INDOOR POSITIONING MODEL
BASED ON PEOPLE EFFECT AND
RAY TRACING PROPAGATION

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UNIVERSITI TEKNOLOGI MALAYSIA

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DEDICATION

This thesis is dedicated to my mother and father,
Bapak Sabikun and Ibu Ina Sartinah,
Bapak Soendjojohadi and Ibu Sri Widajati.
Who taught me that the best type of knowledge
to have is that which can benefit life.
It is also dedicated to my wife and children,
Idha Arfianti, Asma, Husna, Hafshoh.
Who taught me to always struggle with love
and patience to achieve my dreams.

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ABSTRACT

WLAN-fingerprinting has been highlighted as the preferred technology in an Indoor Positioning System (IPS) due to its accurate positioning results and minimal infrastructure cost. However, the accuracy of IPS fingerprinting is highly influenced by the fluctuation in signal strength as a result of encountering obstacles. Many researchers have modelled static obstacles such as walls and ceilings, but hardly any have modelled the effect of people presence as an obstacle although the human body significantly impacts signal strength. Hence, the people presence effect must be considered to obtain highly accurate positioning results. Previous research proposed a model that only considered the direct path between the transmitter and the receiver. However, for indoor propagation, multipath effects such as reflection can also have a significant influence, but were not considered in past work. Therefore, this research proposes an accurate indoor positioning model that considers people presence using a ray tracing (AIRY) model in a dynamic environment which relies on existing infrastructure. Three solutions were proposed to construct AIRY: an automatic radio map using ray tracing (ARM-RT), a new human model in ray tracing (HUMORY), and a people effect constant for received signal strength indicator (RSSI) adaptation. At the offline stage, 30 RSSIs were recorded at each point using a smartphone to create a radio map database (523 points). The real-time RSSI was then compared to the radio map database at the online stage using MATLAB software to determine the user position (65 test points). The proposed model was tested at Level 3 of Razak Tower, UTM Kuala Lumpur (80 × 16 m). To test the influence of people presence, the number, position, and distance of the people around the mobile device (MD) were varied. The results showed that the closer the people were to the MD in both the Line of Sight (LOS) and Non-LOS position, the greater the decrease in RSSI, in which the increment number of people will increase the amount of reflection signals to be blocked. The signal strength reduction started from 0.5 dBm with two people and reached 0.9 dBm with seven people. In addition, the ray tracing model produced smaller errors on RSSI prediction than the multi-wall model when considering the effect of people presence. The k-nearest neighbour (KNN) algorithm was used to define the position. The initial accuracy was improved from 2.04 m to 0.57 m after people presence and multipath effects were considered. In conclusion, the proposed model successfully increased indoor positioning accuracy in a dynamic environment by overcoming the people presence effect.

ABSTRAK

WLAN-cap jari telah diserlahkan sebagai teknologi pilihan dalam Sistem Kedudukan Dalam Bangunan (IPS) kerana hasil penentuan kedudukan yang tepat dan kos infrastruktur yang minimum. Walau bagaimanapun, ketepatan pengecapan jari IPS sangat dipengaruhi oleh turun naik kekuatan isyarat akibat merentasi halangan. Ramai penyelidik telah menggunakan model halangan statik seperti dinding dan siling, tetapi hampir tidak ada yang memodelkan kesan kehadiran manusia sebagai halangan walaupun tubuh manusia secara signifikan mempengaruhi kekuatan isyarat. Oleh itu, kesan kehadiran manusia mesti dipertimbangkan untuk mendapatkan hasil kedudukan yang lebih tepat. Penyelidikan sebelum ini mencadangkan model yang hanya mempertimbangkan laluan lurus antara penghantar dan penerima. Walau bagaimanapun, untuk penyebaran dalam bangunan, kesan berbilang laluan seperti refleksi juga mempunyai pengaruh, tetapi tidak dipertimbangkan dalam kajian lepas. Oleh itu, penyelidikan ini mencadangkan model penentuan kedudukan dalam bangunan yang tepat yang menganggap kehadiran manusia menggunakan Model Surihan Sinar (AIRY), dalam persekitaran dinamik yang bergantung pada infrastruktur sedia ada. Tiga penyelesaian dicadangkan untuk membina AIRY: peta radio automatik menggunakan surihan sinar (ARM-RT), model manusia baru dalam penyurihan sinar (HUMORY), dan pemalar kesan manusia untuk penyesuaian penunjuk kekuatan isyarat yang diterima (RSSI). Pada peringkat luar talian, 30 RSSI direkodkan pada setiap titik menggunakan telefon pintar untuk membuat pangkalan data peta radio (523 titik). RSSI masa nyata kemudian dibandingkan dengan pangkalan data peta radio di peringkat dalam talian menggunakan perisian MATLAB untuk menentukan kedudukan pengguna (65 titik ujian). Model yang dicadangkan diuji di Tingkat 3, Menara Razak, UTM Kuala Lumpur (80m x 16m). Untuk menguji pengaruh kehadiran manusia, jumlah, kedudukan, serta jarak manusia di sekitar peranti mudah alih (MD) diubah. Hasil kajian menunjukkan bahawa semakin dekat seseorang itu dengan MD di kedua kedudukan garis nampak (LOS) dan bukan garis nampak (Non-LOS), semakin besar pengurangan RSSI di mana peningkatan bilangan manusia akan meningkatkan jumlah isyarat pantulan yang disekat. Pengurangan kekuatan isyarat bermula dari 0.5 dBm dengan dua orang dan mencapai 0.9 dBm dengan tujuh orang. Di samping itu, model surihan sinar menghasilkan ralat yang lebih kecil pada ramalan RSSI berbanding model berbilang dinding. Hal ini menunjukkan bahawa model penyurihan sinar meramalkan RSSI lebih baik daripada model berbilang dinding, terutama apabila memandang kesan kehadiran manusia. Algoritma KNN digunakan untuk menentukan kedudukan. Ketepatan awal ditingkatkan dari 2.04 m kepada 0.57 m setelah kehadiran manusia dan kesan berbagai laluan dipertimbangkan. Sebagai kesimpulan, model yang dicadangkan bejaya meningkatkan ketepatan kedudukan dalam bangunan dalam persekitaran yang dinamik dengan mengatasi kesan kehadiran manusia.

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LIST OF ABBREVIATIONS

ANN	-	Artificial Neural Network
AIRY	-	Accurate Indoor Positioning System based on People Effect and Ray Tracing
AP	-	Access Point
ARM	-	Automatic Radio Map
GPS	-	Global Positioning System
IPS	-	Indoor Positioning System
KNN	-	K-Nearest Neighbour
LBS	-	Location-Based Service
LOS	-	Line of Sight
MD	-	Mobile Device
MRM	-	Manual Radio Map
MW	-	Multi-Wall
NLOS	-	Non-Line of Sight
PPE	-	People Presence Effect
RM	-	Radio Map
RSSI	-	Received Signal Strength Indicator
RT	-	Ray Tracing
SBR	-	Shooting and Bouncing Ray
UTM	-	Universiti Teknologi Malaysia
WLAN	-	Wireless Local Area Network
ARM-RT	-	Automatic Radio Map using Ray Tracing
HUMORY	-	Human Model in Ray Tracing

LIST OF SYMBOLS

S_i	-	RSS from available APs
L_i	-	Each site location
T_i	-	A tuple of (S_i, L_i)
d	-	Distance between the transceivers
PL	-	Path Loss
$\prod \bar{\bar{R}}_i$	-	Reflection coefficient
$\prod \bar{\bar{T}}_i$	-	Transmission coefficient
MSE	-	Mean Squared Error

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CHAPTER 1

INTRODUCTION

1.1 Overview and Motivation

Location-based services (LBSs) are a significant permissive technology with a wide range of applications in human life (Horsmanheimo *et al.*, 2019). LBS are services that combine geographic location with other information to give more helpful services (Huang and Gartner, 2018). The LBS market is growing rapidly (Basiri *et al.*, 2015), with a market report estimating the LBS market to generate up to USD 77.84 billion revenue by 2021 (Markets and markets, 2016).

One of the main components of LBS is its positioning system—either indoor or outdoor. For outdoor positioning, Global Navigation Satellite Systems (GNSS) such as the Global Positioning System (GPS) and *Globalnaya Navigazionnaya Sputnikovaya Sistema* (GLONASS) have been used over a wide range of applications. GNNS is a worldwide position and time determination system that includes one or more satellite constellations, aircraft receivers, and system integrity monitoring, augmented as necessary to support the required navigation performance for the intended operation (Zhu *et al.*, 2018). GPS is a satellite navigation system operated by the United States whereas GLONASS is operated by the Russian Federation.

However, GPS cannot be used for indoor positioning because its signals cannot penetrate buildings. Due to GPS failure to work indoors, many researchers have attempted to build an alternative to GPS that can work indoors called the Indoor Positioning System (IPS) (Dardari *et al.*, 2015). When visiting a building for the first time such as an airport, an office building, an exhibition hall or a hypermarket, orientation may be difficult. Direction signs and static plans often do not provide the help one needs to find a specific location in time, resulting in stressful situations and delays. According to ABI Research in 2015, IPS-based services have great economic potential, and are estimated to reach a market value of US$ 10 billion in 2020. Another report in 2016 by Markets and Markets estimated the global indoor location market to grow to $4,424.1 million by 2019, as shown in Figure 1.1 (Dasgupta and Singh, 2016). According to a Research and Markets report, the Global Indoor Positioning and Navigation market is expected to reach $54.60 billion by 2026.

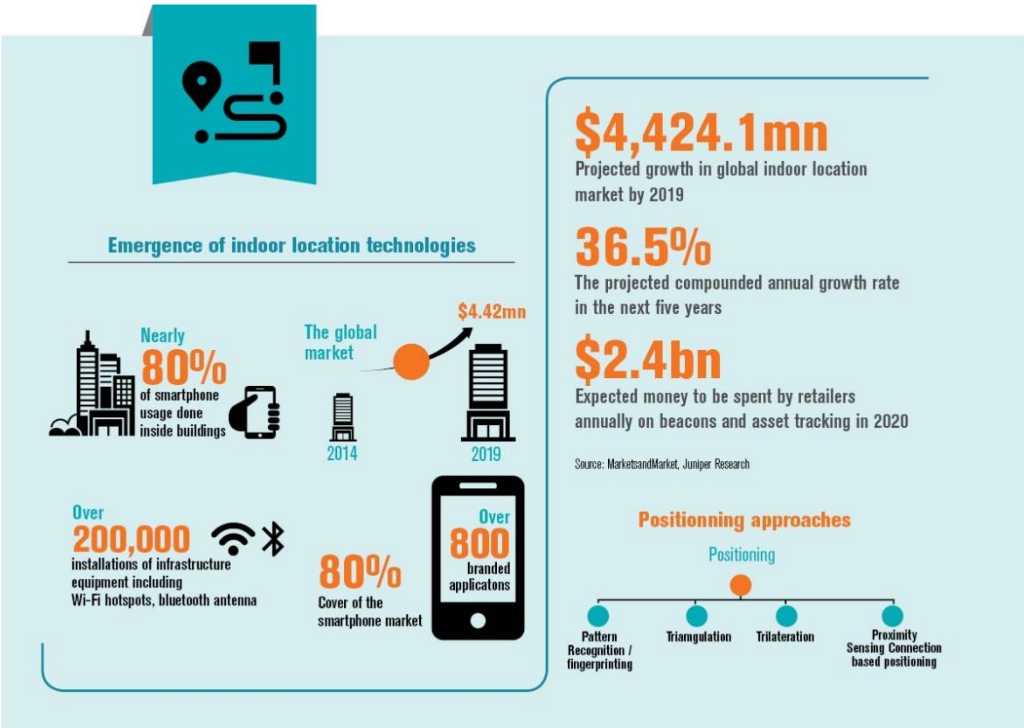

Figure 1.1 Infographic about the future of indoor location technologies

An IPS is any system that gives a precise position inside of buildings, such as a smart building (Turgut *et al.*, 2016), a hospital (Calderoni *et al.*, 2015), an airport, (Molina *et al.*, 2018), a subway (Stockx *et al.*, 2014), a construction site (Ma *et al.*, 2018), industrial sites (Cheng *et al.*, 2018), and university campuses (Golenbiewski *et al.*, 2018).

IPS uses many existing technologies such as radio frequencies (RFs) (Mier *et al.*, 2019), magnetic fields (Shu *et al.*, 2015), acoustic signals (Moutinho *et al.*, 2016), thermal sensors (Lu *et al.*, 2016), optical sensors (Mautz and Tilch, 2011) or other sensory information collected using a mobile device (MD) (Han *et al.*, 2016). Some examples of RF technology used in IPS, among others, are WLAN/Wi-Fi

(Zourmand *et al.*, 2018; Hsieh *et al.*, 2018), Bluetooth (Faragher and Harle, 2015), Zig Bee (Dong *et al.*, 2019), RFID (Tsirmpas *et al.*, 2015), frequency modulation (FM) (Popleteev, 2019), and Ultra-wideband (UWB) (Witrisal *et al.*, 2016). WLAN technology is commonly used in IPS because of its advantages, for example, radio waves can pass through obstacles like floors, walls, ceilings, and human bodies. Meanwhile, WLAN positioning systems can be implemented over a wide coverage area because it does not need any additional device.

One of the performance indicators of IPS is accuracy, which is the difference between the actual location and the estimated location (Rezazadeh *et al.*, 2018). There are many applications that require precise IPS, such as for emergency cases and patient monitoring. For example, it is essential for 911 to know the location of a caller as precisely as possible to control delays in emergency response. Delays in response can lead to a loss of lives. The emergency service has even defined a new standard called the "next-generation 911 (NG911)" (The National 911 Program, 2015; Sedlar *et al.*, 2019). In 2016, the United States (U.S.) National Aeronautics and Space Administration Jet Propulsion Laboratory (NASA JPL) cooperated with the Department of Homeland Security Science and Technology Directorate (S&T) to develop a high precision outdoor and indoor navigation and tracking system for emergency responders (U.S. Department of Homeland Security, 2016). An indoor navigation system that can track firefighters to within a meter is also in the works (Li *et al.*, 2018).

WLAN IPS has been highlighted as a preferred technology due to its accurate positioning results and minimal infrastructure cost (Yang and Shao, 2015). WLAN is a wireless local network standard (IEEE 802.11), a communication standard that is supported in most mobile phones. However, the WLAN signal is greatly influenced by environmental conditions, especially inside indoor areas because of the multipath effect, which can decrease signal accuracy. An example of a signal propagation model that considers multipath effects is the ray tracing model. This model requires an adaptive IPS that can adapt to the multipath effect and environmental changes, mainly the effect of people presence, to provide high-accuracy IPS.

1.2 Problem Background

Location detection techniques are categorised into three: proximity, triangulation, and fingerprint (Farid *et al.*, 2013). Proximity detection or connectivity-based techniques are simple to implement. The location of MD is defined based on the cell of origin (CoO) method with a known position and limited distance. Although this method is easy to implement, it has a large distance error, meaning that it cannot be adopted for WLAN-based IPS because the Access Point (AP) has a wide coverage (up to 100 m). Proximity techniques can be applied using RFID or Bluetooth, but which also have a limited range or coverage.

The triangulation technique uses the geometric properties of triangles to find the location of a target. The technique can be divided into two: lateration and angulation. The lateration technique is based on the measurement of the received radio signal strength (RSS), the signal phase, and the propagation-time such as the time of arrival (TOA), the time difference of arrival (TDOA), and the roundtrip time (RTT)(Makki *et al.*, 2015).

Fingerprinting is based on a pattern recognition technique that combines radio frequency (RF) with location information e.g. a label from the environment, to show the position of the MD. WLAN fingerprinting is usually conducted in two phases: offline and online. In the offline phase, a site survey is conducted to collect the value of the received signal strength indicator (RSSI) at many reference points (RPs) from all the detected access points (APs). In the online phase, a user samples or measures an RSSI vector at his/her position. Then, the system compares the received vector of the RSSI with the stored fingerprints in the radio map (RM) database. The position is then estimated based on the most similar "neighbours", which are the set of RPs with RSSI vectors that closely match the RSSI of the target (He and Chan, 2016).

WLAN-based RSSI Fingerprinting can provide highly accurate position estimates (Wang *et al.*, 2019). It also requires a low-cost investment, as shown in Table 1.1 (Potgantwar *et al.*, 2015; Basri and El Khadimi, 2016). On the other hand, the large bandwidth makes the ultra-wideband (UWB) signal resistant to multipath problems and interference (Gao and Li, 2019), making UWB less influenced by the people presence effect, but it also requires a higher cost of investment.

Table 1.1 Comparison of indoor positioning technology, accuracy, cost, and people effect

Technology	**Accuracy**	**Cost**	**Channel Bandwidth**	**Interference caused by People Effect**
UWB	1 m–2 m	High	500 MHz–7.5 GHz	Low
RFID	1 m–2 m	Low	200 KHz; 500 KHz	High
Bluetooth	2 m–5 m	Low	1 MHz	High
WLAN	2 m–5 m	Low	22 MHz	High
Zigbee	1 m–3 m	High	0.3 MHz/0.6 MHz; 2 MHz	High

Manual radio map (RM) construction is labour intensive and time-consuming. Hence, automatic radio map generation was developed to reduce the time required to construct RM (Alshami, *et al.*, 2015; Du *et al.*, 2015; Lin *et al.*, 2015). An automatic radio map construction method is proposed using multi-sensors including inertial information, video data, and WIFI signals (Liu *et al.*, 2016). Then, a visual-based approach was proposed to construct a radio map in anonymous indoor environments (Liu *et al.*, 2017). On the other hand, Yu *et al.* (2016) and Li *et al.* (2018) constructed a system based on crowdsourcing. In Li *et al.'s* (2018) project, the users walked through a building to generate parts of road paths and then merging the PDR traces based on the similarity of the Wi-Fi fingerprints. These techniques did not need any prior knowledge of floor plans. These construction techniques were able to reduce the time required to construct RMs. However, it still required the user to exert significant effort to collect data using various sensors. New techniques have therefore been proposed based on indoor RF propagation models. This technique only requires information on the room layout and AP location as the system input. Alshami *et al.* (2015) and Caso and De Nardis (2017) used a Multi-wall signal path loss model to automatically generate a radio map. This technique quickly generated a radio map, but the model only considered the direct signal from the transmitter (AP) to the receiver (MD), whereas indirect signals such as reflection, which have a significant influence on indoor propagation, were not included.

The current research proposes a ray tracing model that considers multipath effects to obtain a more accurate radio map. The ray tracing technique obtains channel characteristics by identifying the contributions of individual multipath components (reflection, diffraction, and scattering) and calculates the composition of these components at the receiver. If we use all the multipath components, it will require high computational time (Hossain et al., 2019). Thus, in this research, we will only consider reflection in order to get low computational time and high accuracy.

Another problem faced in past studies is that the RSSI of WLAN is highly affected by environmental changes such as the effect of people presence, which will decrease position accuracy. Hence, environmental changes are still one of the main problems affecting WLAN positioning accuracy. Obstacles that could cause fluctuations in RSSI include walls, ceilings, and people (Farid *et al.*, 2013; He and Chan, 2016). Walls and ceilings have been discussed in Ubom *et al.* (2019), Saito and Omiya (2018), and Santana *et al.* (2016). The effect of people on signal strength was investigated in Slezak *et al.* (2018) for 60 GHz, in Alabish *et al.* (2018) for 18–22 GHz, and in Alshami *et al.* (2014) for 2.4 GHz. The result showed that people's presence in the Line of Sight (LOS) between the AP and the Mobile Device (MD) decreased the RSSI by 2 dBm to 5 dBm. This decline in the RSSI could result in a position error of more than 2 m. People holding a MD (user orientation problem) and people around the user could also block the WLAN signal from the APs depending on their position, in turn, reducing the RSSI value. Meanwhile, for Zig Bee, people's presence in the Line of Sight (LOS) decreased the RSSI by 3.97 dBm (Shukri *et al.*, 2016).

One of the main problems related to PPE is the position of the user holding a MD. This problem is known as the user orientation problem. To solve the user orientation problem, Liu and Wang (2015) collected four orientations of RM in the offline phase and used a KNN positioning algorithm in the online phase. Deng *et al.* (2018) also built a multi-orientation RM in the offline phase and employed a Rotation Matrix and the Principal Component Analysis (RMPCA) method. Their solution proved time-consuming because of the manual process involved, and the RSSI multi-vectors had to be collected at each node. The systems developed in the study focused on the development of a multi-orientation RM database such that the system required a long time for collecting data for the database. Therefore, it is necessary to develop an adaptive system with a more efficient RM database to overcome the user orientation problem.

In addition to users who hold MDs, people around the users also affect the RSSI. People presence has the same effect as obstacles that block WLAN signals. The movement of humans in wireless networks is one of the major effects that cause significant variations in the received signal strength indicator (RSSI) (Booranawong *et al.*, 2019; Booranawong *et al.*, 2018). Alshami *et al.* (2015) presented experimental results showing that people's presence between the AP and the MD reduced the received signal strength by 2 dBm to 5 dBm. However, the study only discussed the effect of one or two people on the RSSI and only a single path signal propagation model was used to analyse the RSSI (Alshami *et al.*, 2017). However, multipath signals such as reflection also have a significant effect on indoor propagation, but these were not discussed. In fact, human tissues have a variety of relative permittivity values that influence the reflection signal (Zhekov *et al.*, 2019). The Foundation for Research on Information Technologies in Society in 2011 released the selected relative permittivity of main human tissues as shown in Table 1.2.

Table 1.2 Selected relative permittivity of some main human tissues

Tissue	Relative permittivity
Air	1
Blood	58.4
Fat	5.29
Muscle	52.8
Dry Skin	38.1
Wet Skin	42.9

Hence, this current research should consider the effect of many people around the user with different positions to improve the accuracy of the proposed IPS. In addition, this research should also consider modelling the human body in the ray tracing multipath signal propagation model to analyse the effect of people presence on RSSI.

1.3 Problem Statement

One of the most popular methods in IPS is the WLAN Fingerprint because this technology has been widely installed inside buildings and provides a high level of accuracy (Yang and Shao, 2015). Although WLAN RSS fingerprinting is the most accurate positioning method, it still has a weakness, for example, constructing the RM is labour intensive and time-consuming, and the multipath signal is vulnerable to obstacle presence, such as walls, furniture, and people.

Many studies have modelled static obstacles such as walls and ceilings, but it is hard to find any research that has modelled the people presence effect. Human bodies absorb, reflect, and diffract WLAN signals, which, in turn, affect the value of RSSI. Thus, if offline mapping is performed when there are no people (or a few people) whereas positioning is performed when there are many people, the system can lose its reliability. The results have shown that, on average, the presence of human bodies increases the positioning error by 11% regardless of the algorithm used (Garcia-Villalonga and Perez-Navarro, 2015). Meanwhile, Alshami *et al.'s* (2015) experimental works showed that people's presence between a mobile device and the access point reduced the RSSI by 2 dBm to 5 dBm. This decline in RSSI could lead to a position error of more than 2 m.

Hence, there is a need to overcome the people presence effect to obtained highly accurate positioning results. In previous researches, as mentioned in Section 1.2, a propagation model was proposed that considered people presence based on a multi-wall model. However, only the direct path between the transmitter and the receiver was considered in the model, and every wall that crossed by this path was assumed to attenuate the passing ray by a constant amount. However, for indoor propagation, multipath effects (reflection, diffraction, and scattering), which were not considered in these studies, have a very significant influence. Therefore, there is a need to develop a new indoor propagation model that considers multipath effects, such as the Ray Tracing model, to model the people presence effect and improve the accuracy of the Indoor Positioning System.

In this research, a new indoor positioning model that considers the people presence effect and multipath propagation based on a ray tracing model was proposed to improve the accuracy of WLAN fingerprinting IPS without the need to install a new device in the existing infrastructure.

1.4 Research Question

Based on the problem statement, the following research questions were derived:

i. What is the best way to develop and validate an accurate automatic radio map construction that considers ray tracing?
ii. How to develop and validate a human model that considered people presence effect on the received signal strength to enhance WLAN-fingerprinting Indoor Positioning based on ray tracing?
iii. How to develop and validate the proposed accurate indoor positioning model in a dynamic environment that also considers people presence effect and ray tracing?

1.5 Aim of the Study

This research proposes a new accurate indoor positioning model based on WLAN Fingerprinting using existing common devices that are already installed in a building (i.e. the Access Point). The proposed model has to adapt to the effect of environmental changes, especially the effect of people presence. The proposed model adopted a modified ray tracing radio propagation model to overcome the multipath effect.

1.6 Objective

The objectives of this research are as follows:

i. To develop and validate an accurate automatic radio map construction technique that considers ray tracing propagation
ii. To develop and validate a human model that considers the people presence effect on the received signal strength to enhance the proposed WLAN-fingerprinting Indoor Positioning System based on ray tracing propagation
iii. To develop and validate the proposed accurate indoor positioning model in a dynamic environment, which considers the effect of people presence effect and ray tracing.

1.7 Scope of Study

This research proposes a novel, accurate WLAN Fingerprinting indoor positioning model that considers the people presence effect and multipath propagation to improve positioning accuracy without adding any extra device. This model can determine the location of a MD accurately in a dynamic environment. Hence, this research is bounded by the following scope.

This research focused on indoor positioning while navigation, tracking, and other LBS fall out of the scope of study. WLAN fingerprinting was adopted as an indoor positioning method and the radio map was constructed using RSS from the available AP beacon.

The users carried the MD in their hand and used the Android Operating System with an internal WLAN adapter. Meanwhile, the access points (APs) were installed in a fixed and known position.

This research used the ray tracing propagation model to estimate the received signal strength. Accuracy and position errors were adopted as performance metrics to validate the proposed model. This research did not investigate human detection or any security or privacy issues.

1.8 Significance of the Study

Recently, LBS has proven to be a significant permissive technology with a wide range of applications. The performance of LBS is significantly affected by its IPS. By building an accurate IPS using existing devices (APs), the performance and coverage of LBS can be improved. The proposed system could be applied in an economic context (shopping centres, train stations, airports), as well as military, health (hospital, healthcare), and social aspects (people traffic management for emergency situations inside buildings).

Many applications require precise IPS such as emergency cases and patient monitoring. For example, 911 has defined a new standard called the "next generation 911 (NG911)" that includes a technique that recognises the precise position of the caller, while the U.S. Department of Homeland Security has developed a high precision outdoor and indoor navigation and tracking system for emergency responders. The U.S. Government is also developing an indoor navigation system that can track firefighters to within a meter.

IPS also plays an important role in the Internet of Things (IoT) (Ali *et al.*, 2019). One of the largest European Union projects on IoT (FP-7 Butler project) stated that location information is one of the key enabling technology in IoT. In the health sector, IoT manages numerous sensors mounted on a patient's body to monitor health conditions. If the patient's health condition deteriorates and he/she needs help immediately, then, the location of the patient would be vital to monitor. Hence, in cases such as these, an IPS with high accuracy is required.

1.9 Thesis Organisation

This thesis consists of six chapters that are organised as follows: Chapter 1 explains the overview and the motivation of this research such as the research questions, the objectives, the scope, and the limitations. The statement of the problem was formulated by highlighting the need for a new, accurate indoor positioning model based on RSSI-WLAN Fingerprinting that could adapt to the people presence effect to improve the accuracy of the IPS without installing any extra devices in a dynamic environment.

Chapter 2 provides fundamental information about WLAN Fingerprinting, the path loss or radio propagation models, and related works on PPE in IPS. Chapter 3 presents the research methodology. It explains the research plan that contains three phases to achieve the desired objectives: 1) the Knowledge Building Phase, which aims to investigate the literature to develop the baseline; 2) the Development Phase in which an Accurate Indoor Positioning Model is designed and developed based on WLAN fingerprinting to improve the accuracy of IPS; and 3) the Validation Phase, which aims to validate the developed AIRY model. The development and validation phases are carried out to in parallel since AIRY has different components and the developed component must be validated before going to the next step.

Chapter 4 discusses the effects of people around the user on the RSSI and the proposed human model and the signal propagation model that consider people presence based on the ray tracing propagation model. Chapter 5 discusses the development of a highly accurate IPS that considers the people effect and was adopted from the ray tracing propagation model. Finally, Chapter 6 presents the conclusions to this study.

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LIST OF PUBLICATIONS

INDEXED JOURNALS (PUBLISHED)

No.	Paper	Index
1	**Firdaus,** Noor Azurati Ahmad, and Shamsul Sahibuddin. 2017. "Indoor Positioning System based Wi-Fi Fingerprinting for Dynamic Environment." In Journal of Engineering and Applied Sciences	Scopus (Q3)
2	**Firdaus**, Noor Azurati Ahmad, Shamsul Sahibuddin, "Indoor Positioning System Based on WLAN Fingerprint and User Orientations with Minimum Computation Time" In TELKOMNIKA	Scopus (Q2)
3	**Firdaus**, Noor Azurati Ahmad, Shamsul Sahibuddin, "Accurate Indoor-Positioning Model Based on People Effect and Ray-Tracing Propagation" In SENSORS	ISI (Q1)
4	**Firdaus**, Noor Azurati Ahmad, Shamsul Sahibuddin, Adi Azlan, and Iyad H Alshami. "A Review of Hybrid Indoor Positioning System Using WLAN Fingerprint and Image Processing" In International Journal of Electrical and Computer Engineering Systems	Scopus (Q4)

CONFERENCES (PUBLISHED)

No.	Paper	Index
1	**Firdaus**; Ahmad, N.A.; Sahibuddin, S. Adapted WLAN Fingerprint Indoor Positioning System (IPS) Based on User Orientations. In *Recent Trends in Information and Communication Technology*; Springer: Berlin, Germany, 2017; pp. 226–236.	Springer, ISI
2	**Firdaus**; Ahmad, N.A.; Sahibuddin, S. *Effect of People around User to WLAN Indoor Positioning System Accuracy*. In Proceedings of the Second Palestinian International Conference on Information and Communication Technology (PICICT 2017), Gaza, Palestine, 8-9 May 2017; pp. 17–21.	IEEE, Scopus
3	**Firdaus,** Noor Azurati Ahmad, Shamsul Sahibuddin, Rudzidatul Akmam Dziyauddin. *Modelling the Effect of Human Body around User on Signal Strength and Accuracy of Indoor Positioning*. In Proceedings of 3rd International Conference on Smart Sensors and Application (*ICSSA*). Kuala Lumpur, Malaysia on the 7-9th April 2020	IEEE, Scopus

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Human model for dynamic changes in indoor positioning system (LY2019008898)