



WIFI-BASED LOCATION-INDEPENDENT HUMAN ACTIVITY RECOGNITION AND LOCALIZATION USING DEEP LEARNING



DOCTOR OF PHILOSOPHY

2024



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

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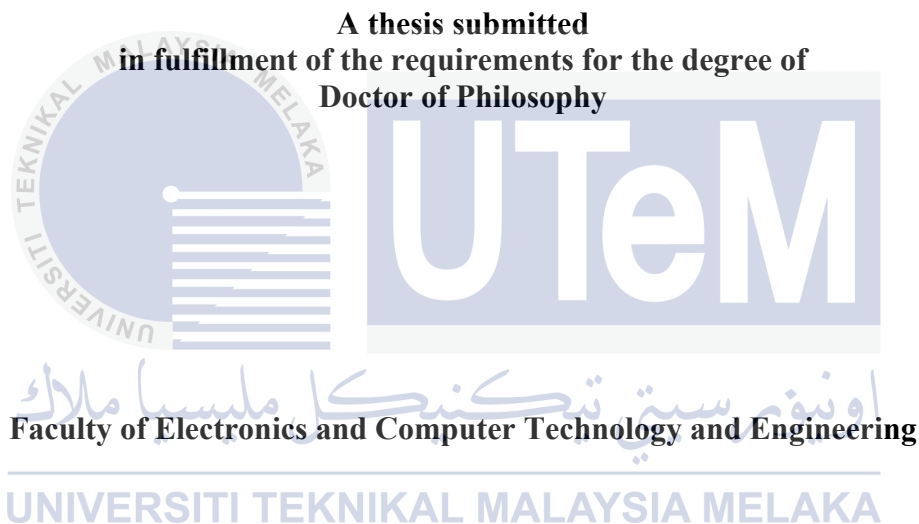
FAHD SAAD AHMED ABUHOUREYAH
اونيور سيتي تيكنيكل مليسيا ملاك
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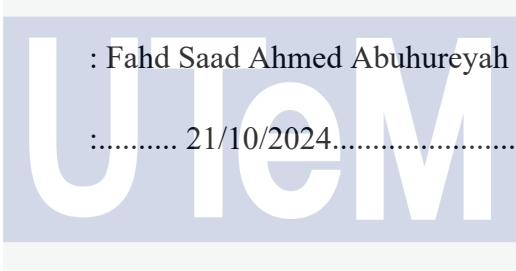
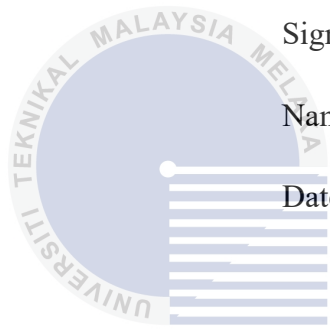
DECLARATION

I declare that this thesis entitled “WiFi-based Location-Independent Human Activity Recognition and Localization Using Deep Learning” 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.

Signature :.....

Name : Fahd Saad Ahmed Abuhureyah

Date :..... 21/10/2024.....



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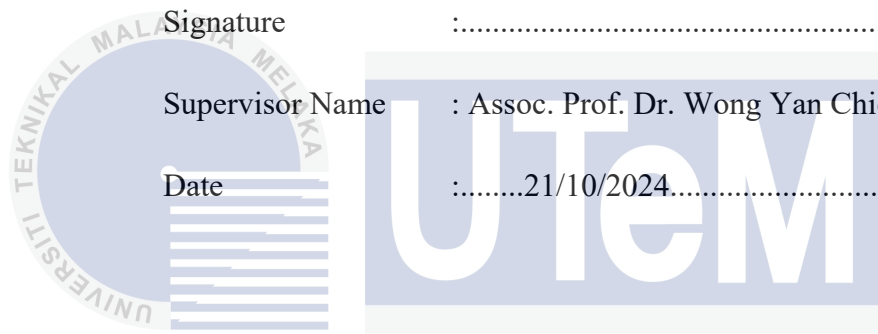
APPROVAL

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.

Signature :

Supervisor Name : Assoc. Prof. Dr. Wong Yan Chiew

Date :21/10/2024.....



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DEDICATION

To my beloved mother and father.



ABSTRACT

Detecting human activities holds paramount significance across diverse domains, encompassing healthcare, security, autonomous driving, and human-computer interaction. Leveraging wireless signals for activity sensing exploits the intricate influence of human activities on signal propagation phenomena such as reflection, diffraction, and scattering. Wireless signal-based human sensing, mainly through WiFi and radar technologies, presents notable advantages, including device-free sensing, resilience to environmental factors, obstacle penetration, and preservation of visual privacy. This work addresses the inherent challenges in WiFi-based Human Activity Recognition (HAR) by focusing specifically on critical aspects: the location dependency of WiFi sensing and the impact of multi-user interactions on signal reliability. Existing HAR systems encounter difficulties recognizing human activities due to variations in physical environments and the complexities introduced by multiple users within WiFi signals. The study aims to advance methodologies to mitigate challenges arising from environmental dependency and multi-user effects, enhancing the precision and adaptability of WiFi-based HAR systems for reliable and robust performance across diverse environmental contexts. The research highlights the role of Deep Learning methodologies in addressing challenges and advancing the capabilities of HAR technology. First, we employ the advanced Seq2Seq Recurrent Neural Network (RNN) technique to achieve high accuracy in HAR with few layers of the Long Short-Term Memory (LSTM) algorithm. Precise activity recognition and incorporation of through-wall sensing capabilities are achieved within the deep learning framework. Second, Multi-head Attention Mechanism Networks capture intricate patterns in Channel State Information (CSI) data, enhancing recognition accuracy for human activities detected through WiFi signals. Third, recognizing the capability of location independence, we propose a novel location-independent HAR using a self-learning CSI-based technique for wireless sensor networks. This innovative approach reduces the impact of environmental factors on HAR accuracy, ensuring robust performance across diverse spatial contexts. Fourth, addressing the challenge of human interaction recognition in multi-user environments, WiFi signal processing with Independent Component Analysis (ICA) and Continuous Wavelet Transform (CWT) techniques is introduced. An efficient real-time localization method is introduced in the fifth section, which achieves location-independent localization by utilizing the fusion of the Received Signal Strength Indicator (RSSI) and CSI. The fusion contributes to the development of reliable and adaptable HAR systems across varying environmental contexts. A trajectory mapping approach using CSI-Triangulation with deep learning is proposed to refine the localization capabilities of WiFi-based HAR, offering an accurate and robust solution for localization in diverse real-world scenarios. The adaptive strategy accommodates variations in signal characteristics and environmental factors, highlighting the robustness of the presented methods in scenarios involving various user interactions and environmental conditions. The findings contribute to the improvement of HAR and localization systems and have achieved high accuracy of classification up to 97.5% with enhancement of 6% of localization and tracking accuracy.

PENYETEMPATAN DAN PENGECAMAN AKTIVITI MANUSIA BERASASKAN WI-FI TAK BERSANDAR LOKASI MENGGUNAKAN PEMBELAJARAN MENDALAM

ABSTRAK

Pengesanan aktiviti manusia adalah sangat penting dalam pelbagai bidang, termasuk penjagaan kesihatan, keselamatan, pemanduan autonomi, dan interaksi antara manusia-komputer. Penggunaan isyarat tanpa wayar untuk mengecam aktiviti telah mengeksplotasi pengaruh aktiviti manusia yang rumit dalam fenomena perambatan isyarat seperti pantulan, pembelauan, dan penyerakan. Pengecaman aktiviti manusia berasaskan isyarat tanpa wayar, terutamanya melalui teknologi WiFi dan radar, menawarkan kelebihan yang ketara, termasuk pengecaman tanpa peranti, kecekapan terhadap faktor persekitaran, penembusan halangan, dan pemeliharaan privasi visual. Kajian ini menangani cabaran yang dihadapi dalam pengecaman aktiviti manusia (HAR) berasaskan WiFi dengan menumpukan khusus kepada aspek penting: penderiaan WiFi dengan kedudukan bersandar dan impak berinteraksi dengan pelbagai pengguna terhadap kebolehan harapan isyarat. Sistem HAR yang sedia ada menghadapi kesulitan mengecam aktiviti manusia disebabkan perubahan dalam persekitaran fizikal dan kerumitan yang diperkenalkan oleh pelbagai pengguna dalam isyarat WiFi. Kajian ini bertujuan untuk memajukan metodologi untuk mengatasi cabaran yang timbul daripada kesan persekitaran dan kesan pelbagai pengguna, meningkatkan kepersisan dan kebolehsuaian sistem HAR dalam pelbagai konteks berkenaan alam sekitar. Pertama, kami menggunakan teknik Seq2Seq Recurrent Neural Network (RNN) untuk mencapai kepersisan tinggi dalam HAR dengan menggunakan beberapa lapisan algoritma Long Short-Term Memory (LSTM). Pengecaman aktiviti yang tepat dan penggabungan keupayaan pengesanan melepasi dinding dicapai dalam kerangka pembelajaran mendalam. Kedua, Rangkaian Mekanisme Perhatian yang berbilang kepala menangkap corak rumit dalam data matlumat keadaan saluran (CSI), meningkatkan kepersisan HAR yang dikesan melalui isyarat WiFi. Ketiga, kami mencadangkan HAR dengan kedudukan tak bersandar menggunakan teknik berasaskan CSI pembelajaran sendiri untuk rangkaian sensor tanpa wayar. Pendekatan inovatif ini mengurangkan impak persekitaran ke atas kepersisan HAR, memastikan prestasi kukuh dalam pelbagai persekitaran. Keempat, menangani cabaran pengecaman interaksi manusia dalam persekitaran pelbagai pengguna, pemprosesan isyarat WiFi dengan ICA dan teknik CWT diperkenalkan. Ini adalah penting dalam senario dengan pelbagai pengguna, di mana kerumitan isyarat memerlukan pemprosesan inovatif untuk mengenal pasti interaksi manusia dengan tepat. Kelima, kaedah penyetempatan masa nyata yang efisien diperkenalkan, menggunakan gabungan RSSI dan CSI untuk mencapai penyetempatan kedudukan tak bersandar. Gabungan ini menyumbang kepada sistem HAR yang boleh dipercayai dan mudah disesuaikan dalam pelbagai konteks persekitaran. Akhirnya, pendekatan pemetaan londar diusulkan menggunakan CSI-segitiga dengan pembelajaran mendalam untuk menyempurnakan keupayaan penyetempatan HAR berasaskan WiFi, memberikan penyelesaian untuk penyetempatan yang tepat dan kukuh dalam pelbagai senario dunia nyata. Penemuan ini menyumbang kepada penambahbaikan sistem HAR dan pengesanan lokasi, serta telah mencapai ketepatan klasifikasi yang tinggi sehingga 97.5% dengan peningkatan 6% dalam ketepatan pengesanan dan penjejakan lokasi.

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Utmost appreciation, respect, and love are reserved for my family, whose unwavering support has been a cornerstone throughout this challenging journey. Their companionship and encouragement have been pivotal in overcoming difficulties and adversities. Without their unconditional support, this achievement would have been insurmountable. I express profound thanks to my parents for not only raising me but also instilling in me the courage to pursue my dreams. Their boundless love and unwavering support will serve as a perpetual source of motivation in all facets of my life.

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LIST OF ABBREVIATIONS

BiLSTM	-	Bi-directional Long Short-Term Memory
CIR	-	Channel Impulse Response
ANN	-	Artificial Neural Network
DNN	-	Deep Neural Network
GPS	-	Global Positioning System
CNN	-	Convolutional Neural Network
CWT	-	Continuous Wavelet Transform
CSI	-	Channel State Information
RL	-	Reinforcement Learning
DWT	-	Discrete Wavelet Transform
DL	-	Deep Learning
FFT	-	Fast Fourier Transform
HAR	-	Human Activity Recognition
HHT	-	Hilbert-Huang Transform
KNN	-	k Nearest Neighborhood
LOS	-	Line-of-Sight
LSTM	-	Long Short-Term Memory
LSTM-RNN	-	Long Short-Term Memory Recurrent Neural Networking
mmWave	-	Millimeter Wave
NIC	-	Network Interface Card
Non-LOS	-	Non-Line-of-Sight
PCA	-	Principal Component Analysis

RFID	-	Radio-Frequency Identification
RNN	-	Recurrent Neural Networking
RSSI	-	Received Signal Strength Indicator
RSSI-based	-	RSSI for WiFi-based
HAR		Human Activity Recognition
SVD	-	Singular Value Decomposition
OFDM	-	Orthogonal Frequency Division Multiplexing
SVM	-	Support Vector Machine
RSS	-	Received Signal Strength



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