to be feasible by applying separate BLE advertising channels:* The uniform reaction of the RSSI measurements from three advertising can be utilized to detect the human body. The results convey that the application of the separate channels in the AI models can correct the human body effect successfully 89% in MLP and 87% in RBF approaches, however, the separate channels in the threshold-based model can only detect 79% of the blockages correctly.
• *The threshold-based system presented a considerable improvement over both the classical path loss modeling and fingerprinting:* The proposed threshold-based system (Section 4.1) improved the positioning solutions by enhancing the RSSI values in indoor environments with the presence of the human body. The model is compared with a classical path loss model with an empirical and non-empirical path loss exponent. The threshold-based system results (Section 6.1) offered 4.4 m position accuracy while the classic algorithm (uncorrected RSSI) showed 7.1 m position accuracy.

• *The proposed artificial-based system provided a remarkable improvement over the threshold-based system:* The proposed AI model (Section 4.2) improved the positioning solutions compared with the threshold-based system. The AI algorithm results (Section 6.2) showed 2.3 m position accuracy in 90% of the time while the thresholding-base presented 4.4 m position accuracy in 90% of the time. Also, the experimental results indicate that, in terms of accuracy for artificial-based systems, MLP slightly outperforms RBF. However, RBF is able to be trained more quickly.

• *The addition of the vision information improved the accuracy of the proposed artificial-based system significantly:* It is observed that the proposed method can be augmented by the vision information (Section 4.3) to improve the position solutions in the complicated lab environments. The AI algorithm augmented by the vision information results (Section 6.3) provided 3.7 m position accuracy in 90% of the time for the MLP algorithm whereas the artificial-based system demonstrated 6.7 m position accuracy in 90% of the time. Nevertheless, fingerprinting and classic algorithms offered 8.7 m and 12.3 m position accuracy in the same situation.
• **The accuracy level:** The proposed artificial-based system for the correction of RSSI is sufficient for less than 7 m position accuracy in 90% of the time which is compatible with most mobile device users in a complicated environment, however, if less than 4 m position level accuracy in 90% of the time is required, further information provided by the wearable camera will be inevitable.

### 7.3 Limitation of the Proposed System

In all positioning systems based on the RSSI measurements, the main limitation is fluctuations in RSSI caused by various environmental factors. Indoor environments are challenging due to their multipath propagation and signal attenuation. In the proposed systems, the human body shadowing effect is considered only when the system is trained to identify a maximum of two human obstructions.

The methods described in this thesis require observation of all three advertising channels. When all channels are not available in some cases, the aggregate method will have to be used. Furthermore, during one round of scanning, there is a possibility of losing the RSSI measurements on one or two channels since the transmitters and receivers are not perfectly synchronized.

As with all ANNs, the prediction of the neural networks highly depends on how well they learn the concepts from the training data and apply them to the testing samples. Reduction in the generalization ability can occur from overtraining, while the expansion in generalization ability can cause undertraining. To avoid this issue a partition of the data is required to be specified for the validation data set as it plays a vital role besides training and testing data sets.
7.4 Applications and Recommendations for Future Work

The obvious application of this research is in the general field of wireless location using BLE technology. At the time of writing, during a worldwide COVID-19 pandemic, digital contact tracing, specifically using BLE RSSI as an observable, has received significant attention. The work described in this thesis could be directly applied to this problem, specifically the possibility of using multiple BLE channels and other data sources to train ANNs to be able to identify when two BLE enabled devices are in proximity. One could imagine a system where a subset of the population are expert users carrying mobile devices with GNSS receivers, wearable cameras, and other sensors and are collecting data to train ANNs to recognize patterns and correct RSSI observations to allow accurate RSSI-based ranges to be obtained from general users whose mobile devices are only recording BLE RSSI values. RSSI measurements from both BLE infrastructure and other mobile users would be used, possibly in conjunction with stationary (non-wearable) cameras.

In the short term, several improvements could be made to the present work. First, the proposed system should be trained and tested in more than two rooms. Then, the system should be tested in additional locations without further training.

Since real environments are more complicated than those tested in this research, with real traffic and multiple obstructions, training the ANN to identify multiple human obstructions is one of the most important areas for future investigation.

Further study on optimizing the ANN to have the best split ratio of the training and test data sets should be conducted. Also, adding online training to the system will enable the ANN to learn faster during the operation which is valuable for dynamic cases.
Identifying the BLE beacons in the imagery, and determining whether the people in the imagery are in LOS or not, should be investigated for future work. The application of an RGB-D camera to enable the detection of all possible static and dynamic obstacles with exact distance from the users to increase the accuracy of the system could be the subject of further research.

7.5 Impact of Proposed Research

The proposed research designed and implemented an artificial-based system augmented by the vision information to detect and compensate the human body effects on the separate BLE RSSI measurements. The corrected BLE RSSI values in the proposed system have shown remarkable improvements in terms of ranging path loss model and the trilateration positioning solutions compared with applying the uncorrected RSSI or even fingerprinting. The proposed system offered significant potential in detecting obstacles for positioning purposes in the complex environments which could lead the system to be adopted for emergency applications and digital contact tracing.
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