

# **UNIVERSITI PUTRA MALAYSIA**

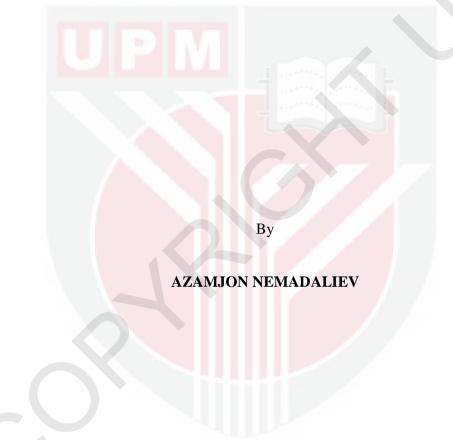
ACCURATE WI-FI SIGNAL STRENGTH RECOVERY METHOD USING CHEBYSHEV WAVELET- BASED APPROXIMATION FOR INDOOR POSITIONING

# **AZAMJON NEMADALIEV**

**FSKTM 2016 16** 



## ACCURATE WI-FI SIGNAL STRENGTH RECOVERY METHOD USING CHEBYSHEV WAVELET- BASED APPROXIMATION FOR INDOOR POSITIONING



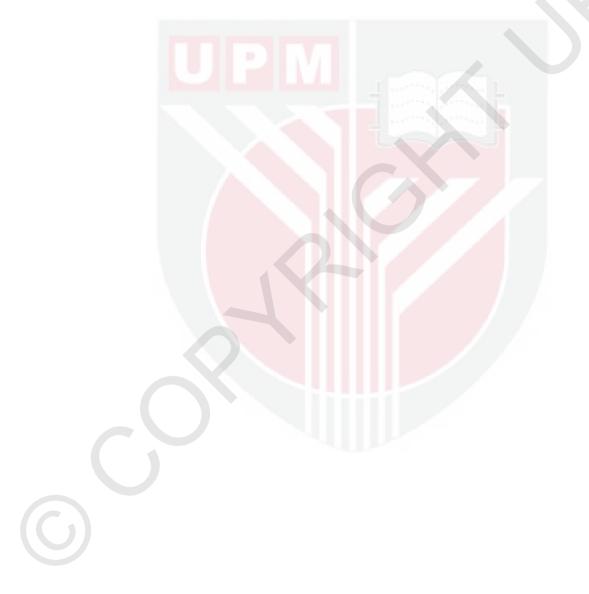
Thesis Submitted to the School of Graduate Studies, Universiti Putra Malaysia, in Fulfilment of the Requirements for the Degree of Doctor of Philosophy

April 2016

## COPYRIGHT

All material contained within the thesis, including without limitation text, logos, icons, photographs and all other artwork, is copyright material of Universiti Putra Malaysia unless otherwise stated. Use may be made of any material contained within the thesis for non-commercial purposes from the copyright holder. Commercial use of material may only be made with the express, prior, written permission of Universiti Putra Malaysia.

Copyright © Universiti Putra Malaysia



# DEDICATION

To The God.



Abstract of the thesis presented to the Senate of Universiti Putra Malaysia in fulfillment of the requirement for the Degree of Doctor of Philosophy.

## ACCURATE WI-FI SIGNAL STRENGTH RECOVERY METHOD USING CHEBYSHEV WAVELET- BASED APPROXIMATION FOR INDOOR POSITIONING

By

## **AZAMJON NEMADALIEV**

#### April 2016

## Chairman : Assoc. Prof. Hj Mohd Hasan b Selamat,PhD Faculty : Computer Science and Information Technology

In many scenarios of everyday life and especially in warehousing, manufacturing and logistics, it is highly desirable to locate objects or persons quickly and accurately. Nowadays, fingerprinting based Wi-Fi positioning system provides enterprises the ability to track their various resources more efficiently and effectively. The main idea behind fingerprinting is to build signal strength database of target area prior to location estimation. This process is called calibration and the positioning accuracy highly depends on calibration intensity. Unfortunately, calibration procedure requires a huge amount of time and effort and makes large-scale deployments of Wi-Fi based indoor positioning systems non-trivial.

In this research, we present a new method of recovering Wi-Fi Radio Map (WRM) database based on few sample received signal strength indicators –RSSI and this recovered data is used as radio map – constructed Wi-Fi RSS based fingerprint database for indoor positing. In contrary to conventional calibration method, our method requires only a few signal samples to be collected and rest of the data are approximated using Chebyshev wavelets. The main goal of our research is to minimize the calibration workload while maintaining recovered data accuracy and achieve acceptable results on positioning accuracy.

Compared to the conventional way, proposed a new method to construct accurate Wi-Fi signal strength indicators using Chebyshev wavelet based approximation requires only a few reference RSSI samples, and this significantly will reduce the calibration effort. Also, field test results showed that proposed method achieves better approximation accuracy than existing interpolation methods, such as VORO and MOSM.

Also recovered RSSI data - fingerprint database was used with positioning software to evaluate results of positioning accuracy. Results show that positioning accuracy is

significantly improved compared with conventional, as well as, other two related methods.



Abstrak tesis yang dikemukakan kepada Senat Universiti Putra Malaysia sebagai memenuhi keperluan untuk Ijazah Doktor Falsafah.

## KETEPATAN KEKUATAN ISYARAT WI-FI BAGI KAEDAH PEMULIHAN MENGGUNAKAN KETEPATAN GELOMBANG CHEBYSHEV UNTUK KEDUDUKAN TERTUTUP

Oleh

#### **AZAMJON NEMADALIEV**

#### April 2016

## Pengerusi : Prof. Madya Hj Mohd Hasan b Selamat,PhD Fakulti : Sains Komputer dan Teknologi Maklumat

Dalam kebanyakkan senario dalam kehidupan seharian dan terutamanya dalam bidang pergudangan, pembuatan dan logistik, ia adalah sangat wajar untuk mencari objek atau individu dengan cepat dan tepat. Pada masa kini, cap jari berdasarkan sistem Wi-Fi merujukan kepada kedudukan objek telah menyediakan satu keupayaan untuk mengesan pelbagai sumber dengan lebih cekap dan berkesan. Idea utama di sebalik cap jari adalah untuk membina isyarat pangkalan data berdasarkan kekuatan kawasan sasaran sebelum ke lokasi anggaran. Proses ini dipanggil penentukuran dan ketepatan kedudukan yang sangat bergantung kepada intensiti penentukuran. Malangnya, prosedur penentukuran memerlukan sejumlah besar masa dan usaha lebih-lebih dalam membuat pergerakan yang luas dalam sistem kedudukan tertutup menggunakan Wi-Fi bukannya remeh.

Dalam kajian ini, kami membentangkan satu kaedah baru iaitu Wi-Fi Peta Radio (WRM) yang mempunyai pangkalan data berdasarkan beberapa isyarat penunjuk kekuatan-RSSI dan data yang disimpan digunakan sebagai peta radio - pangkalan data cap jari dibina berdasarkan Wi-Fi RSS untuk menentukan kedalaman sesuatu kedudukan. Berbeza dengan kaedah penentukuran konvensional, kaedah kami hanya memerlukan beberapa sampel isyarat yang dikumpul dan data yang selebihnya dianggarkan dengan menggunakan riak Chebyshev. Matlamat utama kajian kami adalah untuk mengurangkan beban kerja penentukuran di samping mengekalkan ketepatan data dalam mencapai keputusan yang boleh diterima pada ketepatan kedudukan.

Berbanding dengan cara konvensional, kami mencadangkan satu kaedah baru untuk membina penunjuk kekuatan menggunakan isyarat Wi-Fi yang tepat menggunakan penghampiran berdasarkan gelombang Chebyshev yang hanya memerlukan rujukan beberapa sampel RSSI, dan ini akan mengurangkan usaha penentukuran. Keputusan ujian lapangan menunjukkan bahawa kaedah yang dicadangkan berjaya mencapai

ketepatan anggaran yang lebih baik berbanding kaedah interpolasi yang sedia ada, seperti Voro dan MOSM.

Untuk pemulihan data RSSI - pangkalan data cap jari digunakan dengan perisian kedudukan untuk menilai keputusan ketepatan kedudukan. Keputusan menunjukkan bahawa ketepatan kedudukan semakin bertambah baik berbanding dengan lain-lain kaedah konvensional.



## ACKNOWLEDGEMENTS

I would like to dedicate this dissertation to my mother, Manzura and my wife Firuza who always love and believe in me. Without their support, I could not have finished this work and could not have been where I am now. They are invaluable to me.

I would like to acknowledge my supervisor, Prof. Madya Hj Mohd Hasan b Selamat, for his encouragement and guidance towards this dissertation. I deeply appreciate his help, technical insight, and dedication. After several years, he has tremendously enhanced on how I view research problems on modeling of indoor positioning and wireless networking in general. I also like to thank all my committee, especially Dr. Muhamad Taufik bin Abdullah and Dr. Marzanah bt A. Jabar for spending time reading my work and giving all valuable comments.

I gratefully acknowledge other committee, especially Prof. Madya Dr. Ibragimov Gafurjan from faculty science who provides relevant background for this study during the last years of my study. In addition, I want to thank Dr. Anvar Nazrullaev of the UPM, who helped refine my research statement. I certify that a Thesis Examination Committee has met on 13 April 2016 to conduct the final examination of Azamjon Nemadaliev on his thesis entitled "Accurate Wi-Fi Signal Strength Recovery Method using Chebyshev Wavelet-Based Approximation for Indoor Positioning" in accordance with the Universities and University Colleges Act 1971 and the Constitution of the Universiti Putra Malaysia [P.U.(A) 106] 15 March 1998. The Committee recommends that the student be awarded the Doctor of Philosophy.

Members of the Thesis Examination Committee were as follows:

#### Rodziah binti Atan, PhD

Associate Professor Faculty of Computer Science and Information Technology Universiti Putra Malaysia (Chairman)

Zuriati bt Ahmad Zukarnain, PhD Associate Professor Faculty of Computer Science and Information Technology Universiti Putra Malaysia (Internal Examiner)

#### Shamala a/p K Subramaniam, PhD

Professor Faculty of Computer Science and Information Technology Universiti Putra Malaysia (Internal Examiner)

#### Yongwan Park, PhD Professor

Yeungnam University Korea (External Examiner)

**ZULKARNAIN ZAINAL, PhD** Professor and Deputy Dean School of Graduate Studies Universiti Putra Malaysia

Date: 26 July 2016

This thesis was submitted to the Senate of the Universiti Putra Malaysia and has been accepted as fulfilment of the requirement for the degree of Doctor of Philosophy. The members of the Supervisory Committee were as follows:

#### Hj Mohd Hasan b Selamat,PhD

Associate Professor Faculty of Computer Science and Information Technology Universiti Putra Malaysia (Chairman)

#### Muhamad Taufik bin Abdullah,PhD

Associate Professor Faculty of Computer Science and Information Technology Universiti Putra Malaysia (Member)

## Marzanah bt A. Jabar, PhD

Associate Professor Faculty of Computer Science and Information Technology Universiti Putra Malaysia (Member)

# BUJANG BIN KIM HUAT, PhD

Professor and Dean School of Graduate Studies Universiti Putra Malaysia

Date:

## **Declaration by graduate student**

I hereby confirm that:

- this thesis is my original work
- quotations, illustrations and citations have been duly referenced
- the thesis has not been submitted previously or comcurrently for any other degree at any institutions
- intellectual property from the thesis and copyright of thesis are fully-owned by Universiti Putra Malaysia, as according to the Universiti Putra Malaysia (Research) Rules 2012;
- written permission must be owned from supervisor and deputy vice –chancellor (Research and innovation) before thesis is published (in the form of written, printed or in electronic form) including books, journals, modules, proceedings, popular writings, seminar papers, manuscripts, posters, reports, lecture notes, learning modules or any other materials as stated in the Universiti Putra Malaysia (Research) Rules 2012;
- there is no plagiarism or data falsification/fabrication in the thesis, and scholarly integrity is upheld as according to the Universiti Putra Malaysia (Graduate Studies) Rules 2003 (Revision 2012-2013) and the Universiti Putra Malaysia (Research) Rules 2012. The thesis has undergone plagiarism detection software

Signature:	Date:
Name and Matric No : A zamion Namadaliay	G\$20762

Name and Matric No.: Azamjon Nemadaliev, GS20762

## **Declaration by Members of Supervisory Committee**

This is to confirm that:

- the research conducted and the writing of this thesis was under our supervision;
- supervision responsibilities as stated in the Universiti Putra Malaysia (Graduate Studies) Rules 2003 (Revision 2012-2013) were adhered to.

Signatura	
Signature:	
Name of Chairman	
of Supervisory	
Committee:	Associate Professor Dr. Hj Mohd Hasan b Selamat
Signature:	
Name of Member	
of Supervisory	
Committee:	Associate Professor Dr. Muhamad Taufik bin Abdullah
Signature:	
Name of Member	
of Supervisory	
Committee:	Associate Professor Dr. Marzanah bt A. Jabar

# TABLE OF CONTENTS

APPRO DECLA LIST C LIST C	RAK OWLEDGEMENTS	i iii v vi viii xii xii xiv xvi
CHAP	ſER	
1	INTRODUCTION1.1Motivation1.2Problem Statement1.3Objectives1.4Scope Of The Research	1 1 4 8 8
2	<ul> <li>LITERATURE REVIEW</li> <li>2.1 Introduction</li> <li>2.2 RSS-Based Based Recovery Methods <ul> <li>2.2.1 Signal measurement methods</li> <li>2.2.2 Location Fingerprinting Techniques</li> <li>2.2.3 RSSI-Fingerprinting location estimation</li> </ul> </li> <li>2.3 Positioning Methods <ul> <li>2.3.1 RSSI approximation</li> <li>2.3.2 k-Nearest Neighbor</li> </ul> </li> <li>2.4 Comparison Of Related Works</li> <li>2.5 Summary</li> </ul>	11 11 13 14 16 17 18 20 20 25
3	<ul> <li>RESEARCH METHODOLOGY</li> <li>3.1 Introduction</li> <li>3.2 Formulation Of The Method <ul> <li>3.2.1 Offline (training) phase</li> <li>3.2.2 Online (tracking) phase</li> </ul> </li> <li>3.3 Implementation Of The Method <ul> <li>3.4 Validation of the method</li> </ul> </li> <li>3.5 Summary</li> </ul>	26 26 28 32 34 36 39
4	<ul> <li>ACCURATE WI-FI SIGNAL STRENGTH RECOVERY METHOD</li> <li>4.1 Introduction</li> <li>4.2 Formulation Of The Proposed Method</li> <li>4.3 Recovering Method</li> <li>4.3.1 Measuring - defining training region and selections of APs</li> <li>4.3.2 Calibration: Reference data collection</li> <li>4.3.3 Interpolation: RSSI approximation</li> </ul>	40 40 40 42 42 42 43 44

		4.3.4 Recovery algorithm	46
	4.4	Positioning Based On Recovered RSS	53
	4.5	Summary	54
5		FTWARE IMPLEMENTATION	55
	5.1		55
	5.2	6 6	56
		5.2.1 Objectives	57
		5.2.2 Requirements	58
		5.2.3 Technical Specifications	59
	5.3	Software Applications	60
		5.3.1 Software Application for calibration	61
		5.3.2 Software Application for recovering RSSI	62
		5.3.3 Web Application to represent recovered RSSI	62
	5.4	Positioning Simulator For Retrieving Positioning Results Using	65
		Recovered Rssi	
6		PERIMENTAL RESULTS	66
	6.1		67
		6.1.1 Experiment setup	67
		6.1.2 Recovered RSSI accuracy	68
		6.1.3 Positioning accuracy	74
	6.2	Experiment 2	76
		6.2.1 Experiment setup	76
		6.2.2 Recovered RSSI accuracy	78
		6.2.3 Positioning accuracy	84
	6.3	Experiment 3	87
		6.3.1 Experiment setup	87
		6.3.2 Recovered RSSI accuracy	88
		6.3.3 Positioning accuracy	93
_			0.4
7		NCLUSIONS	96
	7.1	Introduction	96
	7.2	Contributions	96
	7.3	Accurate Wi-Fi Signal Strength Recovery Method	97
	7.4	Future Work	97
DEED	DENC		0.9
REFE			98 104
APPEN			104
		DF STUDENT	112
LIST	JF PU	BLICATIONS	113

R A B L

# LIST OF TABLES

Table		Page
1.1	Environment and location technologies with accuracy comparison	9
2.1	Review of related recent works	21
2.2	Review of VORO and MOSM	24
2.3	Weakness and strengths of related recent works	25
3.1	Measuring step of the method	27
3.2	Implementation step of the method	35
3.3	Software applications	36
3.4	Validation step of the method	37
3.5	Positive achievements of related recent works	38
3.6	Validation steps and targeted achievements of our research	39
5.1	Research and development statements of Mobile App for scanning	57
6.1	Differences of the selected experiment locations	66
6.2	Approximation results of RSSI for one AP based fixed RPs	69
6.3	Approximation of RSSI for all APs based on randomly selected RPs	70
6.4	Results comparison between fixed and randomly selected RPs	72
6.5	Approximation results comparison with other methods	73
6.6	Positioning results in three type of data (fixed, random and existing)	74
6.7	Positioning accuracy results in different methods	75
6.8	Approximation of RSSI for all APs based on FIXED selected RP	80
6.9	Approximation of RSSI for all APs based on RANDOMLY selected RPs	82
6.10	Results comparison between fixed and randomly selected RPs	83
6.11	Approximation results comparison with other methods	84

6.12	Positioning results in three type of data (fixed, random and existing)	85
6.13	Positioning accuracy results in different methods	86
6.14	Approximation of RSSI for all APs based on fixed selected RPs	89
6.15	Approximation of RSSI for all APs based on randomly selected RPs	90
6.16	Results comparison between fixed and randomly selected RPs	91
6.17	Approximation results comparison with other methods	92
6.18	Positioning results in three type of data (fixed, random and existing)	93
6.19	Positioning accuracy results in different methods	94

C

# LIST OF FIGURES

Figure		Page
1.1	History of location technologies	2
1.2	Positioning techniques	10
1.3	Research scope	10
2.1	Most related works	23
3.1	Flow chart of the research methodology	26
3.2	Methodology processes	28
3.3	Offline phase methodology model	29
3.4	Scanning – measurement at RPs	30
3.5	Online phase methodology model	32
3.6	X and Y coordination of the targeted location	34
3.7	Map of fourth floor of the Mines Shopping complex	37
4.1	Flowchart of proposed method	41
4.2	Steps of recovery method	42
4.3	Original RSSI measures vs approximated RSSI using CHEB	44
4.4	Dividing a path into intervals and sub-intervals	44
5.1	High level software architecture	55
5.2	Mobile App design	57
5.3	Data collection process	58
5.4	Software applications in stages of the proposed method	61
5.5	Snapshot of maps	62
5.6	x and y coordinates of selected map	63
5.7 5.8	RSS data set of selected AP in all points at selected Path Original RSS vs estimated RSS where step equal to 4	63 64
5.9	Original RSS vs estimated RSS where step equal to 8	64

6.1	Original Map of first floor of the Block B, Library Campus	67
6.2	Approximation accuracy based on fixed RPs of all APs	69
6.3	Approximation accuracy based on randomly selected RPs of all APs	71
6.4	Approximation results comparison (Fixed VS Random)	72
6.5	RSSI approximation accuracy of three methods	73
6.6	Positioning results comparison (existing, fixed and random)	74
6.7	Comparison of the positioning accuracy results	75
6.8	Original Map of fourth floor of the Shopping Mall	76
6.9	Illustrated map of fourth floor of the Shopping Mall	77
6.10	Training areas at the fourth floor of the Shopping Mall	77
6.11	A plan of the building where experiments were conducted	78
6.12	Power spectrum of measured and approximated (by CHEB) signals	79
6.13	Approximation accuracy based on fixed RPs of all APs	81
6.14	Approximation accuracy based on randomly selected RPs of all APs	82
6.15	Approximation results comparison (Fixed VS Random)	83
6.16	RSSI approximation accuracy of three methods	84
6.17	Positioning results comparison (existing, fixed and random)	85
6.18	Comparison of the positioning accuracy results	86
6.19	2 floor of the campus of the faculty	87
6.20	Approximation accuracy based on fixed RPs of all APs	89
6.21	Approximation accuracy based on randomly selected RPs of all APs	91
6.22	Approximation results comparison (Fixed VS Random)	92
6.23	RSSI approximation accuracy of three methods	93
6.24	Positioning results comparison (existing, fixed and random)	94
6.25	Comparison of the positioning accuracy results	95

# LIST OF ABBREVIATIONS

CONVConventional methodCHEBProposed methodECGElectrocardiogramGISGeographical Information SystemGSPGlobal Positioning SystemsIRInformation SystemsIRInfrared RayKNNK-Nearest NeighborLBSLocation Based ServicesLoSLine Of SightMACMedia Access Control AddressPOAPhase Of ArrivalRFRadio FrequencyRFIDRadio Frequency IdentificationRPReference PointRSSReceived Signal StrengthRSSIReceived Signal StrengthRSSISignal-To-Noise RatioSSSignal StrengthSSIDService Set IdentifierSVMSupport Vector MachinesTDOATime Difference Of ArrivalTOATime Of ArrivalUIUser InterfaceUWUltra-WidebandWRMWiFi Radio Map	AP API BSN BSSI	Access Point Application Program Interface Body Sensor Networks Basic Service Set Identification
ECGElectrocardiogramGISGeographical Information SystemGSPGlobal Positioning SystemIPSIndoor Positioning SystemsIRInfrared RayKNNK-Nearest NeighborLBSLocation Based ServicesLoSLine Of SightMACMedia Access Control AddressPOAPhase Of ArrivalRFRadio FrequencyRFIDRadio Frequency IdentificationRPReference PointRSSReceived Signal StrengthRSSIReceived Signal Strength IndicatorSNRSignal-To-Noise RatioSSSignal StrengthSSIDService Set IdentifierSVMSupport Vector MachinesTDOATime Of ArrivalUIUser InterfaceUWUltra-WidebandUWBUltra-Wideband		
GISGeographical Information SystemGSPGlobal Positioning SystemIPSIndoor Positioning SystemsIRInfrared RayKNNK-Nearest NeighborLBSLocation Based ServicesLoSLine Of SightMACMedia Access Control AddressPOAPhase Of ArrivalRFRadio FrequencyRFIDRadio Frequency IdentificationRPReference PointRSPReceived Signal StrengthRSSIReceived Signal Strength IndicatorSNRSignal-To-Noise RatioSSSignal StrengthSSIDService Set IdentifierSVMSupport Vector MachinesTDOATime Of ArrivalUIUser InterfaceUWUltra-Wideband		*
GSPGlobal Positioning SystemIPSIndoor Positioning SystemsIRInfrared RayKNNK-Nearest NeighborLBSLocation Based ServicesLoSLine Of SightMACMedia Access Control AddressPOAPhase Of ArrivalRFRadio FrequencyRFIDRadio Frequency IdentificationRPReference PointRSSReceived Signal PhaseRSSReceived Signal StrengthRSSISignal-To-Noise RatioSSSignal StrengthSSIDService Set IdentifierSVMSupport Vector MachinesTDOATime Difference Of ArrivalTOATime Of ArrivalUIUser InterfaceUWUltra-Wideband		
IPSIndoor Positioning SystemsIRInfrared RayKNNK-Nearest NeighborLBSLocation Based ServicesLoSLine Of SightMACMedia Access Control AddressPOAPhase Of ArrivalRFRadio FrequencyRFIDRadio Frequency IdentificationRPReference PointRSSReceived Signal PhaseRSSReceived Signal StrengthRSSIReceived Signal Strength IndicatorSNRSignal-To-Noise RatioSSSignal StrengthSSIDService Set IdentifierSVMSupport Vector MachinesTDOATime Difference Of ArrivalUIUser InterfaceUWUltra-Wideband		
IRInfrared RayKNNK-Nearest NeighborLBSLocation Based ServicesLoSLine Of SightMACMedia Access Control AddressPOAPhase Of ArrivalRFRadio FrequencyRFIDRadio Frequency IdentificationRPReference PointRSPReceived Signal PhaseRSSReceived Signal StrengthRSSIReceived Signal Strength IndicatorSNRSignal-To-Noise RatioSSSignal StrengthSSIDService Set IdentifierSVMSupport Vector MachinesTDOATime Difference Of ArrivalUIUser InterfaceUWUltra-Wideband		
KNNK-Nearest NeighborLBSLocation Based ServicesLoSLine Of SightMACMedia Access Control AddressPOAPhase Of ArrivalRFRadio FrequencyRFIDRadio Frequency IdentificationRPReference PointRSPReceived Signal PhaseRSSReceived Signal StrengthRSSIReceived Signal Strength IndicatorSNRSignal-To-Noise RatioSSSignal StrengthSSIDService Set IdentifierSVMSupport Vector MachinesTDOATime Difference Of ArrivalUIUser InterfaceUWUltra Sonic WaveUWBUltra-Wideband		•••
LBSLocation Based ServicesLoSLine Of SightMACMedia Access Control AddressPOAPhase Of ArrivalRFRadio FrequencyRFIDRadio Frequency IdentificationRPReference PointRSPReceived Signal PhaseRSSReceived Signal StrengthRSSIReceived Signal Strength IndicatorSNRSignal-To-Noise RatioSSSignal StrengthSSIDService Set IdentifierSVMSupport Vector MachinesTDOATime Difference Of ArrivalTOATime Of ArrivalUIUser InterfaceUWUltra-Wideband		•
LoSLine Of SightMACMedia Access Control AddressPOAPhase Of ArrivalRFRadio FrequencyRFIDRadio Frequency IdentificationRPReference PointRSPReceived Signal PhaseRSSReceived Signal StrengthRSSIReceived Signal Strength IndicatorSNRSignal-To-Noise RatioSSSignal StrengthSSIDService Set IdentifierSVMSupport Vector MachinesTDOATime Difference Of ArrivalUIUser InterfaceUWUltra Sonic WaveUWBUltra-Wideband		
MACMedia Access Control AddressPOAPhase Of ArrivalRFRadio FrequencyRFIDRadio Frequency IdentificationRPReference PointRSPReceived Signal PhaseRSSReceived Signal StrengthRSSIReceived Signal Strength IndicatorSNRSignal-To-Noise RatioSSSignal StrengthSSIDService Set IdentifierSVMSupport Vector MachinesTDOATime Difference Of ArrivalUIUser InterfaceUWUltra Sonic WaveUWBUltra-Wideband		
POAPhase Of ArrivalRFRadio FrequencyRFIDRadio Frequency IdentificationRPReference PointRSPReceived Signal PhaseRSSReceived Signal StrengthRSSIReceived Signal Strength IndicatorSNRSignal-To-Noise RatioSSSignal StrengthSSIDService Set IdentifierSVMSupport Vector MachinesTDOATime Difference Of ArrivalTOATime Of ArrivalUIUser InterfaceUWUltra Sonic WaveUWBUltra-Wideband	LoS	
RFRadio FrequencyRFIDRadio Frequency IdentificationRPReference PointRSPReceived Signal PhaseRSSReceived Signal StrengthRSSIReceived Signal Strength IndicatorSNRSignal-To-Noise RatioSSSignal StrengthSSIDService Set IdentifierSVMSupport Vector MachinesTDOATime Difference Of ArrivalTOATime Of ArrivalUIUser InterfaceUWUltra Sonic WaveUWBUltra-Wideband	MAC	Media Access Control Address
RFIDRadio Frequency IdentificationRPReference PointRSPReceived Signal PhaseRSSReceived Signal StrengthRSSIReceived Signal Strength IndicatorSNRSignal-To-Noise RatioSSSignal StrengthSSIDService Set IdentifierSVMSupport Vector MachinesTDOATime Difference Of ArrivalTOATime Of ArrivalUIUser InterfaceUWUltra Sonic WaveUWBUltra-Wideband	POA	Phase Of Arrival
RPReference PointRSPReceived Signal PhaseRSSReceived Signal StrengthRSSIReceived Signal Strength IndicatorSNRSignal-To-Noise RatioSSSignal StrengthSSIDService Set IdentifierSVMSupport Vector MachinesTDOATime Difference Of ArrivalTOATime Of ArrivalUIUser InterfaceUWUltra Sonic WaveUWBUltra-Wideband	RF	
RSPReceived Signal PhaseRSSReceived Signal StrengthRSSIReceived Signal Strength IndicatorSNRSignal-To-Noise RatioSSSignal StrengthSSIDService Set IdentifierSVMSupport Vector MachinesTDOATime Difference Of ArrivalTOATime Of ArrivalUIUser InterfaceUWUltra Sonic WaveUWBUltra-Wideband	RFID	Radio Frequency Identification
RSSReceived Signal StrengthRSSIReceived Signal Strength IndicatorSNRSignal-To-Noise RatioSSSignal StrengthSSIDService Set IdentifierSVMSupport Vector MachinesTDOATime Difference Of ArrivalTOATime Of ArrivalUIUser InterfaceUWUltra Sonic WaveUWBUltra-Wideband	RP	Reference Point
RSSIReceived Signal Strength IndicatorSNRSignal-To-Noise RatioSSSignal StrengthSSIDService Set IdentifierSVMSupport Vector MachinesTDOATime Difference Of ArrivalTOATime Of ArrivalUIUser InterfaceUWUltra Sonic WaveUWBUltra-Wideband	RSP	Received Signal Phase
SNRSignal-To-Noise RatioSSSignal StrengthSSIDService Set IdentifierSVMSupport Vector MachinesTDOATime Difference Of ArrivalTOATime Of ArrivalUIUser InterfaceUWUltra Sonic WaveUWBUltra-Wideband	RSS	Received Signal Strength
SSSignal StrengthSSIDService Set IdentifierSVMSupport Vector MachinesTDOATime Difference Of ArrivalTOATime Of ArrivalUIUser InterfaceUWUltra Sonic WaveUWBUltra-Wideband	RSSI	Received Signal Strength Indicator
SSIDService Set IdentifierSVMSupport Vector MachinesTDOATime Difference Of ArrivalTOATime Of ArrivalUIUser InterfaceUWUltra Sonic WaveUWBUltra-Wideband	SNR	Signal-To-Noise Ratio
SVMSupport Vector MachinesTDOATime Difference Of ArrivalTOATime Of ArrivalUIUser InterfaceUWUltra Sonic WaveUWBUltra-Wideband	SS	Signal Strength
TDOATime Difference Of ArrivalTOATime Of ArrivalUIUser InterfaceUWUltra Sonic WaveUWBUltra-Wideband	SSID	Service Set Identifier
TOATime Of ArrivalUIUser InterfaceUWUltra Sonic WaveUWBUltra-Wideband	SVM	Support Vector Machines
UI User Interface UW Ultra Sonic Wave UWB Ultra-Wideband	TDOA	Time Difference Of Arrival
UW Ultra Sonic Wave UWB Ultra-Wideband	ТОА	Time Of Arrival
UWB Ultra-Wideband	UI	User Interface
	UW	Ultra Sonic Wave
WRM WiFi Radio Map	UWB	Ultra-Wideband
	WRM	WiFi Radio Map

## **CHAPTER 1**

## **INTRODUCTION**

## 1.1. Motivation

Tracking assets and equipment has been a long-standing and continuous issue for enterprises. In warehouses, factories and hospitals, for example, staff and important assets should be located and tracked rapidly. With various wireless technologies to facilitate such tracking being introduced in the last decade, enterprises have the opportunity leverage on some form of control over the manageability of its resources. The rapid development of Wi-Fi wireless local area networks and advent of great mobility have facilitated numerous indoor positioning techniques (Fallah et al. 2013), a significant need for localization has emerged (Figure 1.1). This is true not only for automotive applications, but also for personal purposes, thus leading to the necessity of having a technical solution for accurate wireless geolocation. The positioning of mobile users is highly desirable for many location-based services, such as emergency, healthcare, logistics, entertainment, traffic management, and so on (Liu et al., 2007; Narzullaevet al., 2011).

Highly accurate localization systems have received significant attention nowadays with the recent development of mobile devices for the ubiquitous location based services (LBSs) (Mengual et al., 2010) in indoor and underground environments. Location based services that act differently depending on the location of the user are considered to be a promising market. The usage of LBSs have spread widely in different types of public areas such as inside buildings, warehouses, airports and hospitals (Fallah et al. 2013) and also services such as home utilities, asset management, guiding, emergency call, car parking in buildings (Muntz and Pancake , 2003; Lin et al., 2011; Daudi and Yang, 2014).In recent years, positioning has risen in popularity among research in health and its management. Lee et al. (2015) presenta bio-signal acquisition system with the features of low power consumption, wireless transmission, and the on-time monitoring. It shows body sensor networks (BSNs) based applications or devices have become more and more popular as well, and acceptable to the people for monitoring the real-time health information, such as the electrocardiogram (ECG).

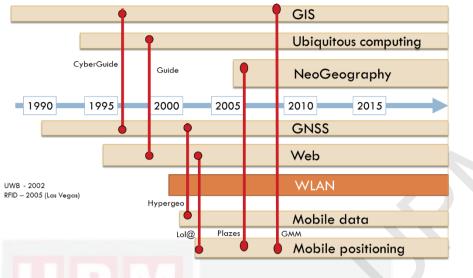


Figure 1.1: History of location technologies

Currently, the most extensively used and commercially successful location system is the Global Positioning System (GPS), which provides a high degree of accuracy and is available worldwide. However, GPS signals originating from satellites fail to reach mobile devices in indoors and dense urban environments (Narzullaev et al. 2011). Thus, considerable research has been devoted to developing alternative systems to provide accurate location information in indoors. Various technologies have been suggested to be a basis for indoor positioning systems (IPS), such as digital TV, Infrared, Bluetooth, Ultra-wideband, ultrasonic and Wi-Fi. Of these IEEE802.11 based WLAN systems, (Wi-Fi) is the most widely deployed, and is also rapidly growing. Wi-Fi access points (AP) are being installed almost everywhere people live and work. Furthermore, Wi-Fi chips are integrated with wide range of handheld devices, such as smartphones, multimedia players, tablet PCs, laptops and etc. Originally designed to provide internet access to mobile users, 802.11 WLAN standards also emerged as a viable alternative for indoor positioning systems (Liu et al. 2007).

Wi-Fi technology has been studied and explored to provide indoor positioning service for years in view of the wide deployment and availability of existing Wi-Fi infrastructures in indoor environments. A large body of Wi-Fi -based IPSs adopt fingerprinting approaches for localization. However, these IPSs suffer from two major problems: the intensive costs of manpower and time for offline site survey and the inflexibility to environmental dynamics (Zou et al., 2015).

Indoor environment characteristics and specific requirements of time-based positioning schemes make received signal strength indicator (RSSI) based positioning techniques more attractive for indoor location estimation (Narzullaev and Park 2013). One of the well-known signal strength based location techniques is the fingerprinting algorithm. Here, signal properties such as RSSI are compared to a database of properties previously collected at a variety of locations. The closest

2

match is returned as the estimated position. Accuracies of a few meters are typically reported (Harle 2013). The main weakness of fingerprinting algorithm is an extensive calibration phase. This procedure is carried on manually, thus requiring a huge amount of time and effort to build signal strength database. Since the signal strength depends on site-specific parameters, a newly built DB may no longer be valid if there are major changes in the target site. As a result, large-scale deployments of indoor positioning systems become non-trivial.

Several studies have been conducted to solve the calibration issue and make IPS more effective and practical. Gallagher et al. (2010), proposes a crowdsourcing system, which encourages users to update system database by pinpointing correct location upon receiving error position. Park et al. (2010) proposed organic positioning system, which similarly proposes to prompt the user to input correct location if an error occurs. Several studies have proposed propagation models that effectively predict signal strengths (Widyawan et al. 2007). However, main problems of conventional path loss prediction algorithms are their low prediction accuracy in indoors and pre-required layout information including the number of walls, floors and most importantly the physical location of APs. This information is often unavailable, due to various reasons.

Also, many fingerprint-based techniques and interpolation methods have been proposed for indoor positioning. However, the fingerprint based techniques usually required a lot of efforts on calibration process on targeted areas, as experimented with in previous approaches (Lee and Han, 2012; Krumm and Platt, 2003). Since several approaches have been made to reduce effort, in most cases, reference points (RPs), where fingerprints are to be collected, are not regularly well defined and not accurate for quick location determination in targeted area (Lee and Han, 2012; Kuo and Tseng, 2011). This is one of the reasons why interpolation methods are widely used in practice for scattered data.

In this research, we propose a new method of constructing RSSI fingerprints database using Chebyshev wavelets. The conventional method for collecting RSSI fingerprint DB is very straightforward. An operator with wireless handheld device makes RSSI measurements at several reference points (RPs), and after some processing, the data is stored in the database. Location accuracy highly depends on the number of RPs, and for an average building the number of RPs may reach up to several hundred per floor. The main objective of this research is to create an accurate and complete RSSI DB from a limited number of on-site measurements using Chebyshev wavelet transforms. Therefore, the cost of time-consuming surveys can be reduced.

Wavelet transforms are one of the relatively new techniques which are being used for signal coding, to represent a discrete signal in a more redundant form, often as a preconditioning for data compression. In recent years, wavelets received considerable attention by researchers in different fields of science and engineering. Hence, its practical applications can be found in signal processing, digital communications, data analysis, image processing and many others. The main characteristic of wavelet functions is the ability to perform a local analysis. Wavelet analysis is able to reveal signal aspects that other methods are missing, such as trends, breakdown points, discontinuities, etc. (Misiti and Misiti, 1996). All of these facts gave us impact to use wavelets to construct received signal strength database for IPS. Although there are many different types of wavelets, in our research, we will consider Chebyshev wavelets (Nasab et al. 2013) due to several reasons: The ability of Chebyshev polynomials to approximate any continuous function, to any desired accuracy, over a prescribed interval; Good representation of piecewise functions (Misiti and Misiti, 1996). We construct Chebyshev wavelet transform coefficients using a system of linear equations, although, in many papers devoted to discrete Wavelet transforms, the coefficients are produced using an inner product (Broughton and Bryan 2008).

We carefully evaluated the proposed method through experiments in one of the shopping malls in Malaysia (Mines Shopping Mall). Both, field tests and computer simulations, demonstrated the effectiveness of the system and a significant reduction in calibration time, while providing comparable location accuracy to that of the traditional calibration-based approach, as well as previously proposed methods. The rest of the thesis is organized as follows. In the literature review Section, we describe the basic principles of fingerprint location technique and RSSI approximation methods. Research methodology and proposed method will be presented in next Sections. Further, software development and implementation have been described in a separate section. We describe the experiment setup and present field test results and analyses and concluding remarks are given in the last Section.

## 1.2. Problem Statement

Developing an indoor positioning system (IPS) to provide reliable and precise indoor positioning and navigation has become a hot research topic recently. Various wireless communication technologies have been studied and developed to provide indoor positioning and navigation services in the past two decades (Liu et al. 2007; Gu et al., 2009; Lloret et al., 2009 and Medina et al., 2013). Unlike other wireless technologies, such as ultra-wideband (UWB) and radio frequency identification (RFID), which require the deployment of extra infrastructure, the existing IEEE 802.11 (Wi-Fi) network infrastructures, such as Wi-Fi routers, are widely available in large numbers of commercial and residential buildings, and nearly every mobile device now is equipped with a Wi-Fi receiver. As such, it is low-cost and practical to develop a Wi-Fi-based IPS to provide LBS in an indoor environment. Wi-Fi provides cost-effective data capacity at hotspots in conjunction with broadband cellular networks. Large scale adoption of smartphones and tablets means that wireless data networks must provide high data rates anytime and anywhere (Ling et al., 2015).

Fingerprinting-based localization methods are widely adopted for Wi-Fi-based indoor positioning, since the received signal strengths (RSS) can be measured easily

from mobile devices (Bahl et al., 2000; Youssef and Agrawala, 2005; Brunato and Battiti, 2005; Liu et al., 2012; Chen et al., 2013). However, the existing Wi-Fi-based IPSs adopting the fingerprinting approach suffer from two major problems. One is that the site measurement involves intensive costs of both time and manpower during the offline calibration phase. In order to achieve sufficient localization accuracy, the Wi-Fi RSS fingerprints from different access points (APs) need to be measured at a huge number of calibration points. The other one is that the existing fingerprintingbased approaches are not robust to environmental dynamics (Bahl et al., 2000; Chen et al., 2005, Youssef and Agrawala, 2005; Brunato and Battiti, 2005; Liu et al., 2012; Chen et al., 2013). Since the Wi-Fi RSS fingerprint database is built up during the offline phase, it cannot reflect the real-time radio map of the Wi-Fi signals well once the environment is altered during the online localization phase. The problem of environment influences (Zhuang et al., 2014) - environmental factors, such as a presence of humans, opening, and closing of doors and variations of humidity, can interfere with the propagation of Wi-Fi signals severely (Chen et al., 2005). This will lead to serious localization errors in the estimation of the target if the same Wi-Fi RSS fingerprint database is adopted (Zou et al., 2015). Due to the limitation and complexity of the indoor environment, the solution to achieve a low-cost and accurate positioning system remains open (Yang and Shao, 2015).

At untrained locations, most of the proposed interpolation methods have high complexity (Krumm and Platt, 2003) and incur a higher computational cost (Kuo and Tseng, 2011) during calibration of WI-FI signal strength for localization. On the other hand, there are numerous efforts required to measure signal strengths (SS). In practice, reducing both the time spent in each location and the number of locations visited increases the error, but not until quite large reductions along both dimensions (fraction of locations visited and time at each location). It is unnecessary to spend much time at each location, as more time beyond a short minimum does not improve accuracy very much (Kuo and Tseng, 2011), so there are still potentials to common techniques in terms of increased accuracy and reduced effort (Kuo and Tseng, 2011).

As we mention above, most conventional measurement based methods have two major problems which are effort and accuracy concerns in calibration stage. Here we are going to propose a method to solve those issues. Therefore, new method requires few reference RSSI samples to be collected, and also significantly reduces the calibration effort need to be formulated.

Moreover, we would like to note that, there are two ways of having a database of Radio map. They are:

- a) Fully fingerprinted database
- b) Fully or partially approximated database

However, the existing Wi-Fi-based Indoor positioning systems (IPS) adopting the fingerprinting approach suffer from two major problems. One is that the site measurement involves intensive costs of both time and manpower. In order to

achieve sufficient localization accuracy, the Wi-Fi RSS fingerprints from different access points (APs) need to be measured at a huge number of calibration points (Bahl et al., 2000; Youssef and Agrawala, 2005; Brunato and Battiti, 2005; Liu et al., 2012; Chen et al., 2013 and others). The other one is that the existing fingerprinting-based approaches are not robust to environmental dynamics (Bahl et al., 2000; Chen et al., 2005, Youssef and Agrawala, 2005; Brunato and Battiti, 2005; Liu et al., 2012; Chen et al., 2013). This will lead to serious localization errors in the estimation of the target if the same Wi-Fi RSS fingerprint database is adopted (Zou et al., 2015). Due to the limitation and complexity of the indoor environment, the solution to achieve a lowcost and accurate positioning system remains open (Yang and Shao, 2015). So, in both ways there are issues. For example, if a database is fully fingerprinted, that means tremendous time and effort to collect locations fingerprints. It requires a lot of labor and time to collect data at each point. It's not difficult to image if the measurement is done in every meter of a location as was done in Kuala Lumpur International Airport (KLIA) when position system was requested to build. If fully approximated, then complexity will be minimum, but accuracy will be almost unacceptable. It has been proven by previous research.

The only way is partially approximated constructed database, which can be done based on the interpolation method. Partially approximated data is not full radio map of the trained area. Here, recovering RSS for missing points where RSS is not measured is required. This is called Path Loss prediction. Path loss prediction method is an estimation of approximation of those missed RSS indicators. Here, accuracy and complexity will be against each other. Even path loss prediction could create accuracy concerns when using this data for tracking in online phase. There are other issues as well:

Existing problems and challenges are: Accuracy of path loss data in both phases (offline and online phases), range of coverage, security, complexity of approximation methods and algorithms, precision and Robustness of those path loss prediction methods, scalability of recovered data, cost of infrastructure and method to have radio map with high accuracy and better coverage and etc.

In this research, we have focused on the recovering of the RADIO MAP databases using approximation method where missed RSS will be recovered with the proposed method. In this proposed method only a few onsite measurements will be required, then the remaining database will be recovered using proposed approximation method.

Here, we focus on three major issues, which are:

**The accuracy of path loss data in both phase** (offline and online phases): Accuracy of constructed Radio Map – WRM database which is recovered using estimation and approximation methods is still considered open topic among the researchers. Most

of the existing techniques have limits and concerns on the accuracy of the constructed radio map. Still, the best-acquired radio map is fully fingerprint based databases. But it's too complicated and constructing fingerprints is a tedious work.

The complexity of approximation and recovery methods and algorithms: Path loss prediction is not an easy task, particularly approximating missed RSS indicators and its usage in recovering process. There are a few proposed approximation methods that can give better accuracy compared to other proposed methods, but their measurement and approximation requirements are quite complex. Means, methods complexity is quite high.

The cost of infrastructure and method to have radio map with high accuracy and better coverage: As we know, accuracy is against complexity, and achieving better results in either one, creates cost problem. This means required additional effort in terms of infra, labor or requirement for changes with an environment for measurements. Creating a balance between ACCURACY and COMPLEXITY will solve COST issues, so here we assume, if we get better accuracy with less complexity, we could achieve minimization of the cost.

So here are the main problem statements which we have focused on:

## Complexity of approximation and path loss reduction processes of the data in untrained locations (points) in training area and usage recovered data in tracking:

- In Off-line phase: Tremendous time and effort to collect locations fingerprints for positioning.
- In Off-line phase: Approximation complexities of the recovery methods and their implementations.
- In On-line phase: Usage of constructed database for the trackingpositioning and it's up to date updates.

# Accuracy issues of recovered data which is approximated and influences for the tracking accuracy:

- In Off-line phase: Recovered data accuracy concerns of constructed database using approximation with few onsite measured data samples.
- In Off-line phase: Keeping the balance between the complexity of the approximation method and the accuracy of the approximated data outcomes.
- In On-line phase: Accuracy concerns of tracking-positioning results based on recovered database.

# 1.3. Objectives

- The main objective of this research is to propose new method to create an accurately recovered RSSI as fingerprints database of radio map for indoor positioning from a smaller number of measurements using Chebyshev wavelet transforms and achieve following objectives:
- New method to create an accurately recovered RSSI dataset as fingerprints database of radio map for indoor positioning from a smaller number of site measurements
- Significantly reducing the time and effort required for fingerprint DB construction
- Usage of Chebyshev wavelet transforms in the proposed to provide high level of path-loss prediction accuracy while maintaining a low computational complexity
- Significantly improved the accuracy of interpolated path loss prediction – approximation results compared to conventional, as well as, state-ofthe-art interpolation algorithms and create an accurate RSSI recovered fingerprint database
- Provide recovered data WRM based on proposed method
- Path loss prediction with high accuracy using interpolation data Additionally, achieve the following targets:
- Significantly reducing the effort in term of time and improve the accuracy of data during calibration phase for positioning.
- Create data of received signals strength (RSS) and estimate missing RSS with high accuracy for other untrained locations in targeted area.
- Presenting position system based on WI-FI signal strengths which are recovered by proposed method
- Providing positioning accuracy results in different cases and proving accuracy by benchmarking with other related works.

## **1.4.** Scope of the research

As we mentioned above, positioning technologies and its techniques are divided into several areas based on environmental and infrastructure specifications. Table 1.1 shows existing dominant technologies in positioning and tracking approaches nowadays.

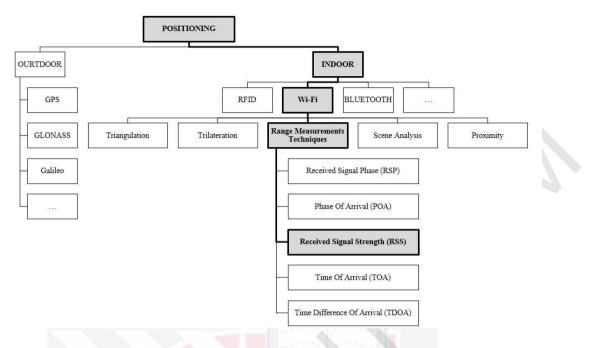
ENVIRONMENT	ESTIMATION ACCURACY		
	≤1m	≤10m	≤100 m
OUTDOOR	<ul><li>GLONASS</li><li>Galileo</li></ul>	– GPS	<ul><li>BDS</li><li>PHS</li><li>Cell Phone</li></ul>
INDOOR and UNDEGROUND	<ul> <li>UWB (Ultra-Wideband)</li> <li>UW (Ultra Sonic Wave)</li> <li>IR (infrared Ray)</li> <li>Bluetooth (IEEE 802.15)</li> </ul>	<ul> <li>WIFI (IEEE 802.11)</li> <li>RFID</li> <li>TMSI</li> </ul>	– IP positioning

Table 1.1: Environment and location technologies with accuracy comparison

In outdoor environments, GPS has dominated the LBS market with excellent localization performance. However, due to the lack of line of sight (LoS) transmission channels between satellites and a receiver, GPS is not capable of providing positioning service with sufficient localization accuracy in indoor environments (Buchli et al., 2012).

While GPS (global positioning system) works well enough outdoors, Wi-Fi RSS (receive signal strength)-based fingerprinting system is the most promising solution for indoors (Wang et al., 2013). Our method is based on Wi-Fi technologies and it's proven that Wi-Fi technologies are a better option for navigation systems with the least effort and cost. One of the advantages of our method is that we use any existing AP signal strengths to measure and estimate RSS at different RPs. And it will not require any extra cost to build infrastructure for navigation system implementation with proposed method usage in future.

We have been focusing on range measurement techniques in Wi-Fi based positioning technologies (Figure 1.2). The reason for selecting Wi-Fi based positioning techniques are described in Table 1.1. As mentioned above, Wi-Fi based positioning techniques will not require costly devices and infrastructure to build positioning systems.



**Figure 1.2: Positioning techniques** 

In this research, we study the accuracy of the RSS data set as radio map - fingering database for Indoor positioning based on Received Signal Strength of Wi-Fi technologies. Our research scope is received signal strength technique to solving accuracy concerns on data and reducing the time of effort to create RSS-based fingerprinting database for Indoor positioning (Figure 1.3).

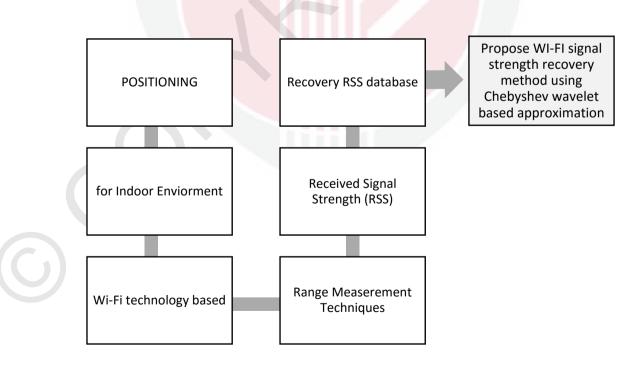


Figure 1.3: Research scope

#### REFERENCES

- Bahl P. and Padmanabhan V., (2000). RADAR: an in-building RF-based user location and tracking system. Proceedings IEEE INFOCOM 2000. Conference on Computer Communications. Nineteenth Annual Joint Conference of the IEEE Computer and Communications Societies (Cat. No.00CH37064), 2.
- Battiti R., Brunato M., and Villani A., (2002). Statistical Learning Theory for Location Fingerprinting in Wireless LANs. *Technical Report*. <u>http://rtm.science.unitn.it/\_battiti/archive/86.pdf</u>
- Bensky A., (2008). Wireless Positioning Technologies and Applications. Artech House, Inc.
- Borrelli, A., et al., (2004). Channel models for IEEE 802.11b indoor system design. 2004 IEEE International Conference on Communications (IEEE Cat. No.04CH37577), 6.
- Broughton, S.A. and Bryan, K.M., (2008). Discrete Fourier Analysis and Wavelets: Aplications to Signal and Image Processing. *Wiley*.
- Brunato M., Battiti R., (2005). Statistical learning theory for location fingerprinting in wireless LANs. *Computer Networks*. 47:825–845.
- Buchli B., Sutton F., Beutel J., (2012). GPS-equipped wireless sensor network node for high-accuracy positioning applications. *In Wireless Sensor Networks*, *Springer: Trento, Italy.* pp. 179–195.
- Chen L., Li B., Zhao K., Rizos C., Zheng Z., (2013). An improved algorithm to generate a Wi-Fi fingerprint database for indoor positioning. *Sensors 2013*, 13:11085–11096.
- Chen Y., Chiang J., Chu H., Huang P., Tsui A., (2005). Sensor-assisted Wi-Fi indoor location system for adapting to environmental dynamics. *In Proceedings of the 8th ACM International Symposium on Modeling, Analysis and Simulation of Wireless and Mobile Systems, Montreal, QC, Canada*, pp. 118–125.
- Daudi S.and Yang S., (2014). Water Quality Monitoring and Control for Aquaculture Based on Wireless Sensor Networks. *Journal Of Networks*, 9(4): 840-849
- Duda R. O., Hart P. E., and Stork D. G., (2000). Pattern Classification. Wiley-Inter science publication. *Expert Systems with Applications*, 37(9): 6165–6175
- Fallah N., Apostolopoulos I., Bekris K., Folmer E., (2013). Indoor Human Navigation Systems: A Survey. Interacting with Computers, Oxford Journals, 25(1): 21-33.

- Gallagher T., Li B., Dempster A.G., Rizos C., (2010). A sector-based campus-wide indoor positioning system. In: 2010 International Conference on Indoor Positioning and Indoor Navigation, IPIN 2010 - Conference Proceedings. pp. 1-8
- Gu Y., Lo A., Niemegeers I., (2009). A survey of indoor positioning systems for wireless personal networks. *IEEE Communication Survey Tutor*. 11:13–32.
- Gunawan, M., Gallagher T., A. Dempster G., Retscher G., (2012). A new method to generate and maintain a WiFi Fingerprinting database automatically by using RFID. In: 2012 International Conference on Indoor Positioning and Indoor Navigation, IPIN 2012 - Conference Proceedings.
- Harle R., (2103). A Survey of Indoor Inertial Positioning Systems for Pedestrians. Communications Surveys & Tutorials, IEEE 15(3): 1281 – 1293
- Hazas M., Hopper A., (2006). Broadband Ultrasonic Location Systems for Improved Indoor Positioning. *IEEE Transactions on Mobile Computing*, 5: 536-547.
- Hu, Y., et al., (2013). Efficient Radio Map Construction Based on Low-Rank Approximation for Indoor Positioning. *Mathematical Problems in Engineering*, 2013, 1-9.
- Kaemarungsi K. (2005). Design of Indoor Positioning Systems based on Location Fingerprinting Technique. *Ph.D. dissertation, Univ. of Pittsburgh, Pittsburgh.*
- Kaemarungsi K. and Krishnamurthy P., (2004).Modeling of indoor positioning systems based on location fingerprinting. In INFOCOM 2004. Twenty-third Annual Joint Conference of the IEEE Computer and Communications Societies, 2: 1012 – 1022.
- Kazemi A., Kilicman A., Babolian E., Pashazadeh Z.(2013). Wavelet analysis method for solving linear and nonlinear singular boundary value problems. Elsevier, Applied Mathematical Modelling 37 (2013) 5876–5886.
- Kelly D., McLoone S., and Dishongh T., (2008). A Bluetooth-based minimum infrastructure home localization system. *Proc. ISWCS'08*, pp. 638-642.
- Kjærgaard M.B, (2011). Indoor location fingerprinting with heterogeneous clients. *Pervasive and Mobile Computing*, 7(1): 31–43
- Kolodziej K. W. and Hjelm J., (2006). Local Positioning Systems: LBS Applications and Services. *1st ed. Boca Raton, FL: CRC Press, Taylor & Francis Group.*
- Krumm J., Platt J., (2003), Minimizing Calibration Effort for an Indoor 802.11 Device Location Measurement System. *Technical Report, MSR-TR-2003-82, Microsoft Research Microsoft Corporation One Microsoft Way Redmond,* WA 98052.

- Kuo S., Tseng Y., (2011). Discriminant Minimization Search for Large-Scale RF-Based Localization Systems. *Mobile Computing, IEEE Transactions on* 10(2): 291 - 304.
- Kwok-Wai, C., Sau, J.H.M., and Murch, R.D., (1998). A new empirical model for indoor propagation prediction. *Vehicular Technology, IEEE Transactions on*, 47 (3): 996-1001.
- Ladd A. M., Bekris K. E., Marceau G., Rudys A., L. Kavraki E., and Wallach D. S., (2002). Robotics-Based Location Sensing using Wireless Ethernet. In Proc. ACM International Conference on Mobile Computing and Networking (MOBICOM'02).
- Lassabe F., Canalda P., Chatonnay P., Spies F., (2009). Indoor Wi-Fi positioning: techniques and systems. *Springer, Ann. Telecommun.* 64: 651-64.
- Lee M., Han D., (2012). Voronoi Tessellation Based Interpolation Method for Wi-Fi Radio Map Construction. *Communications Letters*, *IEEE*, 16(3):404 – 407
- Lee S., Hong J., Hsieh C., Liang M., Wang L., (2015). Low Power Wireless ECG Acquisition and Cardiac Stimulation SOCs for Body Sensor Networks.
- Li B., Wang Y., Lee H.K., Dempster A. and Rizos C., (2005). Method for yielding a database of location fingerprints in WLAN. *IEE Proc.-Commun.*, 52(5). doi:10.1049/ip-com:20050078
- Lin S., Horng S, Lin C., (2011). An Experiment for Estimating Accurate States in Distributed Power Systems. *IEICE Transactions on Fundamentals of Electronics, Communications and Computer Sciences, E94-A (3):* 1015-1018
- Lin, T. and Lin, P., (2005). Performance comparison of indoor positioning techniques based on location fingerprinting in wireless networks. In Wireless Networks, Communications and Mobile Computing, 2005 International Conference on, 2: 1569-1574.
- Ling J., Kanugovi S., Vasudevan S., Pramod A., (2015). Enhanced capacity & coverage by Wi-Fi LTE Integration. *Communications Magazine, IEEE*. 53(3): 165-171
- Liu H., H. Darabi, P. Banarjee, Liu J., (2007). Survey of Wireless Indoor Positioning Techniques and Systems. *IEEE Trans. on Systems, Man and Cybernetics*, 37(6):1067-80.
- Liu J., Chen R., Pei L., Guinness R. and Kuusniemi H., (2012). A hybrid smartphone indoor positioning solution for mobile IBS. *Sensors 2012*, 12:17208–17233.
- Lloret J., Tomas J., Garcia M., Canovas A., (2009). A hybrid stochastic approach for self-location of wireless sensors in indoor environments. *Sensors 2009*, 9:3695–3712

- Medina C. et al., (2013). Ultrasound indoor positioning system based on a low-power wireless sensor network providing sub-centimeter accuracy. *Sensors 2013*, 13:3501–3526.
- Mengual L., Marb O., and Eibe S., (2010). Clustering-based location in wireless networks.
- Misiti M., and Misiti Y., (1996), Wavelet Toolbox User's Guide, Version 1. The MathWorks, Inc.
- Misiti Y., Oppenheim G., Paggi J.M., (2000). Wavelet Toolbox 4 Users Guide.
- Muntz R., Pancake C., (2003). Challenges in location-aware computing. *Pervasive Computing*, *IEEE*, 2(2): 80 – 89
- Narzullaev A. and Park Y., (2013). Novel calibration algorithm for received signal strength based indoor real-time locating systems. *AEU International Journal of Electronics and Communications*, 67 (7): 637-644
- Narzullaev A., Park Y., Yoo K., Yu J., (2011). A fast and accurate calibration algorithm for real-time locating systems based on the received signal strength indication. *AEU International Journal of Electronics and Communications*, 65: 305-311.
- Nasab K. A., et al., (2013). Wavelet analysis method for solving linear and nonlinear singular boundary value problems. *Applied Mathematical Modelling*, 37 (8): 5876-5886
- Pahlavan K., Li X., and Makela J. P. (2002). Indoor Geolocation Science and Technology. *IEEE Commun. Mag.*, 40(2): 112–118
- Panjwani, M.A., Abbott, A.L., and Rappaport, T.S., (1996). Interactive computation of coverage regions for wireless communication in multifloored indoor environments. *IEEE Journal on Selected Areas in Communications*, 14 (3): 420-430.
- Park, J.g., Charrow B., Curtis D., Battat J., et al., (2010). Growing an organic indoor location system. *Proceedings of the 8th international conference on Mobile systems applications and services MobiSys10*, pp. 271.
- Prasithsangaree P., Krishnamurthy, P., and Chrysanthis, P.K. (2002). On indoor position location with wireless LANs. Proc. of 13th IEEE Int. Symp. on Personal, Indoor and Mobile Radio Communications, Lisbon, Portugal, 15– 18 September 2002, Vol. 2, pp. 720–724

- Pirabaharan P., David R., Hariharan G. (2014). An Efficient Wavelet Based Approximation Method for Estimating the Concentration of Species and Effectiveness Factors in Porous Catalysts. Communications in Mathematical and in Computer Chemistry, MATCH Commun. Math. Comput. Chem. 73 (2015) 705-727
- Roos T., Myllymaki P., Tirri H., Misikangas P., and Sievanen J., (2002). A Probabilistic Approach to WLAN User Location Estimation. *International Journal of Wireless Information Networks*, 9(3): 155–164.
- Saha S. et al. (2003). Location Determination of a Mobile Device Using IEEE 802.11b Access Point Signals. In Proc. IEEE Wireless Communications and Networking Conference (WCNC'03), New Orleans, LA.
- Sharma N. K., (2006). A weighted center of mass based trilateration approach for locating wireless devices in indoor environment. In Proceedings of the 4th ACM international workshop on Mobility management and wireless access, pp. 112–115.
- Singh R., Macchi L., Regazzoni C., and Plataniotis K., (2005). A statistical modelling based location determination method using fusion in WLAN. *In Proceedings of the International Workshop on Wireless Ad-hoc Networks*.
- Small J., Smailagic A., and Siewiorek D. P., (2000). Determining user location for context aware computing through the use of a wireless LAN infrastructure.
- Tauber J. A., (2002). Indoor Location Systems for Pervasive Computing. Area Exam Report, Massachusetts Institute of Technology.
- Vahideh M., Andrew G., (2012). WiFi Fingerprinting Signal Strength Error Modeling for Short Distances. International Conference on Indoor Positioning and Indoor Navigation, 13-15<sup>th</sup>.
- Wang F., Huang Z., Yu H., Tian X., (2013). EESM-based fingerprint algorithm for Wi-Fi indoor positioning system. *Communications in China (ICCC)*, 2013 IEEE/CIC International Conference on 12-14 Aug. 2013. pp. 674 – 679
- Widyawan W., Klepal M., and Pesch D., (2007). Influence of Predicted and Measured Fingerprint on the Accuracy of RSSI-based Indoor Location Systems. 2007 4th Workshop on Positioning, Navigation and Communication.
- Widyawan, Klepal M., (2007). Influence of predicted and measured fingerprint on the accuracy of RSSI-based indoor location system. *In Proc. Of IEEE WPNC'07*. pp. 145-151
- Xiang, Z., et al., (2005). A hidden environment model for constructing indoor radio maps. *In proceedings - 6th IEEE International Symposium on a World of Wireless Mobile and Multimedia Networks, WoWMoM 2005*, pp. 395-400

- Yang Ch. and Hou J., (2013). Chebyshev wavelets method for solving Bratu's problem. Springer. Boundary Value Problems 2013, 2013:142
- Yang C., Shao H., (2015). WiFi-based indoor positioning. *Communications* Magazine, IEEE. 53(3): 150 – 157
- Yasar, M. and Ray, A., (2008). Trend detection and data mining via wavelet and Hilbert-Huang transforms. *In: Proceedings of the American Control Conference*, pp. 4292-4297
- Youssef M. A., Agrawala A., and Shankar A. U., (2003). WLAN Location Determination via Clustering and Probability Distributions. In Proc. IEEE International Conference on Pervasive Computing and Communications (PerCom'03), Dallas-Fort Worth, TX.
- Youssef M., Agrawala A., (2005). The Horus WLAN location determination system. In Proceedings of the 3rd International Conference on Mobile Systems. *Applications and Services. Seattle, WA, USA*. pp. 205–218
- Zhuang Jie., Zhang J., Zhou D., Pang H., (2014). An Improved Wi-Fi Indoor Positioning Method via Signal Strength Order Invariance. Computer and Information Technology (CIT), 2014 IEEE International Conference on 11-13 Sept. 2014. pp. 3 – 6
- Zou H., Lu X., Jiang H. and Xie L., (2015). A Fast and Precise Indoor Localization Algorithm Based on an Online Sequential Extreme Learning Machine. Sensors 2015, 15: 1804-1824