



UNIVERSITI PUTRA MALAYSIA

**INDOOR POSITIONING USING WEIGHTED MAGNETIC FIELD SIGNAL
DISTANCE SIMILARITY MEASURE AND FUZZY BASED ALGORITHMS**

CACEJA ELYCA ANAK BUNDAK

FS 2021 26



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By

CACEJA ELYCA ANAK BUNDAK

**Thesis Submitted to the School of Graduate Studies, Universiti Putra
Malaysia, in Fulfilment of the Requirements for the Degree of Master of
Science**

July 2021

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Abstract of thesis presented to the Senate of Universiti Putra Malaysia in
fulfilment of the requirement for the degree of Master of Science

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July 2021

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Indoor localisation based on the magnetic field has drawn much research attention since they have a range of applications in science and industry. Magnetic-based positioning systems are infrastructure-free and can be sensed by magnetometers embedded on smartphones. Unfortunately, magnetic field intensity data only consists of three components magnetic field signals compared to Wi-Fi, using multiple access points. There is a high chance that a similar reading of those three components obtained at multiple locations. A magnetic-based positioning algorithm should fully utilise the three components of the magnetic field intensity data. This thesis analyses the positioning accuracy changes by using different similarity measures on a specific magnetic field vector and proposed an algorithm using different weighted magnetic field signal distance similarity measures. For the first method, various metric distances used for the MF signal components are studied and the results showed that Euclidean distance and square distance give low distance mean error compared to square root and Manhattan distance. Then, three proposed different signal weighting functions, namely actual weight, square weight, and square root weight are applied in each MF signal similarity measure and compared with the state-of-the-art of Euclidean distance to estimate location. Additionally, the effect of signal weighting function is investigated further using multiple K values of K nearest neighbour (KNN) algorithm. According to the results, the square root weighting function has a lower position error of 8.156 m than Euclidean distance with an improvement of 5.5%. Also, the use of (K=5) of KNN for the square weight of $d_{m_{y1}}$ distance measure gives the lowest mean estimation error of 7.188 m.

Another problem in MF IPS is there are few studies focused on using the Euclidean distance and the area between the reference points to improve the accuracy in the position estimation. Therefore, for the second objective, another algorithm named the fuzzy algorithm is designed which combines the clustering algorithm, matching

algorithm, triangle area algorithm and average Euclidean algorithm used to estimate location. Firstly, the MF RPs database is reconstructed into a cluster database using the clustering algorithm. Each trained RP and other nearby RPs are clustered together at a certain distance. A matching algorithm is used to match between the top 10 ranked RPs with the nearest Euclidean distance to the TP with the RPs clustered. For the triangle area algorithm, the smallest triangle area is selected from the triangle formed from the matching RPs cluster to estimate location. In contrast, the average Euclidean algorithm is based on the average Euclidean of the RPs from the RP cluster set. The lowest average Euclidean distance is chosen, and the average estimated location of the RPs is calculated. Lastly, for the fuzzy algorithm, a rule-based decision is applied to select whether the triangle area or average Euclidean algorithm is used to find the final estimated position. The fuzzy algorithm shows a localisation accuracy of 5.889 m, which is better than the KNN and Weight MF signal algorithm with an improvement of 31% and 27% respectively.

Both algorithms have achieved the target accuracy below 8 m and better than KNN. Although the fuzzy algorithm achieved better accuracy than the weighted MF signal distance similarity measure, the weighted MF signal distance similarity measure was less time-consuming than the fuzzy algorithm. Therefore, both algorithms need more improvement in future works to achieve a better estimation location.

Abstrak tesis yang dikemukakan kepada Senat Universiti Putra Malaysia
sebagai memenuhi keperluan untuk ijazah Master Sains

**LOKALISASI DALAM BANGUNAN MENGGUNAKAN ALGORITMA
SUKATAN KESERUPAAN JARAK PEMBERAT KEKUATAN MEDAN
MAGNET DAN ALGORITMA BERASASKAN FUZI**

Oleh

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Lokalisasi dalam bangunan menggunakan medan magnet telah menarik perhatian ramai penyelidik kerana medan magnet mempunyai pelbagai aplikasi dalam sains dan industri. Sistem kedudukan berasaskan magnetik adalah bebas infrastruktur dan dapat dikesan menggunakan manganometer yang terbenam di dalam telefon pintar. Walau bagaimanapun, data keamatan medan magnet hanya terdiri daripada tiga komponen dan tidak seperti Wi-Fi yang menggunakan banyak pusat akses Wi-Fi. Kemungkinan besar bacaan magnet untuk ketiga-tiga komponen itu akan serupa di beberapa lokasi. Algoritma kedudukan berdasarkan magnet harus mempergunakan ketiga-tiga komponen data medan magnet dengan sepenuhnya. Tesis ini menganalisis perubahan ketepatan kedudukan dengan menggunakan ukuran kesamaan yang berbeza pada vector medan magnet yang tertentu dan cadangan menggunakan algorithm sukatan keserupaan jarak pemberat kekuatan medan magnet. Untuk kaedah pertama, pelbagai jarak metrik yang digunakan untuk komponen isyarat MF dikaji dan hasilnya menunjukkan bahawa jarak Euclidean dan jarak persegi memberikan ralat min jarak rendah berbanding dengan punca kuasa dua dan jarak Manhattan. Kemudian, tiga cadangan fungsi pemberat isyarat yang berbeza, iaitu berat sebenar, berat persegi, dan berat kuasa dua diterapkan dalam setiap ukuran kesamaan isyarat MF dan dibandingkan dengan jarak Euclidean yang canggih untuk menganggar lokasi. Selain itu, kesan fungsi pemberat isyarat dikaji lebih jauh dengan menggunakan pelbagai nilai K algoritma K terdekat (KNN). Menurut hasilnya, fungsi pemberat akar kuasa dua mempunyai ralat kedudukan yang lebih rendah 8.156 m daripada jarak Euclidean dengan peningkatan 5.5%. Juga, penggunaan ($K = 5$) KNN untuk berat persegi $d_{m_{y1}}$ memberikan ralat anggaran min terendah iaitu 7.188 m.

Masalah lain dalam MF IPS adalah terdapat beberapa kajian yang difokuskan pada penggunaan jarak Euclidean dan kawasan di antara titik rujukan untuk meningkatkan ketepatan dalam perkiraan kedudukan. Oleh itu, untuk objektif kedua, algoritma lain yang dinamakan algoritma fuzzy dirancang yang menggabungkan algoritma pengelompokan, algoritma padanan, algoritma kawasan segitiga dan algoritma Euclidean rata-rata yang digunakan untuk menganggar lokasi. Pertama, pangkalan data MF RP disusun semula menjadi pangkalan data kluster menggunakan algoritma kluster. Setiap RP terlatih dan RP lain yang berdekatan dikumpulkan bersama pada jarak tertentu. Algoritma padanan digunakan untuk memadankan antara 10 peringkat teratas RP dengan jarak Euclidean terdekat ke TP dengan RP berkelompok. Untuk algoritma kawasan segitiga, luas segitiga terkecil dipilih dari segitiga yang terbentuk dari kluster RP yang sepadan untuk menganggar lokasi. Sebaliknya, algoritma Euclidean rata-rata berdasarkan pada Euclidean rata-rata RP dari kumpulan kluster RP. Rata-rata jarak Euclidean terendah dipilih, dan anggaran anggaran lokasi RP dikira. Terakhir, untuk algoritma kabur, keputusan berdasarkan peraturan diterapkan untuk memilih sama ada kawasan segitiga atau algoritma Euclidean rata-rata digunakan untuk mencari kedudukan anggaran akhir. Algoritma kabur menunjukkan ketepatan penyetempatan 5.889 m, yang lebih baik daripada algoritma isyarat KNN dan Berat MF dengan peningkatan masing-masing 31% dan 27%.

Kedua-dua algoritma telah mencapai ketepatan sasaran di bawah 8 m dan lebih baik daripada KNN. Walaupun algoritma kabur mencapai ketepatan yang lebih baik daripada ukuran kesamaan jarak isyarat berwajaran MF, ukuran kesamaan jarak isyarat berwajaran MF kurang memakan masa daripada algoritma kabur. Oleh itu, kedua-dua algoritma memerlukan lebih banyak penambahbaikan pada masa depan untuk mencapai lokasi anggaran yang lebih baik.

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TABLE OF CONTENTS

	Page
ABSTRACT	I
ABSTRAK	Iii
ACKNOWLEDGEMENTS	V
APPROVAL	Vi
DECLARATION	Viii
LIST OF TABLES	Xii
LIST OF FIGURES	Xiv
LIST OF ABBREVIATIONS	Xv
CHAPTER	
1 INTRODUCTION	1
1.1 Introduction	1
1.2 Overview of Magnetic-based IPS	1
1.3 Magnetic Field algorithm for Indoor Positioning System	2
1.4 Problem Statement	4
1.5 Weighted Magnetic Field Signal Distance Similarity Measure and Magnetic Field Fuzzy algorithm	4
1.6 Research Objectives	5
1.7 Research Frameworks	6
1.8 Thesis Overview	8
2 LITERATURE REVIEW	9
2.1 Introduction	9
2.2 Magnetic-Based Fingerprint Map	10
2.3 Magnetic-based Positioning Using Smartphone	11
2.4 Magnetic-based Database	14
2.5 Magnetic-based Positioning Algorithm	16
2.5.1 Previous studies using Particle Filter and Kalman Filter	17
2.5.2 Matching Algorithm	19
2.5.3 Indoor positioning system using other Algorithms	20
2.6 Summary	22
3 METHODOLOGY	23
3.1 Introduction	23
3.2 Baseline Algorithm	23
3.2.1 Nearest Neighbor Technique	24
3.2.2 K Nearest Neighbor (KNN)	24
3.3 Proposed Weighted MF signal Distance Similarity Measure	24
3.4 Fuzzy Algorithm Positioning Approach	27
3.4.1 Reconstructing Fingerprint to Cluster Database	28

3.4.2	Matching Algorithm	30
3.4.3	Triangle Area Algorithm	32
3.4.4	Average Euclidean Algorithm	34
3.4.5	Average Euclidean Algorithm	35
3.5	Experiments	38
3.6	Dataset Description Original and refined dataset	39
3.7	Computer Specifications	40
3.8	Performance Metrics of Magnetic-based Positioning	41
4	RESULTS AND DISCUSSION	42
4.1	Introduction	42
4.2	Effect of Difference Distance Similarity Measure of Magnetic Field Signal for Indoor Localization Results	42
4.2.1	Comparison with Multiple Distance	43
4.2.2	Mean Error of Different Signal Weighting Function for each MF signal	44
4.2.3	Vary the k value for different signal weighting function	45
4.2.4	Accuracy results of the signal weighting function	46
4.3	Performance of Fuzzy Algorithm	47
4.3.1	Comparison Original and Refined Data	48
4.3.2	Comparison between fuzzy algorithm with other algorithms	48
4.3.3	Percentage accuracy of the positioning algorithms for error distance up to 5m	49
4.3.4	CDF performance of the positioning algorithms	50
4.3.5	Comparison distance errors in each TP between algorithm and KNN	51
4.3.6	Mean Error of the positioning algorithms in different percentage of train data	52
4.3.7	Computation time for all the Algorithms	53
5	CONCLUSIONS	54
5.1	Conclusion	54
5.2	Recommendations for Future Works	55
	REFERENCES	56
	BIODATA OF STUDENT	63
	LIST OF PUBLICATIONS	64

LIST OF TABLES

Table		Page
2.1	Summary of Magnetic-based Positioning Using Smartphone	14
2.2	Example of Magnetic-based Database, related experiment and the limitation from previous studies	16
2.3	Previous studies using Particle Filter and Kalman Filter Algorithms for Indoor Positioning	18
2.4	Comparison of Nearest Neighbor Algorithms used in previous studies.	20
2.5	Magnetic-based Positioning comparison using Other Algorithms.	21
3.1	Example of KNN results between estimated RPs and TP	25
3.2	Cluster Database Description	29
3.3	Nearest Distance and Mean Error Description for Triangle Area and Average Euclidean in certain TP	37
3.4	Original Dataset Description	39
3.5	Refined Dataset Description	39
3.6	Review of Computer Specifications	40
4.1	Mean Error for Different Distance Measure	43
4.2	Mean Error 1NN Difference Distance Similarity Measure for each MF Signal	44
4.3	Maximum Error 1NN Difference Distance Similarity Measure for each MF Signal	44
4.4	Minimum Error 1NN Difference Distance Similarity Measure for each MF Signal	44
4.5	Mean Error multiple KNN Difference Distance Similarity Measure for each MF Signal	46

4.6	Comparison between Original and Refined Data	48
4.7	Comparison between Proposed algorithms with KNN and Weighted MF signal algorithm	49
4.8	Elapsed Times and Mean Errors for all Algorithms	53



LIST OF FIGURES

Figure		Page
1.1	Research framework flow chart	7
2.1	Overall Structure of Literature Review	9
2.2	Localisation flow chart	10
2.3	MF vector axis on Smartphone	12
2.4	Comparison MF signals between RP and TP	13
3.1	The architecture of Fuzzy Algorithm	28
3.2	Illustration of Cluster RP method	29
3.3	Illustration of matching algorithm	31
3.4	Comparison distance between TP and Centre Point of each Triangle.	36
3.5	Floor map of the MF database	38
4.1	Performance comparison between the weight factor of different signal vector in terms of distance error.	45
4.2	CDF Different Signal Weighting Function of MF Signal for 15 m Distance Error	47
4.3	Accuracy of the positioning algorithms within certain meter distances	50
4.4	CDF of Fuzzy Algorithm with other algorithms within 20 m distance error.	51
4.5	Comparison Mean Error of Proposed Algorithm with KNN Algorithm	52
4.6	Mean Error of each algorithm in different percentage of train data	53

LIST OF ABBREVIATIONS

UPM	Universiti Putra Malaysia
GPS	Global Positioning System
IPS	Indoor Positioning System
KNN	K Nearest Neighbour
MF	Magnetic Field
PF	Particle Filter
KF	Kalman Filter
IMU	Inertial Measurement Unit
RP	Reference Point
TP	Test Point
MFS	Magnetic Field Signal
ASD	Average Sorted Distance
AED	Average Euclidean Distance
ED	Euclidean Distance
CDF	Cumulative Distribution Function
CNN	Convolutional Neural Network
RNN	Recurrent Neural Network
ANN	Artificial Neural Network

CHAPTER 1

INTRODUCTION

1.1 Introduction

Global Positioning System (GPS) is widely used for positioning in outdoor environments, which is one of the most famous localisation techniques. However, GPS cannot function indoors due to multipath reflection and signal blockage from buildings resulting in signal attenuation (Walton & Black, 1999). Therefore, the indoor positioning system is designed and developed to be used in a hypermarket, a multi-story indoor airport car park (Molina et al., 2018), and for blind people (Árvai, 2018).

There are various indoor positioning systems (IPS) that have been researched such as Wi-Fi (Lohan et al., 2017), Bluetooth (Q. Wang et al., 2016), ultrasonic (H. S. Kim & Choi, 2008), magnetic field and infrared (J. H. Oh et al., 2014). Wi-Fi positioning has drawn increasing attention since Wi-Fi signals are available in most areas. However, in these complex environments, Wi-Fi positioning systems' performance is affected by severe limitations of wireless signals such as shadowing, human mobility and multipath, which further worsens the Wi-Fi systems (Ashraf et al., 2020). In addition, the accuracy of the Wi-Fi positioning system depends on the number of Wi-Fi access points deployed. Hence, a more suitable technology is needed to achieve a more accurate IPS. One promising solution to this is to use the magnetic field (MF) based IPS.

1.2 Overview of Magnetic-based IPS

In recent years, an increasing number of mobile devices have been embedded with MF sensors, dramatically promoting magnetic-based IPS development. Indoor MF is a promising solution for indoor positioning technology because it is not affected by multipath signal disturbance as in Wi-Fi. Anomalies in the MF for indoor environments are caused by the concrete, metal, pillar structures and furniture (Haverinen & Kemppainen, 2009). A study in Ma et al. (2018) shows that the indoor environment's magnetic fields were relatively stable and reproducible. Moreover, the values of magnetic field signals (MFS) at various positions are different, and hence it is possible to position a smartphone by fingerprint mapping of MFS measurements.

Due to the magnetic field's stability and uniqueness, many researchers have developed a number of magnetic field-based positioning systems. For example, Limeng Cao (2017) analysed real-time geomagnetic sequence performance measured by the smartphone's sensors on multiple mobile devices. In Poulouse

et al. (2019), experiments show that the inertial measurement unit (IMU) sensor data will improve the position estimation systems for indoor localisation. The magnetic field plays an essential role in solving IPS problems.

The location estimation technique usually used in magnetic-based positioning is the fingerprinting method. The fingerprinting method first requires real surveying by collecting the signal signature at every unique physical location called fingerprint location. The measurement data is stored in a database. The database contains coordinates of reference points (RPs) and the magnetic field measure along a smartphone's three axes vector x , y and z . The observed magnetic field fingerprint is compared to the one stored in the database during the online phase. Then the coordinate with the closest match is determined as the user's estimated location.

Magnetic field positioning system could be divided into two main problems: in ample indoor space, the magnetic fingerprints may not be unique, and the embedded magnetometer of the smartphone is sensitive. The collected magnetic field intensity may be very different for different smartphones. The algorithms should be accurate and quickly processed in the database to give an estimation of the location. Therefore, a magnetic-based algorithm is essential to improve positioning accuracy.

1.3 Magnetic Field algorithm for Indoor Positioning System

In today's application, indoor localisation systems should be embedded in mobile devices such as smartphones which have small computing capability. With the impressive performance of machine learning and deep learning, an increasing number of researchers have attempted to use these methods to solve magnetic-based IPS and have achieved good performance (Pasku et al., 2017). These algorithms can be divided into deterministic and probabilistic methods.

Probabilistic approaches are among the most popular methods in magnetic-based positioning due to the effectiveness and robustness, such as Kalman-filter based techniques (G. Wang et al., 2019), particle-filter based techniques (Ma et al., 2018; Xinheng Wang et al., 2017; Zhang et al., 2017), and maximum likelihood (ML) probability (Bozkurt Keser et al., 2018). In these algorithms, probabilistic methods provide a probability distribution function (PDF) estimate of the given location's magnetic field signal. In Xie et al. (2016), the authors proposed an indoor navigation method based on reliability-augmented particle filter and use a hybrid measurement model, combining a new magnetic fingerprinting model and the existing magnitude fingerprinting model, to improve system performance, and importantly avoid calibrating magnetometers for different smartphones. Huang et al. (2018) proposed an improved particle filter algorithm based on initial positioning error constraint, while at the same time pointing out that the particle filter performs poorly which often suffers filtering

divergence when there is continuous variation of the indoor magnetic distribution. However, an interference source will disturb other multiple reference points when they use the irregular magnetic field for positioning. The change in the magnetic field measurement at a reference point can cause another reference point in the magnetic field to change field (X. Huang et al., 2017). Therefore, probabilistic methods assumption on each reference point is independent cannot be applied in the magnetic field positioning.

Another approach is using the deterministic methods, which are easier to be implemented (Bahl & Padmanabhan, 2000) because they only harness the similarity between each point, then calculate positioning results as the closest fingerprint locations in signal space. The deterministic methods usually used similarity metrics include Euclidean distance (Moghtadaiee & Dempster, 2015), Manhattan distance, and cosine similarity (Caso et al., 2015). There are various Nearest Neighbour (NN) method such as single NN (Bozkurt et al., 2015), KNN (Dai et al., 2019; J. Oh & Kim, 2018), and K- Weighted NN methods (Abd Rahman et al., 2019; van et al., 2017) which are the most popular deterministic methods. Therefore, a localisation algorithm must be designed and developed to utilise as small processing power as possible and at the same time retain good positioning accuracy.

1.4 Problem Statement

Indoor positioning does not have standardised technology. Unlike the GPS, the indoor positioning system depends on nearby anchors (nodes with a known position), which either actively locate tags or provide environmental context for devices to sense. In strange complexity and different pattern interference in the buildings, researchers used many different indoor positioning technologies such as Wi-Fi, Bluetooth and MF. Magnetic-based positioning systems are used in research due to the stability (X. Huang et al., 2017; Wu et al., 2017) and uniqueness (Jiaxing et al., 2017) of the magnetic field. However, the main problem in magnetic-based positioning systems is to figure out a suitable machine learning algorithm that can differentiate between different positions with the same MF value. Specifically, to develop an efficient and robust magnetic-based indoor positioning system, this thesis investigates the following problems:

1. Magnetic-based positioning only has three components signal measure that can be used compared to Wi-Fi which can use multiple access points. Therefore, the possibility of obtaining a similar reading of those three components at multiple locations within a limited space is high.
2. Although different indoor localisation systems utilise various magnetic field algorithms, there are limited studies between the Euclidean distance and the area between the RPs.
3. KNN is the state-of-the-art algorithm used for IPS. However, using KNN might have an error due to the chosen estimation point might be far from the TP although the MF signal between the TP and RP is almost the same.

1.5 Weighted Magnetic Field Signal Distance Similarity Measure and Magnetic Field Fuzzy algorithm

To solve the problems mentioned in section 1.4, two types of algorithms are proposed. The first algorithm proposed is weighted magnetic field signal distance similarity measure which uses three different weight functions applied on each of the magnetic vectors signal difference. The second algorithm is the Fuzzy algorithm. Fuzzy algorithms consist of three proposed algorithms which are the triangle area algorithm, the average Euclidean algorithm and lastly the Fuzzy algorithm which based on a rule decision to choose either triangle or average Euclidean algorithms. The foundation and the implementation of the proposed algorithms is described in detail in Chapter 3.

1.6 Research Objectives

According to the algorithm proposed in Section 1.5, this thesis main aim is to develop a robust and efficient magnetic-based positioning emphasising to achieve an accuracy to be better than the state-of-the-art algorithm, KNN. So, the mean distance error is expected to be below 8 m as obtained in Chapter 4. Detail objectives are given as follows:

1. To design and develop weighted Magnetic Field signal distance Similarity Measure which weighting based on MF signals. Three different similarity measures are used with different weight factors which are applied on specific MF vectors.
2. To design and develop Fuzzy algorithms which combine multiple techniques which are clustering algorithm, matching algorithm, triangle area and Average Euclidean algorithm and using a rule-based decision technique.
3. To develop KNN used it with previous algorithms to evaluate and compare the proposed algorithms mentioned above in terms of accuracy and computation time.

1.7 Research Frameworks

Figure 1.1 shows the research framework for the thesis. From the figure, for the first problem the possibility of obtaining a similar reading of three components MF signals at multiple locations within a limited space is high. To investigate this problem, a proposed weighted MF signal distance similarity measure is designed and developed. This design is shown in Section 3.3 for Chapter 3 and the result of the proposed algorithm is discussed in Section 4.2 for Chapter 4. For the second problem which is that there is limited study between the Euclidean distance and the area between the RPs, a Fuzzy algorithm is designed and developed. In the proposed algorithm, the relationship between the Euclidean distance and the area between the RPs were studied by designing the triangle area and Average Euclidean algorithm. Both of the algorithms are presented in Chapter 3 Section 3.4.3 and 3.4.4. Before using three of the proposed algorithms which are the triangle area, average Euclidean and the Fuzzy algorithms, pre-processing and matching signals between TP and RPs were done by using Clustering Algorithm and Matching Algorithm. The method for clustering algorithm is mentioned in Chapter 3 Section 3.4.1 and the matching algorithm is introduced in Chapter 3 Section 3.4.2. The results of the proposed algorithms for the second objectives are presented in Chapter 4 Section 4.3. For the last objective which is to evaluate and compare all the proposed algorithms with KNN and previous studies in terms of accuracy and time consuming, the baseline of the KNN is presented in Chapter 3 Section 3.2. Two performance metrics used to evaluate the performance of the proposed algorithms are mean error and CDF in which the formula mentioned in equation (3.18) and equation (3.19) respectively in Chapter 3 Section 3.8. For the time consuming, the results are shown in Chapter 4 Section 4.4.

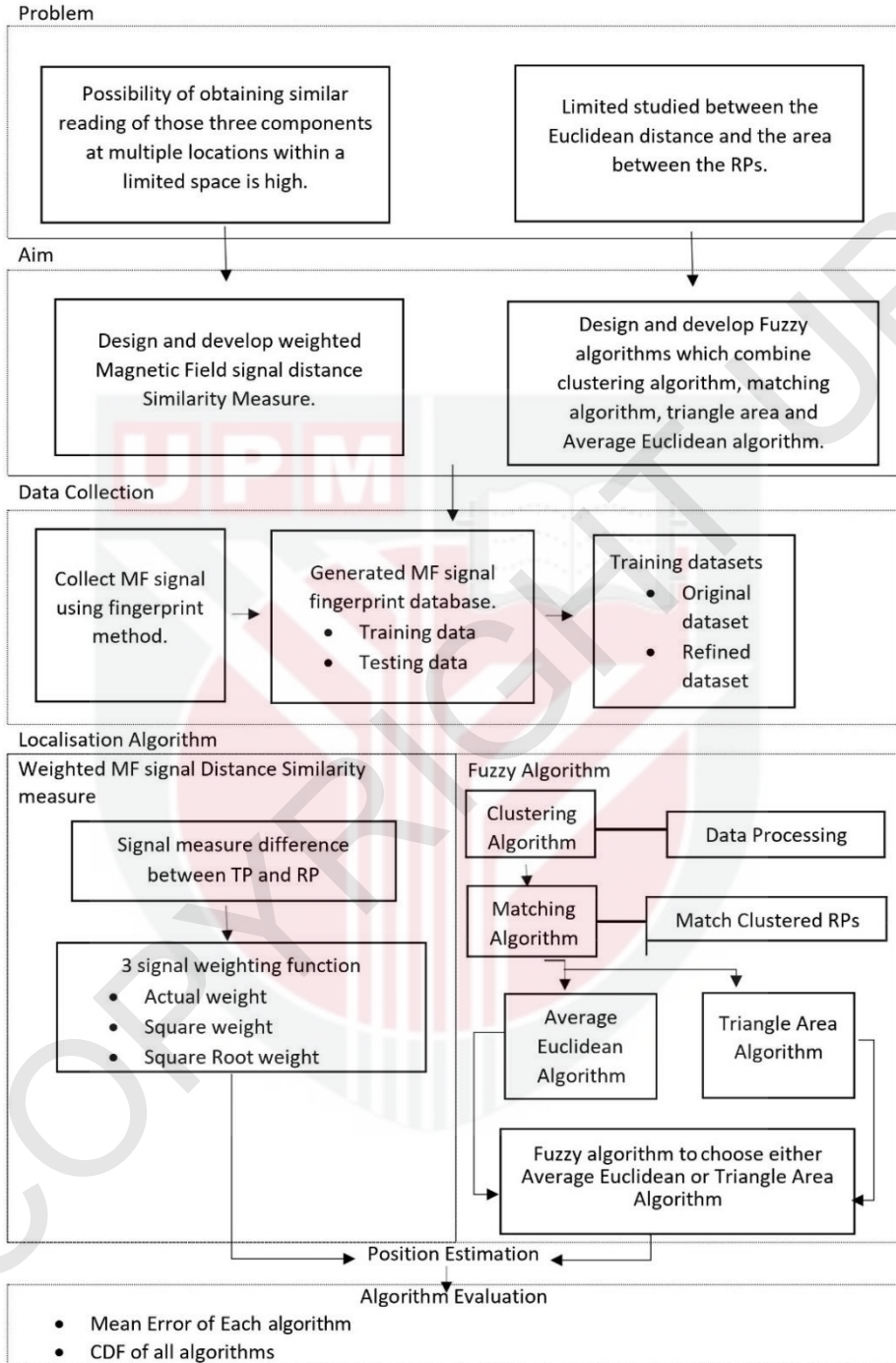


Figure 1.1 : Research framework flow chart

1.8 Thesis Overview

This dissertation discusses developing robust techniques and improving the algorithm for indoor tracking and localization applications.

Chapter 1 (Introduction): In this chapter, an overview of indoor localization and some of the existing systems and algorithms are given. The aim and problem facing this research are mentioned in this chapter.

Chapter 2 (Literature review): In this chapter, the technologies used for IPS and the introduction of IPS based on magnetic fields are described. Other than that, this chapter reviews some of the related work approached for magnetic-based positioning algorithm of estimation indoor location.

Chapter 3 (Research methodology): In this work two methods are used to improve magnetic-based positioning. Firstly, using the different MF signal similarity measure applied on different weight functions. Secondly, Fuzzy algorithm is used to provide magnetic field indoor positioning estimations.

Chapter 4 (Results and Discussion): In this chapter, the performance of proposed algorithms is shown and compared with KNN and weighted MF algorithms. The discussion about the algorithms and the accuracy of the estimation are mentioned in this chapter.

Chapter 5 (Conclusion): In this chapter, conclusion on the proposed algorithms of magnetic field used in IPS is discussed. Future work is mentioned in this chapter to improve the algorithm used in the future.

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LIST OF PUBLICATIONS

- Bundak, C. E. A., Abd Rahman, M. A., Abdul Karim, M. K., & Osman, N. H. (2021). Fuzzy rank cluster top k Euclidean distance and triangle based algorithm for magnetic field indoor positioning system. *Alexandria Engineering Journal*, September. <https://doi.org/10.1016/j.aej.2021.08.073> (Published)
- Bundak, C. E. A., Abd Rahman, M. A., Abd Karim, M. K., & Osman, N. H. (2022). Effect of Different Signal Weighting Function of Magnetic Field Using KNN for Indoor Localization. *Lecture Notes in Electrical Engineering*, 730(January), 571–581. https://doi.org/10.1007/978-981-33-4597-3_52 (Accepted)
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