



**HYBRID INDOOR POSITIONING UTILIZING MULTIPATH-
ASSISTED FINGERPRINT AND GEOMETRIC ESTIMATION FOR
SINGLE BASE STATION SYSTEMS**



ZAHARIAH BINTI MANAP

DOCTOR OF PHILOSOPHY

2025



**Faculty of Electronics and Computer Technology and
Engineering**

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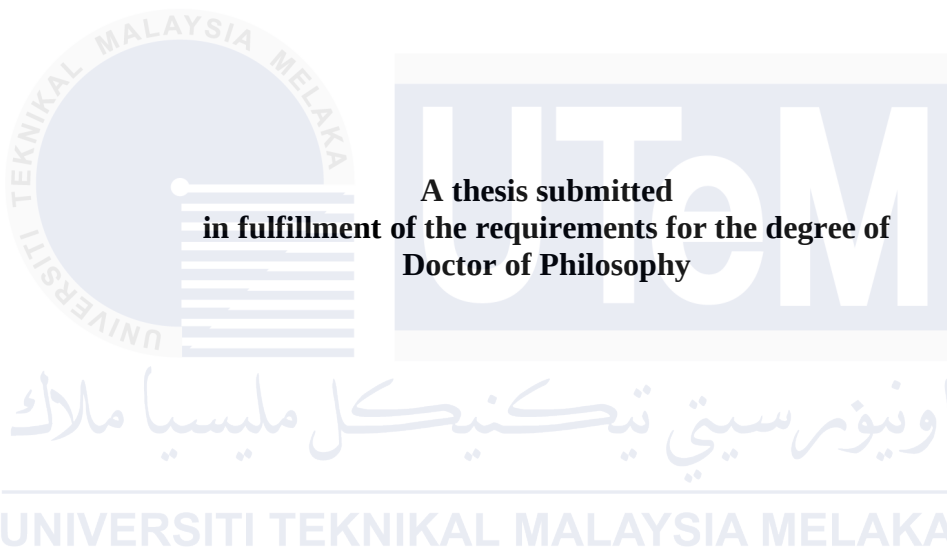
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STATION SYSTEMS**

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Faculty of Electronics and Computer Technology and Engineering

UNIVERSITI TEKNIKAL MALAYSIA MELAKA

2025

DECLARATION

I declare that this thesis entitled “Hybrid Indoor Positioning utilizing Multipath-Assisted Fingerprint and Geometric Estimation for Single Base Station Systems” is the result of my own research except as cited in the references. The thesis has not been accepted for any degree and is not concurrently submitted in candidature of any other degree.



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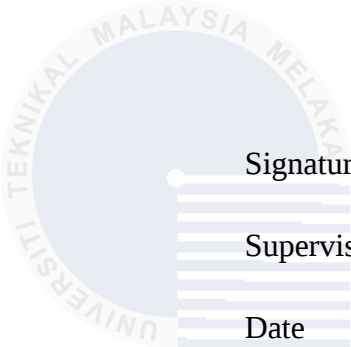
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APPROVAL

I hereby declare that I have read this thesis and in my opinion this thesis is sufficient in terms of scope and quality for the award of Doctor of Philosophy.

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DEDICATION

To my beloved ones

– my mother, husband and children – Nuha, Zahin, Amna.



ABSTRACT

Indoor positioning technology is becoming increasingly influential in indoor applications, akin to how Global Navigation Satellite Systems revolutionized outdoor navigation. One of the primary challenges in indoor settings is multipath propagation, where wireless signals encounter reflections, diffractions, and scattering, yielding less accurate position estimates. Rather than combating multipath errors, this thesis leverages them as they encapsulate how radio waves interact with the environment that stores the position-related information of the base station (BS) and the mobile station (MS). This thesis proposes a hybrid indoor positioning method for single base station systems by jointly utilizing the fingerprinting method and geometric multilateration. The proposed method leverages room geometry and takes advantage of the multipath signal propagation to construct multiple virtual base station system model. This is done based on the concept of mirror image to determine potential virtual base stations (VBSs) with respect to the reflection surfaces where the multipath rays bounce off before arriving at the MS. The methodological framework of the proposed method comprises two main phases which are fingerprinting phase and position estimation phase. In the fingerprinting phase, classifiers are trained in two stages, each to predict the MS regions and reflection surfaces, respectively. The key attributes that establish the classification learning sessions are the channel parameters extracted from the ray tracing generated multipath signals. The channel parameters such as received power, time of arrival, and angle of arrival are used as fingerprint features that act as predictors in both learning sessions. The performance of the selected trained classifiers is evaluated based on the accuracy, precision, sensitivity and the F1-score. The results show that Coarse K-Nearest Neighbours is the optimal classifier that predicts MS regions at an exceptionally high accuracy, while Support Vector Machine Kernel is the optimal classifier that perfectly predicts the reflection surfaces. In the position estimation phase, a novel Geometric Random Sample Consensus (Geometric-RANSAC) multilateration method is proposed by optimizing the MS position estimate over several potential position estimates calculated using regional 3D geometric equations. When compared to a simple fingerprinting method, the median error for the hybrid method is observed to be 4.06 cm, which is substantially lower than the 538 cm median error of the fingerprinting method. Furthermore, 95% of the MS's positions are estimated with less than 7.86 cm of error, in contrast to the 773 cm 95th percentile error exhibited by the fingerprinting method. Notably, the proposed Geometric-RANSAC exceptionally outperforms various least squares methods by achieving a median distance error and the 95th percentile at 4.06 cm and 7.86 cm, respectively. Despite the reduced robustness of the Geometric-RANSAC algorithm when applied to scenarios with a limited number of VBSs, its exceptional accuracy compensates for this limitation. This study makes a significant contribution by introducing a hybrid method that leverages multipath signals to achieve centimeter-level accuracy in indoor positioning systems.

PENENTUAN KEDUDUKAN DALAM BANGUNAN HIBRID MENGGUNAKAN CAP JARI BERBANTU LALUAN BERBILANG DAN ANGGARAN GEOMETRI UNTUK SISTEM STESEN PANGKALAN TUNGGAL

ABSTRAK

Teknologi penentuan kedudukan dalam bangunan semakin berkembang dalam aplikasi di dalam bangunan, seperti mana Sistem Satelit Navigasi Global menjadi revolusi bagi sistem navigasi di luar bangunan. Salah satu cabaran utama dalam persekitaran di dalam bangunan ialah perambatan berbilang laluan, di mana isyarat wayarles mengalami pantulan, pembelauan dan penyerakan, yang mengakibatkan anggaran kedudukan yang kurang tepat. Daripada memerangi ralat berbilang laluan, tesis ini memanfaatkannya kerana ia mengandungi maklumat bagaimana gelombang radio berinteraksi dengan persekitaran yang menyimpan maklumat berkaitan kedudukan stesen pangkalan (BS) dan stesen mudah alih (MS). Tesis ini mencadangkan kaedah penentuan kedudukan dalam bangunan hibrid untuk sistem stesen pangkalan tunggal dengan menggunakan gabungan kaedah cap jari dan kaedah multilaterasi geometri. Kaedah yang dicadangkan menggunakan pengetahuan geometri bilik dan memanfaatkan perambatan isyarat berbilang laluan untuk membina model sistem stesen pangkalan maya berbilang. Ini dilakukan berdasarkan konsep imej cermin untuk menentukan stesen pangkalan maya (VBS) yang berpotensi berdasarkan permukaan pantulan di mana isyarat berbilang laluan memantul sebelum tiba di MS. Rangka kerja metodologi yang dicadangkan terdiri daripada dua fasa utama iaitu fasa cap jari dan fasa anggaran kedudukan. Dalam fasa cap jari, model pengelas dilatih dalam dua peringkat, masing-masing untuk meramalkan rantau MS dan permukaan pantulan. Ciri utama yang membentuk sesi pembelajaran klasifikasi ialah parameter saluran yang diekstrak daripada isyarat berbilang laluan yang dijana oleh simulasi pengesanan sinar. Parameter saluran termasuk kuasa yang diterima, masa ketibaan, dan sudut ketibaan digunakan sebagai ciri cap jari yang bertindak sebagai peramal dalam kedua-dua sesi pembelajaran. Prestasi pengelas terpilih yang dilatih dinilai berdasarkan ketepatan, kejituan, kepekaan dan skor F1. Keputusan menunjukkan bahawa K-Jiran Terdekat Kasar ialah pengelas optimum yang meramalkan rantau MS pada ketepatan tinggi, manakala Kernel Mesin Vektor Sokongan ialah pengelas optimum yang meramalkan permukaan pantulan terbaik. Dalam fasa anggaran kedudukan, kaedah multilaterasi Konsensus Sampel Rawak Geometri (Geometric-RANSAC) yang baharu dicadangkan dengan mengoptimalkan anggaran kedudukan MS ke atas beberapa anggaran kedudukan berpotensi yang dikira menggunakan persamaan Geometri 3D. Jika dibandingkan dengan kaedah kedudukan cap jari yang mudah, ralat median untuk kaedah hibrid ialah 4.06 cm, jauh lebih rendah daripada ralat median 538 cm bagi kaedah cap jari. Tambahan pula, 95% daripada kedudukan MS dianggarkan dengan ralat kurang daripada 7.86 cm, berbeza dengan ralat persentil ke-95 yang ditunjukkan oleh kaedah cap jari iaitu 773 cm. Jelasnya, Geometric-RANSAC yang dicadangkan mengatasi pelbagai kaedah kuasa dua terkecil dengan mencapai ralat jarak median dan persentil ke-95, masing-masing pada 4.06 cm dan 7.86 cm. Walaupun kaedah Geometric-RANSAC menunjukkan ketahanan yang kurang apabila digunakan pada senario dengan bilangan stesen pangkalan maya yang terhad, ketepatannya yang tinggi mengimbangi kekurangan ini. Kajian ini memberi

sumbangan penting dengan memperkenalkan kaedah hibrid yang memanfaatkan isyarat berbilang laluan untuk mencapai ketepatan pada tahap sentimeter dalam sistem penentuan kedudukan di dalam bangunan.



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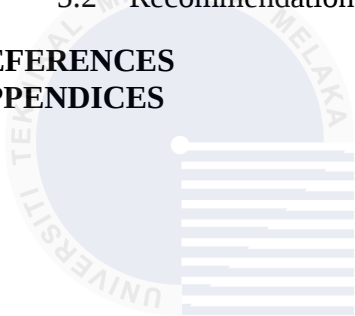
To my close friends, though I cannot name you all, your support and inspiration have been invaluable. Thank you for standing by me. To all of you who have touched my life in ways big and small, thank you from the bottom of my heart. Your love, support, and encouragement have been the sweetest blessings throughout this journey.

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LIST OF ABBREVIATIONS

2D	-	Two-Dimensional
3D	-	Three-Dimensional
3GPP	-	The 3 rd Generation Partnership Project
5G	-	The Fifth Generation
ADCPM	-	Angle Delay Channel Power Matrix
AOA	-	Angle of Arrival
AOD	-	Angle of Departure
AP	-	Access Point
BIM	-	Building Information Modelling
BJU	-	Beijing Jiaotong University
BLE	-	Bluetooth Low Energy
BLUE	-	Best Linear Unbiased Estimator
BS	-	Base Station
CFR	-	Channel Frequency Response
CG-SVM	-	Coarse Gaussian Support Vector Machine
CIR	-	Channel Impulse Response
CLA	-	Classification Learning Applications
CNN	-	Convolutional Neural Networks
CSI	-	Channel State Information
DA	-	Discriminant Analysis
DFL	-	Device-Free Localization
DFT	-	Discrete Fourier Transform

DT	- Decision Tree
EBT	- Ensemble Bagged Tree
ECDF	- Empirical Cumulative Distribution Function
EKF	- Extended Kalman Filter
ELR	- Efficient Logistic Regression
EM	- Ensemble Methods
EOA	- Elevation of Arrival
EOD	- Elevation of Departure
ESPRIT	- Estimation of Signal Parameters via Rotational Invariance Techniques
ETSI	- European Telecommunications Standards Institute
FDTD	- Finite-Difference Time Domain
FEM	- Finite Element Method
FIT	- Finite Integration Technique
FT	- Fine Tree
GA	- Genetic Algorithm
GNSS	- Global Navigation Satellite System
GO	- Geometric Optics
GPS	- Global Positioning System
IEEE	- Institute of Electrical and Electronics Engineers
IoT	- Internet of Things
ITU	- International Telecommunication Union
JADE	- Joint Approximate Diagonalization of Eigenmatrices
JADSC	- Joint Angle Delay Similarity Coefficient
KNB	- Kernel Naïve Bayes

KNN	- K-Nearest Neighbours
LBS	- Location-based Services
LD	- Linear Discriminant
LED	- Light Emitting Diode
LLS	- Linear Least Squares
LOS	- Line of Sight
LS	- Least Squares
MAMPI	- Magnitude and Phase Information
MAP	- Multipath-assisted Positioning
MB	- Multiple Bound
MDT	- Minimization of Drive-Tests
MIMO	- Multiple Input Multiple Output
M-MP	- Multiple Packets-based Matrix Pencil
MoM	- Method of Moments
MPC	- Multipath Component
MPS	- Multipath Signal
MS	- Mobile Station
MUSIC	- Multiple Signal Classification
MVDR	- Minimum Variance Distortionless Response
NFC	- Near-Field Communication
NLLS	- Non-linear Least Squares
NLOS	- Non-line of Sight
NN	- Neural Network
NNN	- Narrow Neural Network

OB	- One Bound
OFDM	- Orthogonal Frequency Division Multiplexing
PDP	- Power Delay Profile
PLE	- Path-loss Exponent
PSO	- Particle Swarm Optimization
QR	- Quick Response
RANSAC	- Random Sample Consensus
RF	- Radio Frequency
RFID	- RF Identification
RMS	- Root Mean Square
RMSE	- Root Mean Square Error
RSRP	- Reference Signal Received Power
RSS	- Received Signal Strength
RSSI	- Received Signal Strength Indicator
RT	- Ray Tracing
SAGE	- Space-Alternating Generalized Expectation-Maximization
SLAM	- Simultaneous Localization and Mapping
SNR	- Signal-to-Noise Ratio
SVM	- Support Vector Machine
TDOA	- Time Difference of Arrival
TOA	- Time of Arrival
ToF	- Time of Flight
UAV	- Uncrewed Aerial Vehicle
UE	- User Equipment

UTD	-	Uniform Theory Diffraction
UWB	-	Ultra-Wide Band
VA	-	Virtual anchor
VBS	-	Virtual Base Station
VLC	-	Visible Light Communication
VMBS	-	Virtual Multiple Base Station
VO	-	Visual Odometry
VS	-	Virtual Station
Wi-Fi	-	Wireless Fidelity
WINNER	-	Wireless World Initiative New Radio
WKNN	-	Weighted K-Nearest Neighbours
WLAN	-	Wireless Local Area Network
WLS	-	Weighted Least Squares
WNN	-	Wide Neural Network

LIST OF SYMBOLS

c	-	Speed of Light
θ	-	Angle of Arrival
φ	-	Elevation of Arrival
L	-	Path Loss
f	-	Frequency
P_f	-	Floor Loss Penetration Factor
ϵ_r	-	Relative Permittivity
μ_r	-	Permeability
μ_0	-	Permeability of Free Space,
σ	-	Conductivity of Medium
S	-	Reflection Surface
Rx	-	Receiver
Tx	-	Transmitter
R	-	MS Region
FM-1	-	Fingerprint Matrix 1
FM-2	-	Fingerprint Matrix 2
CL-1	-	Classification Learning Session 1
CL-2	-	Classification Learning Session 2

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