Optimization of RSSI Based Indoor Localization and Tracking using Machine Learning Techniques

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Thesis submitted in partial fulfillment of the requirements for the
Degree of Master of Science (Research) in Computer Science and Engineering

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University of Moratuwa
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February 2021

DECLARATION

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ACKNOWLEDGEMENTS

I express my humble gratitude to my supervisors Dr. Chandana Gamage, Dr. Navinda Kottege, and Dr. Sulochana Sooriyaarachchi for guiding me along the correct path in my research work while enhancing my research skills remarkably with constructive and invaluable feedback. This research becomes the turning point of my life because of being surrounded by extraordinary people who made me realize the beauty of scientific work.

First of all, I would like to express my thanks to Dr. Chandana Gamage and Dr. Sulochana Sooriyaarachchi who noticed and enhanced my research skills and motivated me to start this MSc. Also, they guided me through the challenges and strengthened me with knowledge to successfully conclude my master degree despite busy academic life.

I feel privileged to get selected for the scholarship offered by Autonomous Systems Group of Commonwealth Scientific and Industrial Research Organisation (CSIRO) in Australia. I was based in CSIRO site in Pullenvale - QLD during this research work. I would like to express my humble gratitude to all the staff members and my colleagues in CSIRO site in Pullenvale - QLD. During that period, I gathered unforgettable experiences and memories from the amazing people there.

It would have been a dream without Dr. Navinda Kottege to complete my on site practical experiments. Dr Kottege provided me with the necessary equipment and advised me to drive this research work into a reality. I never forget his generous and humble support given for me to walk through my student life.

I would like to extend my special thanks to the then Head of the Department of Computer Science and Engineering, Dr. Shehan Perera and my research co-ordinator Dr. Charith Chitraranjan for giving me advice and providing me with the necessary administrative support to properly carry out my research work.

It was a privilege to have Dr. Ranga Rodrigo as the chairperson of the progress review panel in my master degree program. I would like to extend my gratitude to all the panelists including Dr.Rodrigo for their time and effort spent on reviewing my work and for giving comprehensive and insightful feedback.

This thesis would not be a success without the help of my mother Kanthi Paranamana. I would extend my gratitude to my wife Rumeshi, all the extended family members and friends including Mr. Sanjaya Pathirana for the unconditional support and encouragement rendered to me.

ABSTRACT

Localization and tracking of persons in industrial environment is critical in terms of safety, privacy and security, particularly when there are hazardous zones. In this research, RSSI of RF signals were used to localize, track and uniquely identify a person in a cluttered environment with a case study into a doorway from a safe zone to a hazardous zone in a cluttered warehouse. Vision based localization was impractical both due to visual obstruction by moving large objects and privacy issues. There were three approaches in RF based localization reviewed in this work.This research uses the approach in which RF receivers are fixed and the transmitter is worn by the target person. RSSI data in a doorway area of 420 cm × 450 cm was analysed both in simulation and in a real test bed and it was proved that DNN and RNN based location prediction was feasible with an accuracy of over 80% even though the environment had noise in the range of ±2 dB to ±15 dB and ±7 dB on average for RF signals. The experiments carried out with a test bed consisting of Raspberry Pi-3 as receivers and Kontakt-io Tough Beacon TB15-1 module as transmitter connected over POE module to a centralized server. The results show that a bounded type RF receiver arrangement to cover the whole area with at least few receivers mounted at a high elevation to capture line of sight signals was effective in accurately localizing the person. The density of positions at which the RSSI data is collected to train the DNN also considerably affected the localization accuracy. The body attenuation was found to be another critical factor affecting the localization accuracy. When the DNN was trained with data captured at one orientation of the person, this DNN was successful in localizing a person with the same orientation but not in localizing a person in completely different orientations. This behaviour was used to detect the body orientation of a person using multiple neural network. A straight path traversed by a walking person at an average speed of 25 cm/s was successfully tracked at a point-wise accuracy over 80% using time series RSSI data with a threshold of 25 cm. The threshold was reduced to half by averaging the data over three consecutive predicted positions in the form a centroid. Lastly, Time-domain based RSSI data were used to train RNNs. Deep-LSTM model showed around 95% path-wise localization accuracy for constructed walking paths. Also, RNNs were able to detect the walking direction in single RNN network compared to multiple DNN approach. Finally, this research was able to uniquely identify, localize, detect body orientation and track the walking path of a person and since the person is uniquely identified and RSSI data is MAC addressed this work can be extended to localization of multiple persons.

LIST OF FIGURES

Figure2.1 Three basic RSSI based localization approaches 12

Figure3.1 Framework for selecting suitable approaches for proposed RSSI based localization system 22

Figure3.2 RF signal propagation paths and consequence 26

Figure4.1 Target tracking area and the a receiver arrangement 32

Figure4.2 Visualization of distance array elements with respect to receiver arrangement and transmitter position 34

Figure4.3 System block diagram 35

Figure4.4 Used basic electronics devices 36

Figure4.5 Time synchronization procedure for RF receivers and data collection procedure using time stamps with position coordinates 37

Figure4.6 Camera based position coordinates vs manually collected position coordinates 39

Figure4.7 DNN structure for analysing RSSI data 40

Figure4.8 Visualization of localization error and error margin 41

Figure4.9 Labels of DNN models according to the number of neurons in three hidden layers 42

Figure4.10 Model numbers vs resulted highest accuracies of the models accordingly three learning rates 43

Figure4.11 Accuracies of DNN models according to the number of neurons in three hidden layers 43

Figure4.12 Explaining two walking direction of the target person relative to the test-bed 44

Figure4.13 Receiver arrangements 45

Figure4.14 Top view of receiver arrangement for real RSSI data collection 45

Figure4.15 Subset of position coordinates 46

Figure4.16 Temporal RSSI data extraction method for RNN 47

Figure4.17 Basic structure of the standard LSTM network 48

Figure4.18 Block diagram representation of stacked-LSTM layers combined with fully connected regression layers in proposed Deep-RNN network 49

Figure5.1 Variation of RSSI value with distance for ideal (equation 3.1) and noisy environments (equation 3.2) 54

Figure5.2 Test setup diagram of calibrating the relation between RSSI vs Distance 54

Figure5.3 Average RSSI vs nominal distance between BLE-Beacon and five RPIs 56

Figure5.4 Validation accuracy Vs training iteration of five different RPI arrangements 59

Figure5.5 Accuracy of the DNN when RSSI data collection position density increased from Dataset-1 through 4 60

Figure5.6 Prediction from Forward-DNN and Backward-DNN model for similar two walking path section 61

Figure5.7 Four real paths and relevant predicted positions given by Forward-DNN model 63

Figure5.8 Improving walking path accuracy using centroid of consecutive RSSI arrays over the time 65

Figure5.9 Constructing a walking path using prediction outputs from Deep-LSTM networks 71

Figure5.10 Plotted walking path predictions for two walking directions by the Deep-LSTM model 72

LIST OF TABLES

Table 2.1 Comparison of related research in person localization and tracking 13

Table 2.2 Summary of conclusions drawn from previous research in RSSI based indoor localization 20

Table 4.1 Path loss exponents (η) of RF signals in different environments 32

Table 4.2 Level-3 configuration used in Tough Beacon TB15-1 module 36

Table 5.1 Training and validation accuracies of DNN models for five RPI arrangements in figure 4.13 58

Table 5.2 Localization accuracies of four DNN models for RSSI data position coordinate density 60

Table 5.3 Localization accuracies and resulted threshold levels of four LSTM models for single layer LSTM model architecture 67

Table 5.4 Localization accuracies and resulted threshold levels of five stacked LSTM models for select suitable number of LSTM layers and units for RSSI data 67

Table 5.5 Localization accuracies for different time steps based LSTM 69

LIST OF ABBREVIATIONS

GPS	Global positioning system
PPE	Personal protective equipment
OSHA	Occupational safety and health administration
RF	Radio frequency
TOF	Time of flight
TDOA	The Time difference of arrival
DOA	Direction of arrival
RSSI	Radio signal strength indication
LQ	Link quality
WSN	Wireless sensor network
RPI	Raspberry pi
ML	Machine learning
NN	Neural network
DNN	Deep neural network
BLE	Bluetooth low energy
NLOS	Non Line Off Sight
LOS	Line Off Sight
Hz	Hertz
RFID	Radio frequency identification
WPAN	wireless personal area networks
IEEE	Institute of Electrical and Electronics Engineers
WLANs	wireless local area networks
Mbit/s	megabit per second
CDMA	Code-Division Multiple Access
LF	Low Frequency
HF	High Frequency
UHF	Ultra-High Frequency
POE	Power Over Ethernet

CSIRO	Commonwealth scientific and industrial research organisation
MNN	Multiple neural network
LF-DLSTM	Local feature-based deep long short-term memory
BPANN	Feed-forward back propagation artificial neural network
RMSE	Root mean square error
IoT	Internet of Things
LoRaWAN	long-range wide-area network
UWB	Ultra Wideband
NN-HMM	Hierarchical neural network hidden Markov model
RBF	Radial Based Function
ReLU	Rectified linear units
COTS	commercial off-the-shelf
NTP	Network time protocol
CNN	Convolution neural network
RNN	Recurrent neural networks
MSE	Mean squared error
MAE	Mean absolute error

TABLE OF CONTENTS

List of Figures vi

List of Tables viii

List of Abbreviations ix

Table of Contents xi

1 Introduction 1

- 1.1 Problem statement 4
- 1.2 Objectives 4
- 1.3 Research Contributions 4
- 1.4 Thesis Outline 5

2 Literature Review 6

- 2.1 RSSI based indoor localization 6
  - 2.1.1 Model-1: Transmitter on target 6
  - 2.1.2 Model-2: Receiver on target 8
  - 2.1.3 Model-3: Device free localization type approaches 10
  - 2.1.4 Summary of RSSI based approach 11
- 2.2 RSSI based indoor localization accuracy improvements 14
  - 2.2.1 Machine learning technique based approaches 14
  - 2.2.2 Data capturing enhancements based approaches 16
  - 2.2.3 Summary of localization accuracy improvements 19

3 Methodology 21

- 3.1 Selection of the RSSI based localization model 21
- 3.2 Selection of RSSI parameters for measurements 24
- 3.3 RSSI measurement approach 25
- 3.4 RF receiver arrangement 27
- 3.5 Method of analysing RSSI data 27
- 3.6 Summary 29

4 Experimental Setup 30

- 4.1 Target tracking terrain 31

4.2 The relationship between RSSI readings vs distance 31
4.3 Simulation for RSSI based indoor localization system 33
4.4 Capturing RSSI radio map in real testbed 35
  4.4.1 Hardware 35
  4.4.2 Capturing time synchronized RSSI arrays 36
  4.4.3 Annotating RSSI arrays with transmitter position information 38
4.5 Deep Neural Network approach for analysing RF signal based data 39
  4.5.1 Preparing the dataset for DNN based analysis 42
4.6 Recurrent Neural Network approach for analysing Temporal-RSSI data 46
  4.6.1 Preparing the datasets for RNN based analysis 50
4.7 Summary 51
5 Results and Discussion 53
5.1 The relationship between RSSI readings and distance between transmitters and receivers 55
5.2 Feasibility of using DNN for analysing RSSI data 57
5.3 Effect of the number and arrangement of RF receivers 58
5.4 The effect of position coordinate density for RSSI based localization accuracy 59
5.5 Effect of body orientation on RSSI based localization accuracy 61
5.6 Improving tracking and localization accuracy in realtime using DNN predictions 63
5.7 Improving tracking and localization accuracy using time-domain filtered RSSI data 66
5.8 Implementing RSSI body attenuation effect using single RNN network and improving accuracy by analyzing the time steps 68
6 Conclusion 73
References 77

Chapter 1

INTRODUCTION

Person localization and tracking is useful in many areas of applications such as transportation and logistics, disaster management, military, and health care. Localization and tracking applications are not only useful in improving the lifestyle and efficiency of the mankind but also in protecting endangered species and their natural habitats. ‘Indoor localization’ is a major aspect of localization due to technical limitations such as global positioning system (GPS) like common technologies are not working in indoor environments [1]. Large scale building structures such as factories, warehouses, hospitals, education centers, skyscrapers and hotels are not simple structures anymore for supplying the growing demands for goods and services around the globe thus making indoor localization a complex task.

Indoor person localization and tracking is important in terms of worker safety concerns, especially in industrial processes. Tracking and localization systems provide an extra layer of protection in hazardous working environments. This can also be considered as a necessary requirement in Personal Protective Equipment (PPE) mentioned in Occupational Safety and Health Administration (OSHA) act in USA. A continuous and reliable tracking system or multiple systems are required in indoor localization applications that have safety as a priority [2].

Existing indoor localization approaches can be categorized into cooperative and non-cooperative methods. Non-cooperative systems are advantageous because they function without any devices attached to the target person. However, these systems in general fail to uniquely identify the persons except for vision systems with face recognition capability. In a cooperative tracking system the target person should carry a device or a part of a tracking system. In this approach person identification is straight forward. Several technologies, such as video, pressure, infrared, and ultrasound, have been proposed. These technologies are usually costly, including infrastructure, deployment, and maintenance, and have restrictions placed on the environments in which they are applied.

Video-based face recognition systems are a popular non-cooperative method that has been used to identify, localize and track a person in an indoor environment. However, they fail in continuous tracking of a target person in cluttered environments, for example, the target would be blocked by obstacles [1] or the target would be missed in blind-spot areas.

Radiation based detection is another popular approach that has been used to identify a person in an indoor environment. Change of radiation levels due to human activity is used for identifying the presence of a person and the activities. LiDAR, Radar, Ultrasound, and RF-based technologies are the mainly used radiation-based technologies in indoor localization. LiDAR, Radar like technologies require high processing power and costly equipment to operate. Also, these signal waves are blocked by obstacles. RF-based signals, for example, WiFi, RFID, Zigbee are able to penetrate through the barriers. Moreover, RF technologies are suitable for indoor localization by considering their wide availability, affordable cost, reliability, and accuracy. However, continuously tracking of multiple persons in real-time with their identity in an indoor cluttered environment is difficult because radio signals are sensitive to many effects such as attenuation, distortion, and reflection.

RF-based technologies are able to detect a target in hazardous environments. RF technologies have been used in both cooperative and non-cooperative ways particularly in industrial applications. Non-cooperative RF approaches are unable to capture person-wise information and therefore it cannot do multiple target localization. Therefore we consider RF cooperative approaches in this study.

There are many types of information given by RF based technologies, such as the Time of Flight (TOF) ,the Time Difference of Arrival (TDOA), the Direction of Arrival (DOA), Radio Signal Strength Indication (RSSI) [3, 4], Link Quality and Transmit Power Level [5]. TOF and TDOA information are not accurate without using nano-level clock synchronization for short distance monitoring. RSSI measurement is one of the trust worthy measurements that can be used to localize the location of a target.

A number of commercial systems and research prototypes currently exist for indoor localization such as Sonitor [6], Ekahau [7], and Ubisense[8]. Some of these devices are high-cost and not compatible with all types of environments and applications. In this research we focus on important parameters and factors of RSSI based indoor localization to improve the accuracy.

Many techniques have been used to analyse RF signal based data to optimize localization accuracy [9, 10, 11, 12, 13]. The traditional analysis approaches such as mean-variance modeling methods, sigma point Kalman filter are less effective as their accuracy is saturated in changing environments. Especially, continuous tracking in a noisy environment is challenging due to the fact that RF signals are affected by many events. Latest Machine learning approaches [14, 15, 16] are shown to be more suitable and proved to reach a higher accuracy of around 95% for RF signal based person localization.

Real-time person localization in terms of their walking paths is a challenging task to achieve, due to RF signals are affected by many impairments such as attenuation, reflection, and distortion. However, accuracy of tracking the walking path has been improved using the latest Recurrent Neural Network approaches based on time domain-based RSSI fingerprints as mentioned in [17, 18, 19, 20].

1.1 Problem statement

This study focuses on a practical scenario in which a person enters from a safe zone to an extremely hazardous zone by walking through a small doorway. This scenario is common in industrial workplaces for example where workers move from forging, moulding, machining, welding chambers through doorways. It is important to track and monitor the person's movement through such doorways. Further, vision based tracking are not allowed when such workplaces are secured with strict confidentiality. The workplaces are cluttered with large object carried so that vision systems will often fail to capture the tracked persons.

In this research we explore human localization and tracking using RSSI of RF signals in an indoor cluttered doorway. We also explore machine learning based techniques to improve the localization accuracy.

1.2 Objectives

- To develop a hardware and software system to collect RSSI data in an identified indoor cluttered environment
- To develop a method to optimize localization and tracking accuracy

1.3 Research Contributions

A testbed was implemented using a BLE transmitter as a wearable device and fixed receivers to collect RSSI data in an indoor cluttered doorway and the experiments lead to the following conclusions:

- The number and the arrangement of RF receivers, the position coordinates density of collecting RSSI data and the body orientation of the target person who carries the transmitter are critical factors that affect localization accuracy.

- DNN was feasible in localizing the person and even time series RSSI data is successfully analysed with DNN to predict the walking path of the person.
- Multiple DNNs each trained with RSSI data pertaining to different body orientations can successfully used to detect the body orientation of the target person.
- Deep-LSTM performs better in detecting both body orientations and improving walking path accuracy compared to DNN approaches.

1.4 Thesis Outline

In this work, RSSI data recorded by RF receivers is analysed by Neural Networks and it was found to successfully localize and track a person in an indoor cluttered environment. The related research work in indoor localization and signal processing techniques is reviewed in Chapter 2 to find a research gap. Our methodology is presented in Chapter 3. Chapter 4 presents the experimental design along with the design of hardware and software architecture of the proof of concept system. Here, the important factors affecting the localization accuracy and suitable parameters for DNN and RNN structure are presented. In Chapter 5 the experimental results are presented and discussed including the effect of numbers and arrangements of RF receivers and RF signal attenuation through the body of the target person for localization accuracy. Finally the thesis concludes with Chapter 6.

Chapter 2

LITERATURE REVIEW

In this chapter, we set the theoretical background for devising a solution to improve the accuracy of RSSI based person localization in an indoor cluttered environment. Firstly, we present the most related previous work in this area of research.

2.1 RSSI based indoor localization

There are several research attempts in indoor localization [21, 14, 22, 23, 15, 16, 24, 17]. Three basic models can be identified for RSSI based real-time person tracking in the above research. The first model is where the tracked object has to carry a RF transmitter such as an active RFID tag to periodically transmit beacon messages with information such as the ID. Multiple receivers such as RFID readers with known locations may measure the RSSI values of received beacon messages and collectively estimate the locations of the target objects [3]. In the second model, the target object has to carry a receiver, for example a mobile phone. The target object is able to receive RSSI information from nearby transmitters and estimate its current location using the RSSI value of received data packets[11, 25]. In the last model, target object carries neither a transmitter nor a receiver. Pre-located transmitters and receivers for example a Wireless Sensor Network estimate the RSSI changes due to the arrival of a human body [26, 27].

2.1.1 Model-1: Transmitter on target

The work by Altini et al[16] is a prominent research that can be considered under the Model-1 approach. They proposed a novel approach for indoor localization using Bluetooth RSSI signals and data analysis using machine learning technique.

They used Bluecove JSR-82 modules as the transmitter mounted on the target person. In addition to that a Honeywell-HMC6352 compass module has been used to collect the information about user orientation. This research emphasizes on the importance of the direction of movement of the person when collecting RSSI data. They used a combination of Neural Network (NN), Multiple Neural Network (MNN), and Decision Tree techniques to localize the target and predict the direction of movement. A 90% precision and a 0.5 meter accuracy were achieved during a walk along the corridor. Their work is limited to the detection of the person at any of the 8 selected positions rather than the whole corridor.

In the work by Chen et al[17] the person carries a smart phone as the transmitter and there fore it can be considered under Model-1 approach. Their research proposed a local feature-based deep long short-term memory (LF-DLSTM) approach for WiFi fingerprinting indoor localization. They changed the configuration of TP-LINK WDR4300 WiFi routers to operate as a RF receiver to collect RSSI from the smart phone. Two different environments have been set up in this research; (i) a complex research lab environment and (ii) a highly complex office and the routers were mounted on top of the arena to collect line of sight signals. Mean localization errors of 1.48 m and 1.75 m were achieved in the two environments above respectively. This work proves that Model-1 approach is suitable for complex environments. However, The orientation of the person has not been considered in this research.

Sahin et al[24] experimented a different approach in indoor localization using RF-based RSSI signals under the Model-1 approach. They developed smart tags that operate as beacons with different transmit power levels to be carried by the target persons. These tags were able to operate as receivers as well. RF receivers known as local and global readers were arranged in this research in a way that the target area inside a lab was covered and these receivers were assigned different duties. The researchers used Monte Carlo simulations to find the location of the target and achieved a 96% accuracy. This work highlights the importance of time synchronization of RF receivers and the hardware arrangement of the test-bed to collect more line of sight signals.

2.1.2 Model-2: Receiver on target

Sabto et al [14] conducted research to navigate a robot between any two identified locations using RSSI signals of Radio-Frequency Identification (RFID) tags. In this research the robot carried an RFID tag configured to work as a receiver and therefore this work is considered under the Model-2 approach. The robot can locate itself depending on the classification result provided by a feed-forward back-propagation artificial neural network (BPANN). Ultrasound sensors were used to calculate the actual distances in a given test-bed. After successfully training the BPANN classifier, a minimum of 0.02m Root Mean Square Error (RMSE) was resulted between the Calculated and Actual distances of robot movements. Continuous tacking was implemented in this research.

Sadowski et al [22] proposed a Model-2 type indoor localization approach using Internet of Things (IoT) wireless technologies. The receiver carried by the target person was a mobile phone. This research experimented with four IoT based wireless technologies namely, Wi-Fi, Bluetooth Low Energy (BLE), Zigbee, and long-range wide-area network (LoRaWAN) for indoor localization. RSSI values of the above four technologies were used and the location was estimated using tri-lateration. Two test-beds were used in this research; (i) A research lab as a noisy environment due to the availability of large number of computers, WiFi and BLE devices that cause radio interference and (ii) A meeting room as an ideal environment. Three transmitters per each of the four technologies were used and the received RSSI signals were used to estimate the position by simple tri-lateration. WiFi resulted in the lowest error level whereas LoRa recorded the highest error. BLE and ZigBee recorded the second and third error levels respectively. The maximum accuracy was 1 m for any of the technologies above. BLE showed the highest accuracy in the noisy environment i.e. (i) above while WiFi showed the best results in the ideal environment i.e. (ii). However, the error also increased when the distance increased.

Elbakly et al [21] used an existing WiFi network to accurately identify the user's floor level in a noisy environment using mobile phones. The WiFi RSSI data is analysed in this research using a multi-layer perception neural network. The system is able to accurately identify the user's exact floor level at an accuracy of 91.8%. It recommends using neural networks, particularly Multi-Layer perception Neural Network for analysing noisy data. However, this research merely identifies the floor level of the person rather than continuously tracking the person over the floor.

Gharat et al [23] present a Model-2 type indoor localization system using on Low Frequency (LF) RFID, Ultra-High-Frequency (UHF) and Ultra-Wideband (UWB). TOF data was collected for UWB while RSSI data was collected for other two technologies. Furthermore, their experiments involved three environmental conditions, namely smooth, medium, and extremely noisy environments set up is a total area of around 315 square meters. Data was collected at 352 positions spread over all the three environment conditions using receivers at Non Line of Sight (NLOS) arrangement. They estimated the 2D position using the above TOF and RSSI data and created a 2D position error map. These maps were compared among the three technologies and concluded that UWB with TOF outperforms the other two technologies with a mean positioning error of 0.58 m. However, TOF measurement required a high cost high precision equipment. The LF-RFID technology was the low cost solution and the mean positioning error for this technology was 1.53m with a standard deviation of 0.91 m. UHF showed the worst performance. Their environment characterized as "extremely noisy" consisted of heavy metal barriers and thus it can be considered as an example for a cluttered environment. This research recommended LF-RFID as a low-cost, accurate technology for cluttered environments.

2.1.3 Model-3: Device free localization type approaches

Paul et al[28] conducted a research on device free person localization using RSSI of RF signals which can be considered as a Model-3 type work. Nine EmbedRF access-points were mounted on the wall to capture the changes in RSS values. The radio field is disrupted when a person moves through the room and this results in changes of the RSS readings recorded by the access points and hubs. A hierarchical neural network hidden Markov model (NN-HMM) classifier is used for estimating the movement patterns and to detect whether the person is standing or walking. The room was divided into several regions and the person was detected to be in a particular region with an accuracy more than 90%. The system was also capable of estimating the number of people in a given region. Research showed that the classification accuracy decreases over the time due to background changes of the tested arena when the testing was conducted over several weeks. In a cluttered environment the background will rapidly change over hours and this impact of the time on the accuracy will be more critical in such environments. Furthermore, the system was able to estimate the walking speed at an RMSE of less than 8 cm/s using timing information between RSS link crossings.

Dian et al [26] proposed a method to track transceiver-free objects using RF signal dynamics and therefore this work can be considered under Model-3 type. They place an array of MICA2 sensor nodes in a grid arrangement on the roof in an empty room of 129 square meters. The non line of sight signals reflected by the objects in the room are observed. These signals are distracted by a person who walks across the room and this signal changes are used for localizing the person. They introduced three localization algorithms known as midpoint, intersection, and best-cover. The best-cover algorithm achieved the highest localization accuracy of 0.99 m and this algorithm has the potential to track multiple objects after sufficient calibration.

2.1.4 Summary of RSSI based approach

Three models of localization were introduced in the previous sections, namely, Model-1, Model-2 and Model-3. All these three models operate in a process consisting of two stages, namely, calibration and prediction. All the models are required to create a data structure known as an RSSI radio map during the calibration phase. An RSSI radio map records RSSI signal values against the location coordinates in the selected area. In the prediction phase the location is predicted based on the observed RSSI value by looking up the RSSI radio map. This prediction is used to navigate or track moving objects. The basic structural arrangement of these three models are compared in figure2.1.

In a Model-1 system, a person carries a small sized wearable device with low processing capabilities and low power unlike in Model-2. This feature is useful in continuous monitoring of persons in safety critical industrial applications. However, Model-1 requires to gather the data to a centralize system to monitor and track a person. Time synchronization is important in model-1 type system to construct an accurate RSSI radio map. Model-1 type approach is widely used in target monitoring applications while Model-2 is used in direction guidance applications. In Model-2 type systems the wearable device requires sufficient processing power to analyse the received RSSI data in order to get the position of the target in real time. Model-2 is not suitable for monitoring the target because the object having only a receiver cannot report its location back to a central monitoring station. Moreover, Model-2 systems can be modified to work as Model-1 systems by incorporating a transmitter to report its coordinate to the central server.

All the three models are able to track multiple targets but, only Model-1 and Model-2 are able to uniquely identify each target using the MAC addresses [29] of the wearable devices. This feature is useful in person monitoring applications that prioritise security and safety for example industrial worker safety and monitoring

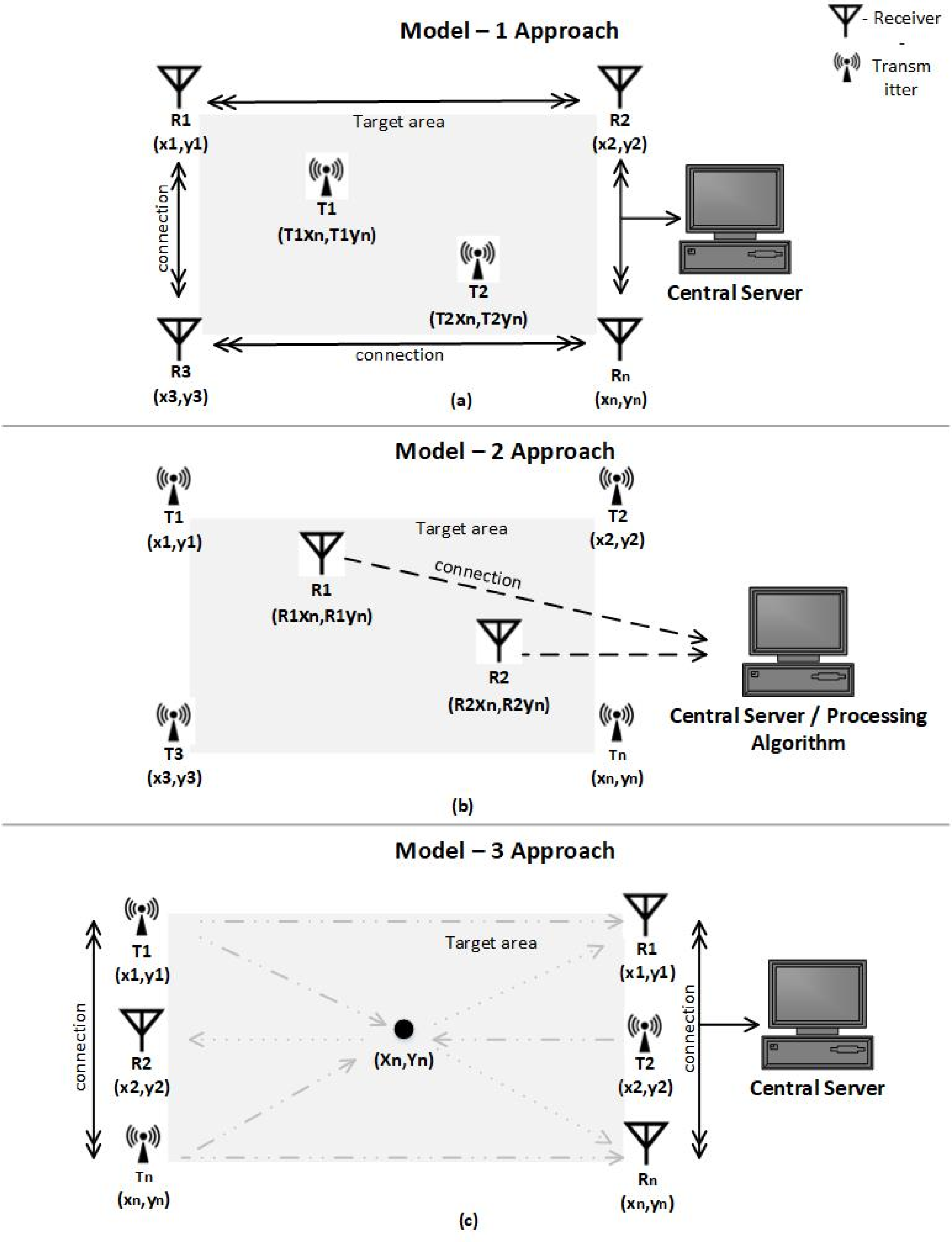


Figure 2.1: Three basic RSSI based localization approaches

Features / Research References	[28]	[26]	[16]	[17]	[21]	[24]	This work
Detect presence of person	✓	✓	✓	✓	✓	✓	✓
Identify the person	X	X	✓	✓	X	✓	✓
Detect direction of person movement	✓	✓	✓	X	X	✓	✓
Detect multiple persons	✓	✓	X	X	✓	✓	✓
Identify multiple persons	X	X	X	X	✓	✓	✓
Classify region of presence	✓	✓	✓	✓	✓	✓	✓
Track all points in region	X	✓	X	X	X	X	✓
Support for cluttered environment	✓	X	X	✓	✓	X	✓
Real time tracking	✓	✓	✓	✓	✓	X	✓
Use machine learning based approaches	✓	X	✓	✓	✓	X	✓

Table 2.1: Comparison of related research in person localization and tracking

applications. As stated in the OSHA act in USA, workers must be continuously monitored to detect unsafe conditions and to protect from potential injuries and fatal accidents in work place. Park et al [30] proposed a system to continuously monitor using BLE-based location detection technology and manually identify all the potential risky incidents based on the prior knowledge about the work site.

Model-3 is able to detect a target in a given area without capturing the identity of the target. This model also requires a centralized system to analyse the data. In conclusion, Model-1 approach is suitable to track multiple targets moving in a selected cluttered indoor area and this approach has a high potential to enhance worker safety in hazardous working environments. More details and different features in each model are described in Table 2.1. Table 2.1 presents the conclusions drawn from the above analysis in designing the proposed solution in this research.

2.2 RSSI based indoor localization accuracy improvements

Different techniques have been used for predicting the location using the RSSI data. Traditional statistical techniques are also used based on variety of mathematical models that infer the relationships between variables such as RSSI values and relevant coordinate positions. A few examples of such statistical models are midpoint, intersection and best-cover algorithms proposed by Dian et al [26] for tracking person movement. Similarly, Sigma-point Kalman Filter used in Anindya et al[4], linear, compensated linear and multiple regression methods used in Chen et al [3] are statistical models for analysing RSSI data. Further, Chen et al[3] shows that the location error increases when the signal strength error increases particularly when the target arena is large. On the other hand Palumbo et al [11] infer the user position based on stigmergy. They exploit the stigmergic marking process [31] to create an online probability map for user position in an indoor environment. Hossain et al [5] proposed a hybrid system that involves both RSSI and LQ that gives the maximum localization accuracy compared to the case when either RSSI or LQ is separately used. However, RSSI data analysis using statistical based approaches show poor accuracy due to noise in RSSI data. Therefore, machine learning models were explored as they are designed to make the most accurate predictions possible compared to statistical techniques.

2.2.1 Machine learning technique based approaches

Machine learning techniques have shown high accuracy level compared to traditional mathematical and optimization algorithms in the presence of noisy type data. This is also concluded by Ahmadi et al [32] in their survey on machine learning techniques for localization in WSNs using RSSI. Another work that proves the capability of neural networks in tackling noisy measurements is found in [16]. Neural networks are widely used as above when the correlation between the input and output values of a system is unclear or subject to noise. Altini et al [16] have used both Multiple Neural Networks (MNN) and Neural Networks (NN) models to localize the target. Main factors studied in the above research are proper placement of Access Points and transceivers (APs) and range of location error [3].

Simulation data is also useful to understand the basic behavior of RSSI. A simulation study by Tian et al [33] proposed a Radial Based Function (RBF) based NN approach to improve the RSSI localization accuracy. This simulation addresses multi-route propagation and the complexity of signal attenuation environment. However, it takes a longer time to predict the location due to large number of computations and this model does not automatically adapt to the varying RSSI data according to the environment.

Further studies into use of DNN for highly noisy data called bio-activity data in [34] found that optimized DNNs obtained statistically better performance compared to popular shallow methods such as Bernoulli Naive Bayes, k-nearest neighbor, random forest and support vector machines. Several research works such as [35] and [34] further gives the following findings related to the selection of hyper parameters:

- Rectified linear units (ReLU) activation function performed better than Sigmoid or Tanh
- The number of hidden layers should be at least 2 or 3 in order for DNN to achieve strong performance. It has not been beneficial to increase the number of hidden layers above 3
- The number of neurons per hidden layer was found to depend on the dataset and should be optimized on a case-by-case basis
- Learning rates of 1,0.1,0.01,0.001,0.0001 were better choices.

Hsieh et al[19] has proposed a robust algorithm for indoor positioning system using an available dataset online. Their proposed RNN based WiFi RSSI analysis achieved 99.7% accuracy for predicting which floor the sensor belongs to with a distance error of around ± 2.7 meters. Also, they analysed the dataset both as a regression problem and as a classification problem. Multiple layer LSTM RNN networks have showed the highest accuracy for the given dataset in their work.

Zhuo et al[20] proposed an indoor localization model to track and monitor a target person in two types of indoor environments, namely a LAB and a warehouse scenario. They mount IoT devices, namely a user tag on the target person's helmet and Bluetooth gateways on top of the storage rack. These Bluetooth gateways receive Bluetooth signals sent by the user tags. The authors used a LSTM type neural network combined with typical tri-lateration method to analyse the Bluetooth RSSI signals. This system can achieve around 0.9 m and 1.5 m localization accuracies in LAB and warehouse scenarios, respectively.

Minh et al[18] experimented on enhancing the localization accuracy using temporal fluctuations of WiFi-RSSI signals with an in-house measurement dataset and a published dataset (UJIIndoorLoc). They used different types of RNNs including vanilla RNN, long short-term memory (LSTM), gated recurrent unit (GRU), bidirectional RNN (BiRNN), bidirectional LSTM (BiLSTM) and bidirectional GRU (BiGRU) to optimize localization accuracy. LSTM and Bi-LSTM resulted in higher accuracy of around 80% within a threshold of 1 m and the average localization error was 0.75 m.

2.2.2 Data capturing enhancements based approaches

The following three parameters were identified from previous work in RSSI based indoor localization as key parameters that affect localization accuracy:

- The number of devices (transmitters or receivers) involved and their spatial configuration
- Orientation of the target person and RSSI body attenuation effect
- Continuous tracking with different walking speeds

Two different environments were used in [17]; (i) a complex research lab of 35.3 m 16.0 m, and (ii) a highly complex office environment of 55.0 m 50.0 m. Nine routers were used in 568.4 m^2 lab and 20 routers were used in 2750 m^2 size office environment. There are 102 reference points and 353 reference points used in lab and office environments respectively. An average of 63.1 m^2 was covered per a router in the lab and an average of 137.5 m^2 per a router in the office. A single data point represents an area of around 5.5725 m^2 in the lab and the area represented by a data point in the office is about 7.7904 m^2. A mean localization error of around 1.48 m and 1.75 m resulted for 10 and 30 test reference points in the lab and the office area respectively. However, results have shown that mean localization error for 100 reference points in the office environment has increased to 2.0 m level.

According to the statistics in [17] above, the number of devices and the number of training data samples directly affect the RSSI based localization accuracy. Here, Chen et al have used eight different ML approaches (ANN, ELM, SVR, WKNN, SDA, DELM, DLSTM, LF-DLSTM) to analyse the RSSI data and Deep-NN based approach showed an accuracy improvement by 40% to 50% compared to the lowest (ANN) resulted accuracy in both environments. However, this work did not consider the body orientation of the tracked person and all the routers were mounted on top of the roof therefore NLOS paths were not captured. They also did not implement continuous tracking of the walking path in real time.

The work in [16] used a Honeywell-HMC6352 compass module to collect the information about user orientation. They mainly monitored 8 selected position in a 20 m long corridor using 5 RF receivers. An important observation in this research was that some of the receivers were unable to read the transmitter signal in certain points on the corridor. They used multiple NN to address this situation. They did not change the positions of the receivers or the numbers of receivers during the experiment. They noted that the systems performance is slightly reduced if the user is walking. The lowest accuracy was 2.5 m and the highest was 0.5m at a 90% precision. MNN and Decision Tree techniques are useful approaches for achieving high precision and high accurate predictions.

In the work described in [24] the authors used a room with an area of of 6m X 7m and a height of 3m. They setup this room with 2 receivers at one time and with 5 receivers next time. Accuracy has increased when the number of receivers were increased. Then, two neighbouring rooms were also tested with 3 receivers and 10 receivers separately. Accuracy also increased in 10 receivers setup.

A system known as TrueStory is built in [21] that uses existing WiFi routers were used to estimate the floor level of a person. They used three buildings; (i) shopping mall of 11614m^2 with 3 floors, (ii) Building-1 of 7114m^2 with 4 floors and (iii) Building-0 of 2725m^2 with 4 floors. An accuracy of 91.8%, 86% and 84% was recorded for the shopping mall, Building-1 and Building-0, respectively. Shopping mall had 35:28:38 routers in the three floors, Building-1 has 51:27:21:22 in the four floors and routers Building-0 has 15:18:14:14 routers in four floors. MLP-based model is proposed to analyse the RSSI data and TrueStory can accurately identify the floor level of a user for around 90% of the times and accuracy of the floor level prediction was 99%. It was proved that more routers per area gave more accuracy.

In the work described in[23], used LF-RFID, UHF-RFID based RSSI signals to improve localization accuracy inside a large indoor environment of 315 square meters. They marked 352 points separated by 0.2 m from each other inside the area to collect the RSSI data. Also 31 points used for calibration. LF-RFID based positioning system recorded an accuracy of 1.53 0.91 m for 352 position estimates compared to 3.78 2.12 m achieved using the UHF-RFID based positioning system. Six RF transmitters of LF-RFID and UHF-RFI were arranged in the edges of the target tracking area. However, data collecting point density and the transmitter arrangement was not changed in this experiment.

As already explained in section 2.1.3, the researchers in [28] used a small apartment of approximately 9m x 7.5m in size to estimate both the movement patterns and the status whether the person is standing or walking to perform accurate tracking. They installed 9 APs and 1 hub by marking 7 regions in the apartment. Also, they removed 4 APs and tested for the tracking accuracy. NN-HMM classifier was used to analyse the RSSI variation and the results showed that the accuracy level decreases over 1 month due to the changes made in the environment. Accuracy that the person was detected to be standing was 97% and that for walking was 96% with a maximum walking speed of 8 cm/s.

Minh et al[18] studied accuracy of tracking a walking path at different walking speeds. According to the results, the average error stayed stable at a value of around ± 0.85 and ± 0.75 m when the maximum speed increases from 0.5 m/s to 2.5 m/s while a LSTM model was in use.

2.2.3 Summary of localization accuracy improvements

Recurrent Neural Networks and Deep Neural Networks based approaches were successful in analysing RSSI data compared to several other machine learning techniques as reviewed in the literature above. Main factors affecting localization accuracy were RF-Receiver arrangements and data collecting location density. For example when the number of receivers per unit volume of space increased the accuracy has increased in the above literature [17, 18, 19, 20, 21, 24, 28]. However, these receiver arrangements were also a critical factor, for example when there are more receivers at LOS paths have given better results in the previous literature [23].

However, most of the research has not considered RF signal attenuation through body of the person and the resulting impact of the orientation of the person in RSSI data collection. The work by Altini et al[16] that considered body orientation, used Multiple Neural Network (MNN) and Decision Tree depending on the orientation to accurately track the person. Table 2.2 shows the main conclusions drawn from the literature review.

References	**Factors in RSSI based localization**	**Contribution taken to this research**
[4] [22] [16] [24] [5]	RF technologies and devices: Wi-Fi, BLE, ZigBee	BLE-Beacon technology is more suitable and reliable
[36] [37] [5] [21] [14] [3] [4]	RF signal parameters for analysis	RSSI and LQ are the best parameters for RF based localization
[26] [38]	Signal dynamic behaviour of the RF signals	Mathematical model of RF signal for simulating the signal behaviour
[3] [11] [25] [26] [27]	RSSI based indoor localization approaches: Model-1, Model-2 and Model-3	The Model-1 approach suits safety critical applications in indoor cluttered environments
[4] [26] [3] [11] [32] [16] [17]	Optimization and tracking algorithms for higher localization accuracy	Machine learning is suitable for noisy RSSI data analysis
[39] [15] [40] [16] [41] [3] [23]	Analysis of environmental factors that reduce the localization accuracy (Body attenuation, Background noise)	Multiple NN approaches can be used to detect the direction of target person
[23] [15] [16] [22]	Background parameters that affect localization accuracy	Orientation of person, RF-receiver arrangement and density of training data set directly effect on accuracy
[17] [20] [19] [18]	Walking path accuracy is affected by walking speed	Deep-RNN models are suitable to optimize walking path accuracy.

Table 2.2: Summary of conclusions drawn from previous research in RSSI based indoor localization

Chapter 3

METHODOLOGY

The problem addressed in this research is to improve the accuracy of RSSI based indoor person localization in cluttered environments. The application scenario in concern in this research is for safety and security and it is undesirable to use any vision based techniques for person localization. Further, the vision based techniques are unusable due to the cluttered nature of the environment. The problem can be decomposed into the following sub problems:

1. Selection of a suitable RF based localization model
2. Selection of suitable RSSI parameters for measurement
3. Selecting a proper RSSI measurement approach
4. Identifying a suitable approach to collect data
5. Identifying a suitable data analysing technique

This chapter presents the overall methodology used in this research. The above sub problems are analysed and the justification is given for the selection of appropriate approaches.

3.1 Selection of the RSSI based localization model

Three types of approaches have been identified for RF based indoor localization in section 2.1 presented as Model-1, Model-2 and Model-3. These three models can be divided in to two main groups, namely Active Tracking, and Passive Tracking. In Active tracking systems, a person must carry an RF device to broadcast his

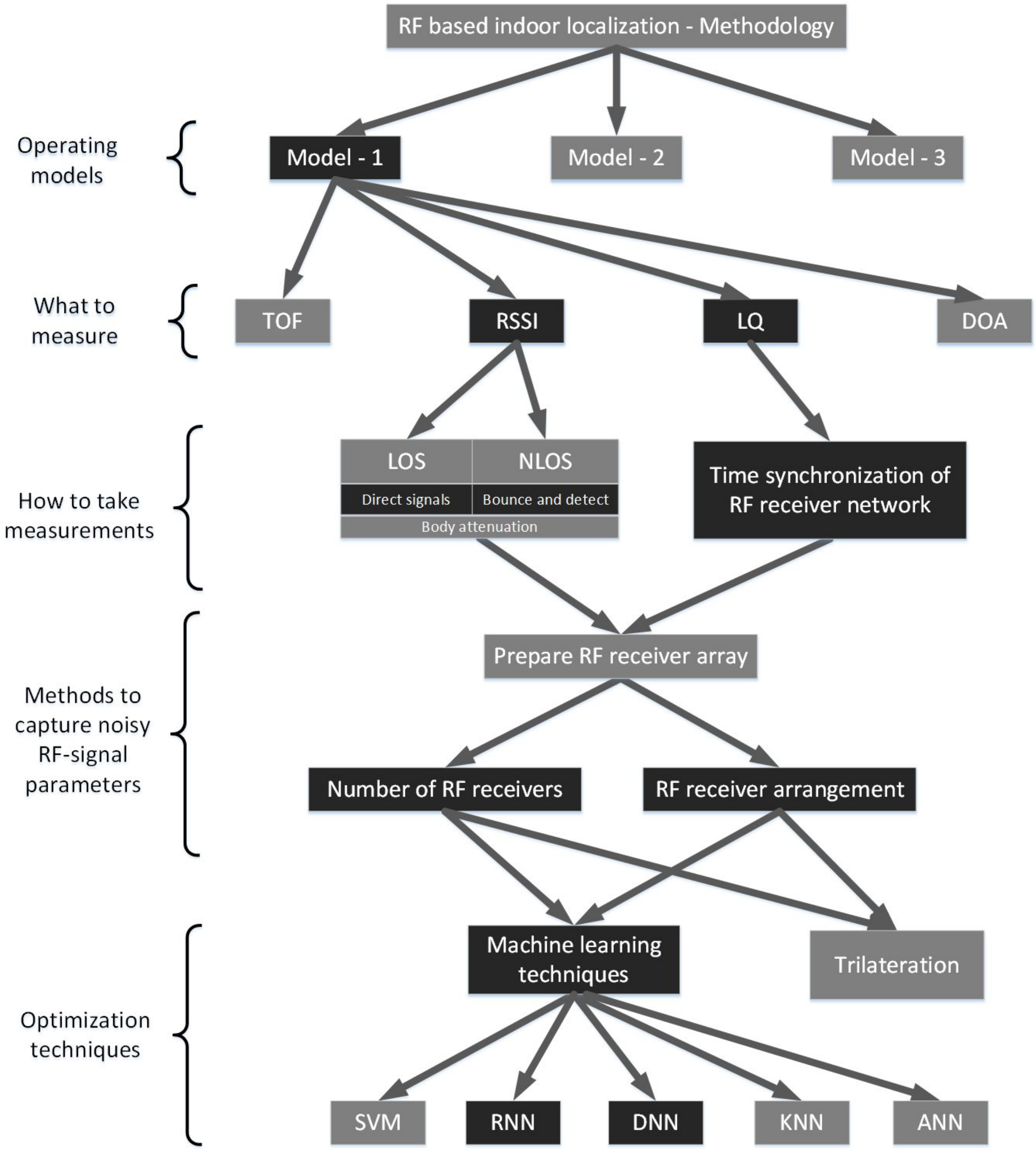


Figure 3.1: Framework for selecting suitable approaches for proposed RSSI based localization system

identity. In passive tracking systems, the target person does not carry a device and the aim is to detect the presence of a target in the environment as mentioned in section 2.1.3.

It is mandatory to uniquely identify the person for the security and safety related application domain in concern in this study. In model-3 approach the person is device-free and therefore the person cannot be uniquely identified using RSSI signals. This causes model-3 to be omitted.

Active tracking systems can be further categorised in to two groups;(i) transmitter on target (model-1) as explained in section 2.1.1, and (ii) receiver on target (model-2) as explained in section 2.1.2. In both these models a person can be uniquely identified by the device carried by the person.

However, all the transmitters are required to transmit all the time in model-2. That would require significant amount of processing and energy. Also the radio environment gets more cluttered when all the transmitters are transmitting. In contrast, the receivers are passive and the target person carries the transmitter in model-1. In this model the radio environment is not cluttered compared to model-2. The transmitter does not do any processing and receivers are not required to do a significant amount of processing as in model-2. The transmitter needs less amount of energy to transmit a data packet.

Therefore model-1 was selected as it is a better solution for the application scenario in concern where, vision based localization is not possible and the person needs to be uniquely identified with less resource consumption such as energy and processing power.

3.2 Selection of RSSI parameters for measurements

There are several parameters of RF-signals such as RSSI, LQ, DoA, ToF that are used to estimate the distance between RF transmitters and receivers. ToF parameter is difficult to measure as the distances involved are too small thus it requires sensitive, high precision and high cost equipment. For example, specialist hardware named DecaWave EVB1000 evaluation boards were used to capture and analyse TOF data in a UWB system in [23]. Davide et al [42] have used Nordic Semiconductor nRF52840 devices to capture and analyse TOF data. All those devices mentioned above are commercially available off-the-shelf (COTS) devices customized for a particular environmental setting. These COTS devices are usually expensive and they also require supportive software and hardware platforms. Therefore using RF based TOF data for indoor localization is costly.

Direction of arrival (DoA) is another RF signal parameter which is used to track and localize a target in indoor environments. Two techniques have been used to capture the DoA parameter: (i) The RF transmitter is designed to operate as a directional transmitter[43] and (ii) an array of RF receivers are used to capture the direction of the received RF signals as in [44]. DOA parameter can not be captured using the first technique in this research because the transmitter is not directional. Second technique requires estimation of smaller time duration and smaller distances as in TOF due to high cost. Low cost solutions such as modifying the configuration of RF antenna is also not effective due to large size and poor portability. Further, we focus on safety and security based person monitoring systems rather than direction guiding systems. Therefore, DoA was not considered in this study.

RSSI is a useful RF signal parameter which is proportional to distances as mentioned in equation 3.1.

$$P(D) = P(D_0) - 10\eta \lg(\frac{D}{D_0}) \tag{3.1}$$

where $P(D)$ is the signal strength at the RF receiver, D is the distance between the RF transmitter and the receiver, $P(D_0)$ is the reference signal strength at D_0 distance.

Further, RSSI power varies because it may include energy from background noise, attenuation and interference in addition to the energy from the desired signal. Ahmadi et al [32] derived the equation 3.2 by adding Gaussian random noise variable, X_σ with zero mean and mean variance of σ and body attenuation factor, AF.

$$P(D) = P(D_0) - 10\eta \lg(\frac{D}{D_0}) + X_\sigma + AF \tag{3.2}$$

According to the signal behaviour in equation 3.2 RSSI signal may not be received by some of the receivers. Therefore, another RF parameter namely Link quality (LQ) was considered. Link quality (LQ) can be estimated by the percentage of the number of receivers that receive a specific RSSI signal with respect to the number of all the receivers. This percentage should exceed a certain threshold to decided whether the received RSSI data is trust worthy.

3.3 RSSI measurement approach

RF receivers receive RF signals mainly from two paths, known as Line-of-sight (LOS) path and Non-line-of-sight (NLOS) path [40],[26]. Figure 3.2 shows three main possible incidents that affect RF signals. LOS signal path in figure 3.2(a) gives the strongest and trust worthy signals for accurate position prediction. However, heavy and large objects such as metal barriers and vehicles can absorb the signal before it reaches the receiver through LOS path as shown in figure 3.2(b). On the other hand, small changes of background environment directly affect the NLOS path of figure 3.2(c). This way, the path of the signals from a moving

BLE beacon towards receivers vary with the relative position of the beacon with respect to the environment over the time.

The number of available receivers in the environment directly effects the localization accuracy [17, 24, 28] as previously mentioned in section 2.2. Moreover, these RF receivers must be arranged in an optimum way to capture RF signals having the proper Link Quality. In many research attempts RF receivers or transmitters are arranged on top of the indoor environment to get more LOS signals [17, 21, 23]. In the work such as [16, 24, 28, 26] combinations of both the LOS and NLOS are used for capturing RF signals.

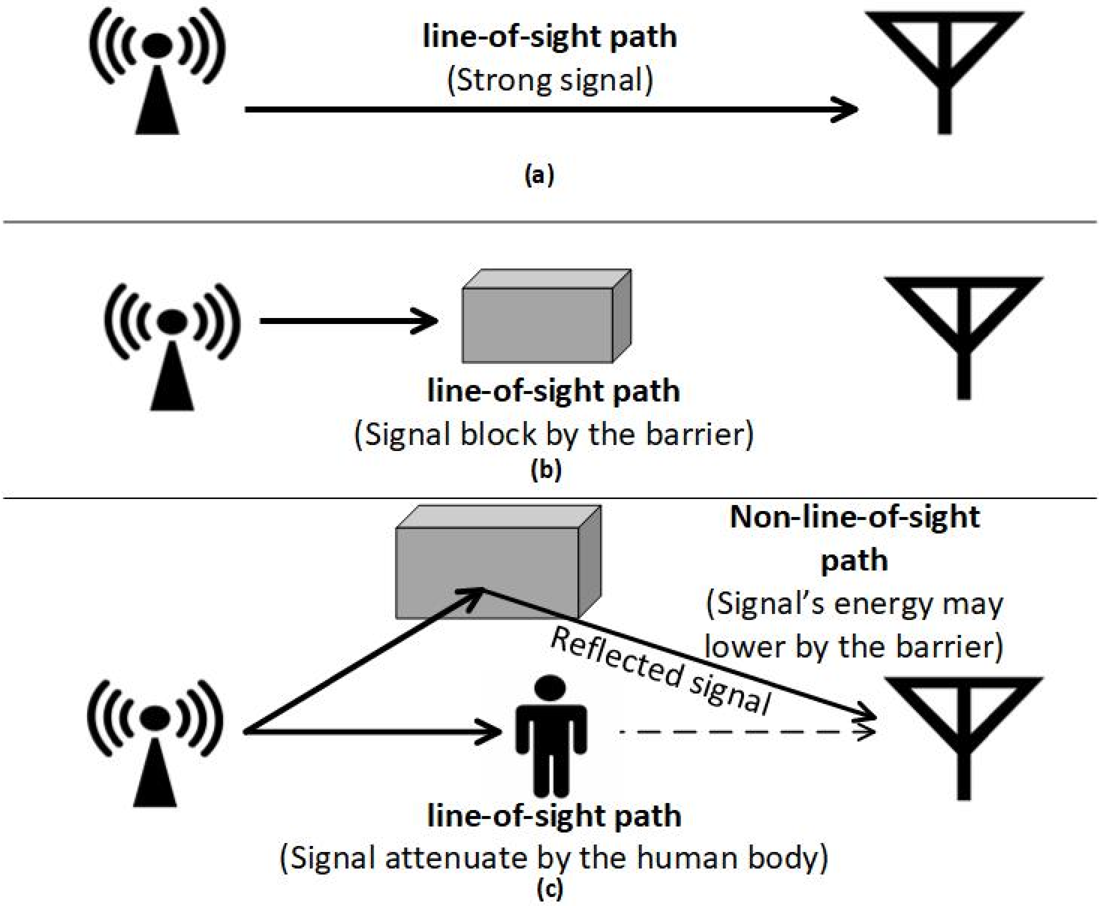


Figure 3.2: RF signal propagation paths and consequence

It is desirable for receivers to capture maximum LOS RSSI signals. However, in cluttered environments LOS signals are rare. Therefore, algorithmic processing will be required to handle both the LOS and NLOS signals. Machine Learning based algorithmic processing is observed to handle body attenuated RSSI signals well in other research [17, 32, 16].

3.4 RF receiver arrangement

In previous research, target tracking environments have been categorised in terms of the difficulty of capturing signal dynamic behaviour of RF signals. Gharat et al [23] considered three environmental conditions as smooth, medium, and extremely noisy in collecting RSSI signal from several RF technologies. Sadowski et al [22] used two separate environmental conditions as noisy environments and ideal environments to compare accuracy differences of two RF based localization techniques. Park et al [30] use BLE based localization system to monitor workers in hazardous working environments in order to improve safety.

RF receivers or transmitters were placed mainly in two different ways; (i) on the boundary of the target area (bounded type) and (ii) grid type. A bounded type transceiver arrangement can be observed in [23, 22]. RF transceivers are arranged as a matrix in [26] and this grid type arrangement is quite popular. RF receivers or transmitters are placed in different horizontal and vertical planes in the target environment in [28, 24, 23, 22] to capture more LOS RSSI signals.

3.5 Method of analysing RSSI data

Many optimization algorithms and mathematical models have been used to improve the RSSI based indoor localization accuracy as mentioned in section 2.2. Interestingly, Machine Learning based approach was desired because it could handle noisy data as explained in section 2.2.1. Compared with many supervised ML techniques SVM, KNN, ANN, DNN, and RNN have been widely used for RSSI based localization data analysis. SVM is better when the number of features in a data point is greater than the number of data points in the data set. In this case, SVM is not applicable because the number of data points is large. The KNN method is also not suitable because of the noisy data that causes many iterations to calculate the cluster centroids and it may result in many centroids. Hence, it would require more processing power and take longer time to predict thus making it hard to perform real-time predictions.

On the other hand, ANN uses neurons to transform data from input values to output values through connections, while DNNs are associated with the transformation and extraction of features. DNN finds the correct mathematical manipulation to turn the input into the output, whether it be a linear relationship or a non-linear relationship. DNN have capability to handle large data sets with noisy data. Also DNNs are able to find fast and reliable paths for predictions. Hence, DNN is the best solution for real-time RSSI data analysis.

As already recommended in section 2.2.1 our DNN was structured with 3 hidden layers with all neurons activated with ReLu function. The main advantage of using the ReLU function is that it does not activate all the neurons at the same time. For the negative input values, the result is zero, that means the neuron does not get activated. Since only a certain number of neurons are activated, the ReLU function is far more computationally efficient when compared to the Sigmoid and Tanh functions. Further, the experiments were designed (section 4.5) to optimize the DNN with suitable number of neurons for hidden layers and proper learning rates.

Furthermore, the change of position coordinates of a walking person over time is considered as a dataset to predict the walking path. Latest Deep-RNN based ML analysis showed higher accuracy in predicting target persons' walking paths while DNN based ML analysis is suitable for analysing position wise predictions for steady targets as mentioned in section 2.2.1. Hardware and system architecture must be designed to collect sequentially changed RSSI data over the target area. Also collecting the sequential position coordinates and their RSSI reading for training phase would be a challenging process in the real test-bed scenario. Camera-based position coordinates were collected as a supportive system to filter the sequential RSSI data and position coordinates.

3.6 Summary

Model-1 type approach was selected in this study considering processing power and energy consumption of RF receivers. This setup is more suitable for cluttered environment because, it emits less radio signals to the environment. This setup is also able to track multiple target persons with their identity.

RSSI signals with its Link Quality (LQ) parameter gives trust worthy data for feeding into the data analysing models to localize a target. RSSI data reaches RF receivers in both LOS and NLOS paths. LOS signals are the strongest signals that lead to precise localization results but they are rare in cluttered environments. However, RF receiver arrangement can be optimized to capture more LOS RSSI signals and NLOS signals with better Link Quality.

Supervised machine learning techniques are suitable for analyzing noisy data like RSSI data. DNNs and RNNs are able to handle large number of noisy data with minimum processing power requirements to predict location of a person in real-time compared with other ML techniques.

Chapter 4

EXPERIMENTAL SETUP

A hardware software integrated system was developed in this research to track a person in real-time in a cluttered indoor environment. Model-1 type localization approach was used as explained in section 2.1.4 and accordingly, the RF receivers were fixed in the environment while a wearable RF transmitter was carried by the target person. Bluetooth Low Energy (BLE) beacon technology was used as the RF medium and the RSSI and LQ parameters were measured to estimate the location. Many research attempts such as [22, 15, 16, 24] have proved that Bluetooth and WiFi based RF-technologies are able to achieve considerable accuracy levels in indoor localization. Also, Bluetooth based RF signals have shown the highest accuracy especially in short range distances compared to WiFi. WiFi is more suitable in long range applications.

RSSI and LQ values were captured against the distance of the target person in a noisy arena. A simulation program was developed to understand the RSSI signal behaviour in the context in concern. A DNN based approach was used to analyse both the simulation data and real world RSSI data. This chapter details the experimental design process. In this process, a target terrain was selected and analysed for its noise level, types of receiver arrangements were identified, a method was designed to locate the position coordinates of the target person, RSSI readings of the receivers were collected in the form of an array at a centralized server, the RSSI data was annotated with position coordinates and timestamps and finally the data was analysed using DNNs with necessary optimizations.

4.1 Target tracking terrain

A terrain was selected to mimic a practical scenario in which a person enters from a safe zone to an extremely hazardous zone by walking through a small doorway in industrial workplaces. The entrance to a large warehouse called W-block situated in CSIRO - Pullenvale Site in Australia was selected. The warehouse was made of metallic material such as metal sheets and large scale metal beams. Moreover, there were many objects such as vehicles, hydraulic machines, metallic tools, legged robots and a number of research test equipment inside the building that can interfere with RF signals. This location has similar characteristics for a cluttered and noisy environment according to Park et al [30] explained in section 3.4. One side of the terrain was an entrance to the warehouse with a width of 4.2 m and other three sides were bounded by metal walls. Hence a walking area of 420 cm × 450 cm was selected for the study.

The target tracking location was marked with a grid of size 420 cm × 450 cm inside the warehouse as shown in figure 4.1 and RF receivers were arranged to collect RSSI data within this terrain. The objective of the experiment was to track and monitor a target person who carries a RF transmitter and walks through the door way.

4.2 The relationship between RSSI readings vs distance

Equation 3.1 describes how the signal strength of a transmitter varies with the distance due to path loss in an ideal environment (without noise). where $P(D)$ is the signal strength at the RF receiver, D is the distance between the RF transmitter and the receiver, $P(D_0)$ is the reference signal strength at D_0 distance. The manufacturer of Kontakt-io beacon provides a reference signal strength of $-77dBm$ at the reference distance (D_0) of 1 m. η is the path loss function which

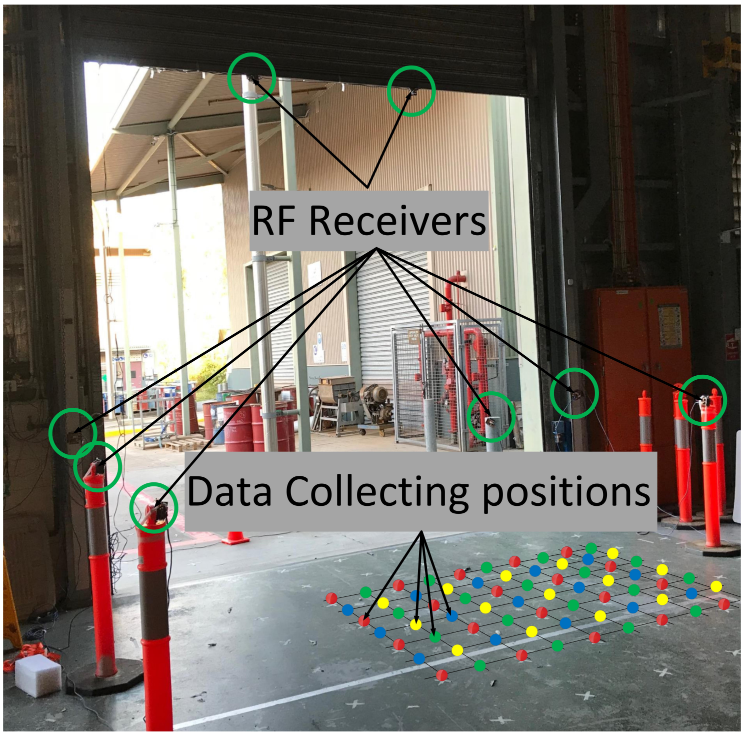


Figure 4.1: Target tracking area and the a receiver arrangement

varies depending on environmental conditions. Jenny et al [45] described and calculated η according to different environmental conditions as shown in Table 4.1.

Environment	Path Loss Exponent (η)
Free Space	2
Urban Area Cellular Radio	2.7–3.5
Shadowed Urban Cellular Radio	3-5
Line-of-Sight in Building	1.6–1.8
Obstruction in Building	4–6
Obstruction in Factories	2–3

Table 4.1: Path loss exponents (η) of RF signals in different environments

Practically, all the RSSI packets are not received by all the receivers within the transmission range due to environmental effects such as reflection, diffraction, absorption and signal attenuation though the person. Ahmadi et al [32] derived equation 3.2 by adding Gaussian random noise variable, X_σ with zero mean and variance of σ and body attenuation factor, AF.

In summary, the ideal scenario is when there is no noise and the signal strength of the transmitter varies according to Equation 3.1. The practical scenario is when there is noise in the environment and signal is attenuated by the body of the person according to Equation 3.2. The ideal and practical scenarios above were simulated and the results and analysis is given in section 5.1.

4.3 Simulation for RSSI based indoor localization system

A simulation program was designed to analyse the behaviour of RSSI received at multiple RF receivers. The target terrain was modeled in the simulation as a two dimensional plane as shown in figure 4.2. X-axis ranges from 0 cm to 450 cm and Y-axis ranges from 0 cm to 420 cm. At the beginning, RF receivers denoted by R1 to R10 were arranged in two lines as shown in figure 4.2 because this area was a doorway and two lines of receivers on either side will bound the walking person.

The X-Y coordinates of the ten fixed RF receivers and the X-Y coordinate of the moving transmitter were input to the simulator. Accordingly, the simulator calculated the distances of these ten RF receivers from a given transmitter position. The resulting ten distance values are represented by D1 through D10 in figure 4.2 and this set of values is called the *distance array* hereafter. This distance array is used to calculate the relevant ten RSSI values for a particular (X,Y) coordinate according to equations 3.1 and 3.2, and we call this set of RSSI values as *RSSI array.*

Ideal RSSI array is generated by substituting distance array in equation 3.1. Similarly, noisy RSSI array is generated by using equation 3.2. Target terrain of 420 cm × 450 cm was divided into a grid of 25 cm × 25 cm cells in simulation

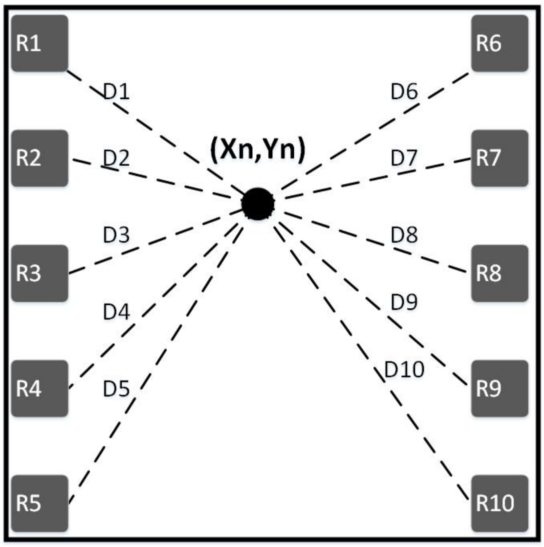


Figure 4.2: Visualization of distance array elements with respect to receiver arrangement and transmitter position

resulting in 18 rows and 19 columns along the X and Y axis. Considering the size of rows and columns inside the grid, 342 data collecting position coordinates were resulted. Thereby, the simulator calculates RSSI arrays corresponding to all 342 coordinate points on the grid. Noisy RSSI arrays corresponding to the same coordinate differ at repeated calculations due to random noise in equation 3.2. Therefore, 50 possible noisy RSSI arrays were generated for a given coordinate. The resulting data set is a map of 342 position coordinates and corresponding 50 RSSI arrays per position. We call this data set the *simulated RSSI radio map*. The objective is to calculate the position coordinate of the RF transmitter using RSSI radio map.

As previously explained in section 3.5 machine learning algorithms were used because they perform well for noisy data compared to statistical methods. Machine learning does not require prior assumptions about the underlying relationships between the variables.

4.4 Capturing RSSI radio map in real testbed

A hardware test bed was implemented to capture RSSI data in the target terrain explained in section 4.1. The abstract view of this test bed and important system parameters are shown in figure 4.3. Transmitter in the figure frequently transmits RSSI data packets. RF receivers were programmed to capture any RSSI data packets from the RF transmitter. The transmitters are referred by MAC addresses and this makes it possible to uniquely identify and track multiple targets. It is essential to time synchronize the server and the receivers in order to capture RSSI and LQ factors. The server constructs the RSSI array defined in section 4.3. Position coordinates were manually input to the server to annotate RSSI arrays for the training phase of supervised machine learning models. This section details the hardware specifications, data collection process and data analysing methods.

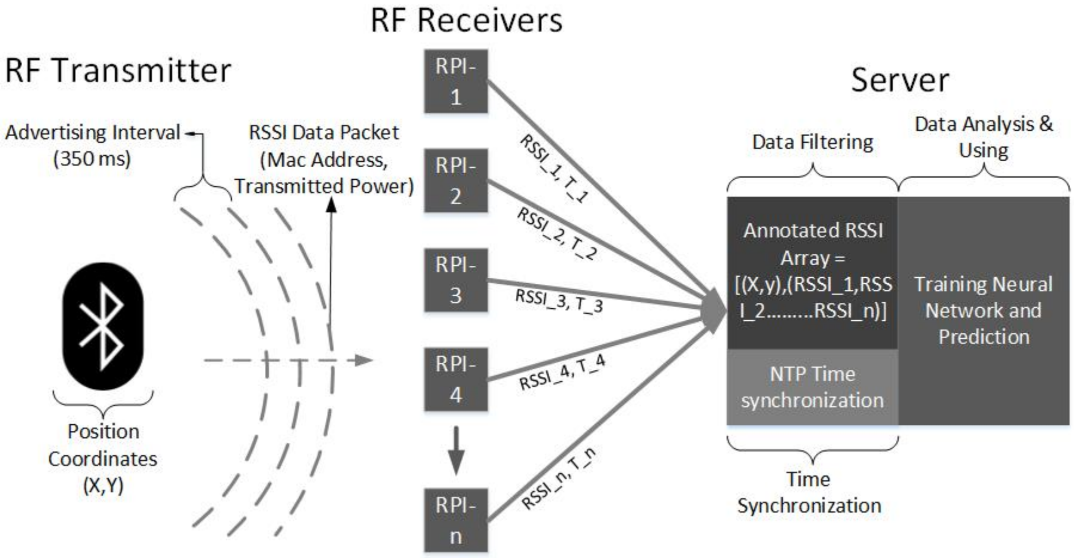


Figure 4.3: System block diagram

4.4.1 Hardware

Raspberry Pi-3 micro computers (RPI) with Bluetooth 4.1 as in figure 4.4a were used as RF receivers. Wireless communication is not allowed in the industrial application scenario involving a high security zone in concern of this study. Further, separate power and network cabling were not desired because of this doorway was quite active often with motion of people and large metallic objects. Therefore, the ten RPIs were connected to a central server by means of Power Over Ethernet (POE) boards in figure 4.4b mounted on RPIs. A Kontakt-io Tough Beacon TB15-1 module in figure 4.4c was used as the RF transmitter. The RF beacons were configured with setting as shown in Table 4.2.

(a) Raspberry Pi-3

(b) Power Over Ethernet shield

(c) Kontakt-io Tough Beacon TB15-1 module

Figure 4.4: Used basic electronics devices

Features	Values
Transmit Power	-12 dBm
Transmit Power @ 1 m	-77 dBm
Expected Range	20 m
Advertising Interval	350 ms
Expected Battery Life	4 year

Table 4.2: Level-3 configuration used in Tough Beacon TB15-1 module

4.4.2 Capturing time synchronized RSSI arrays

Receivers must record RSSI values and received time of RSSI data packet particularly for tracking the person. Therefore, receivers must be time synchronized so that the RSSI data can be analysed with reference to a common time frame. Such timestamped data is also useful in understanding the RSSI data behaviour at individual data packet level. Figure 4.5 shows the proposed time synchronization procedure. RF receivers are time synchronized every 10 minutes using Network

Time Protocol (NTP) by the server.

One RSSI data packet emitted by the transmitter may be received at slightly different time stamps at different receivers due to the effects of NLOS and distance differences between RF receivers. These time differences are at most few milliseconds. These time differences are negligible compared to the time differences between two consecutive data packets emitted by the transmitter at an advertising window of 350 ms.

On the other hand, some receivers may miss an RSSI packet due to a background effect such as being blocked by signal attenuating objects (e.g. metal barriers, machines, presence of human...etc) depending on the position of the person. This situation is addressed by Link Quality (LQ) factor at the server.

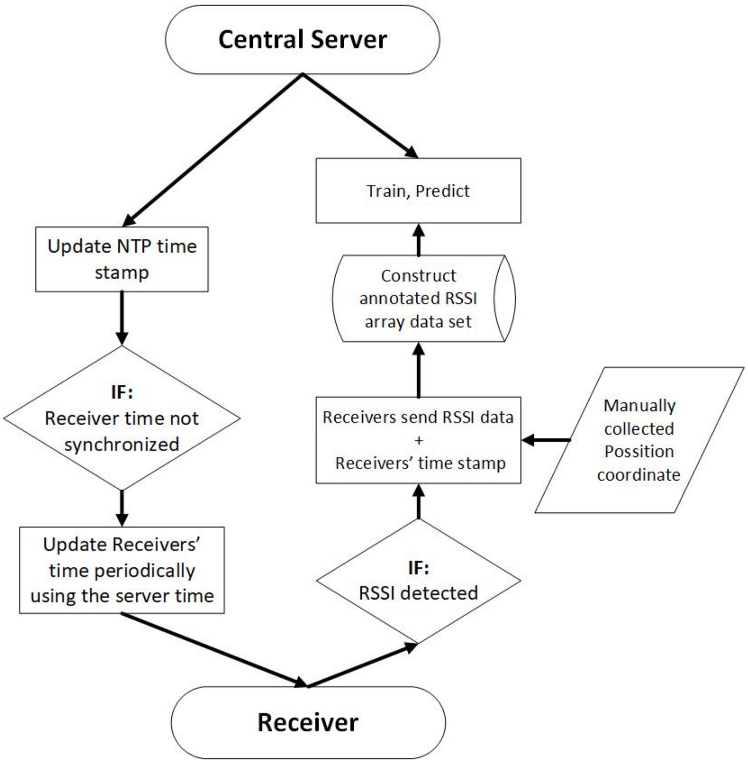


Figure 4.5: Time synchronization procedure for RF receivers and data collection procedure using time stamps with position coordinates

The server constructs the RSSI array defined in section 4.3 by gathering timestamped RSSI data from all the receivers. If the number of non zero elements in a RSSI array is less than a threshold of 60%, the Link Quality was considered insufficient and such RSSI arrays were ignored.

4.4.3 Annotating RSSI arrays with transmitter position information

The RSSI arrays constructed in section 4.4.2 must be annotated with the transmitter position at the server. Previous research has used either sensor based methods or manual methods to identify the position coordinates. For example distances are measured using sonar sensors in [14] and distances are measured with reference to manually marked positions on the ground in [24].

Initially, our study tried to use a camera based approach to capture the position coordinates. As shown in figure 4.6, a roof mounted camera detected the person using a Convolution Neural Network (CNN) and the coordinates were assigned to the person using pixel coordinates of the image. It was observed as in figure 4.6 that the assigned coordinates varied by 10 cm to 30 cm range from the actual position coordinate. This happens due to the difference of camera height and projected height of the target. When the direct distance between camera and the object is increased, difference between actual position and given position is increased depending on the projected height. Hence, a grid was marked on the floor as shown in figure 4.6 to manually capture the position coordinates.

The white crosses marked on the floor in figure 4.6 are separated by 50cm from each other. However, this grid was further divided into 25 cm × 25 cm cells by considering the length between the two feet of a standing person. Datasets were prepared by considering the two different body orientations, five different receiver arrangements, four different position densities detailed in section 4.5.1 .

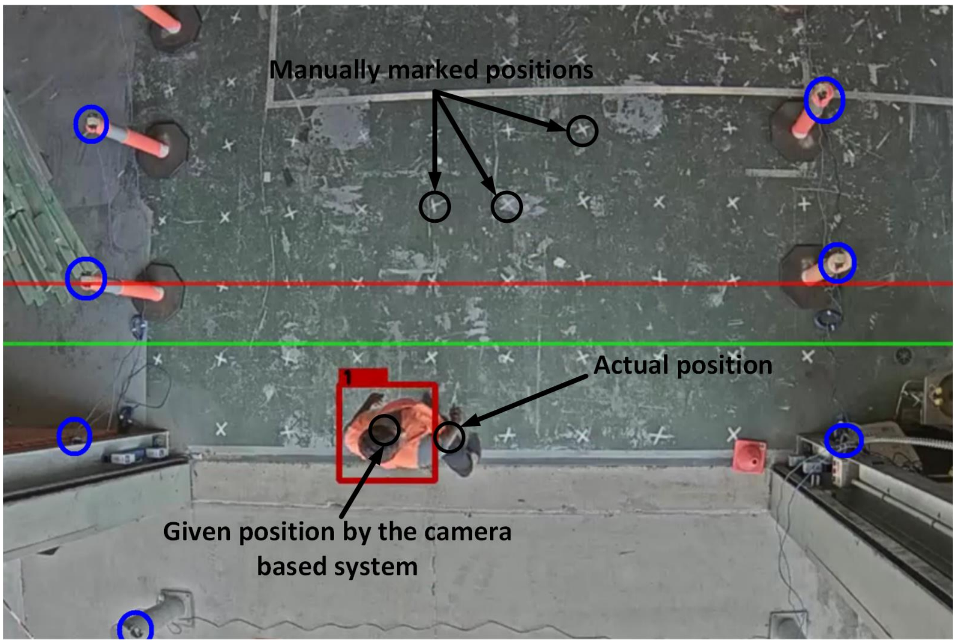


Figure 4.6: Camera based position coordinates vs manually collected position coordinates

Moreover, camera based position coordinates and manually marked position coordinates were used in combination for analysis of time domain based RSSI data. An average walking speed of 0.25 cm/s and two walking directions were maintained in camera based data collection process.

4.5 Deep Neural Network approach for analysing RF signal based data

Problem being researched and shown in this study is predicting the position of a target person in a terrain according to the RSSI values recorded at fixed receivers. This problem is modelled here as a regression problem because the output is a position coordinate which is a numerical value.

As shown in Figure 4.7 we feed RSSI array data from input layer. All the readings from n RF receivers denoted by X0,X1,X2,...,Xn are fed as inputs at the input layer of the DNN. The output is the predicted position coordinate (denoted by Y0,Y1) relevant to that RSSI array in each batch.

ReLu activation function was used as the activation function of all the neurons in this DNN model to make it computationally efficient as previously explained in section 3.5 and the DNN was structured to have 3 hidden layers as justified in section 3.5. Two loss functions called Mean Squared Error (MSE) and Mean Absolute Error (MAE) are used.

The error between the predicted and actual position is visualized in figure 4.8. A threshold is set depending on the required localization accuracy. The DNN is tuned to maximize the number of positive predictions. Then the threshold is also reduced and the DNN is further tuned to maximize positive predictions. There were two types of factors that were varied for the these optimizations; (i) internal factors of DNN such as number neurons in hidden layers, batch size and learning rate and (ii) external factors such as orientation of the target person, receiver arrangement and data collection position density.

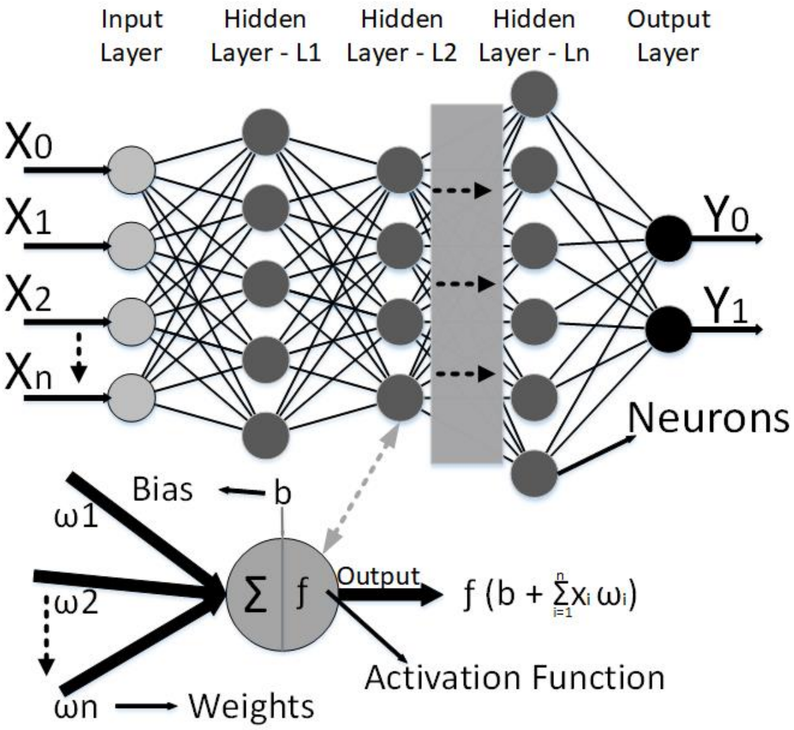


Figure 4.7: DNN structure for analysing RSSI data

There are multiple datasets collected as explained in section 4.5.1 considering the external factors affecting RSSI data as explained in section 2.2.2. In general all these RSSI array data sets were divided as 70% for training, 20% for validation, and 10% for testing. Batch size was in the range of 50 to 150. Cross validation was performed in every 100 epochs. All DNN models were trained in 50,000 to 60,000 training iterations on average.

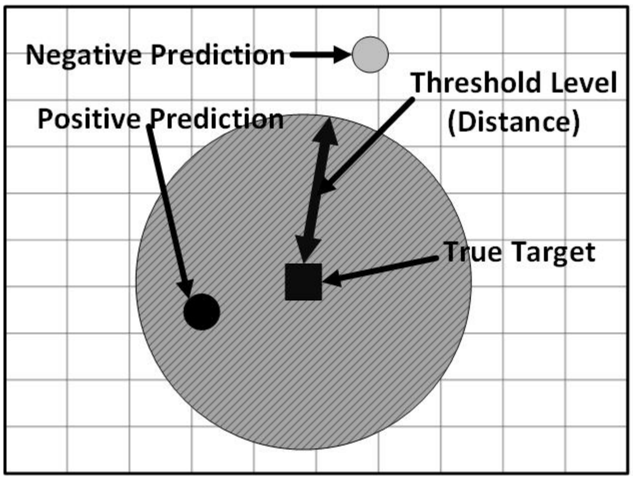


Figure 4.8: Visualization of localization error and error margin

The above DNNs were trained at three learning rates; 0.1, 0.01 and 0.001 as also recommended in section 2.2.1. The number of neurons in each hidden layer was changed from 5 to 75 in steps of 5 thus resulting in 3375 different DNN models to find an optimized DNN according to the RSSI dataset in concern. These 3375 models are labeled according to the number of neurons in each hidden layer as shown in figure 4.9. The training accuracy obtained from these DNN models are plotted against the model labels in figure 4.10 and best learning rate was found to be 0.01 as it gave the best accuracies. Further, an analysis was conducted into the validation accuracies obtained with learning rate 0.01 to find the best hidden layer sizes. Figure 4.11 shows the accuracies plotted against the three hidden layer sizes. According to the figure it was concluded that the best accuracies are obtained when the first hidden layer had a number of neurons between 25 and 60.

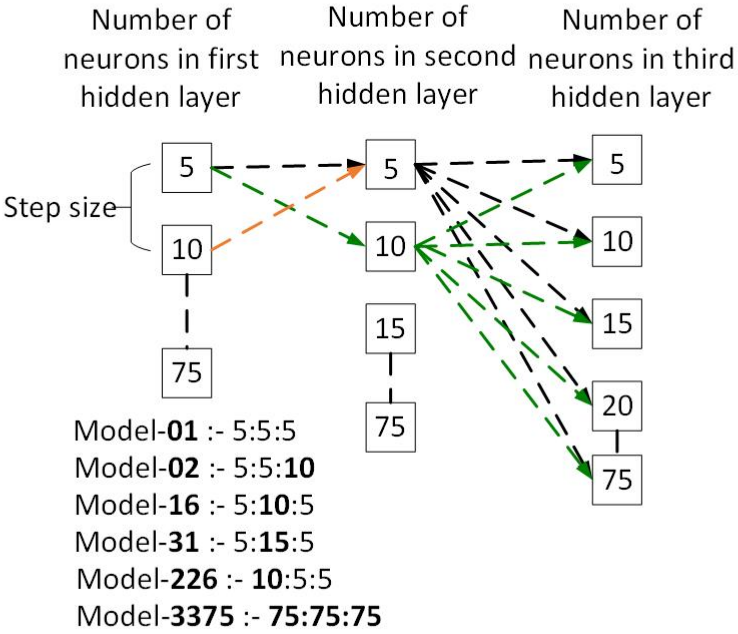


Figure 4.9: Labels of DNN models according to the number of neurons in three hidden layers

The second layer had a number of neurons between 45 and 75, and this number should be higher than the size of the first hidden layer. The third hidden layer size should be between 35 and 75.

4.5.1 Preparing the dataset for DNN based analysis

In this experiment person carried the transmitter as a wearable while the receivers recorded RSSI data arrays. The person kept standing at each position coordinate on each grid for 30 s on average. There were around 40 data packets collected in one coordinate position.

Body orientation is an important factor affecting RSSI data as in section 2.2.2. The transmitter was worn on the chest area of the person. Two orientations were considered in collecting RSSI arrays; (i) facing the body towards the door inside

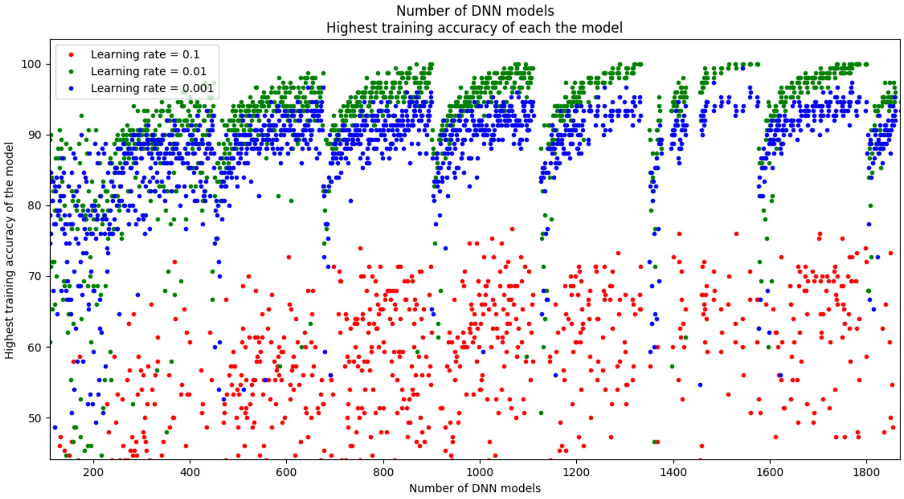


Figure 4.10: Model numbers vs resulted highest accuracies of the models accordingly three learning rates

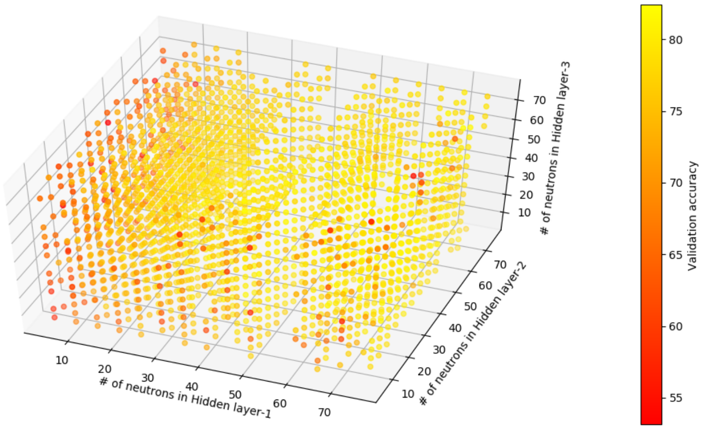


Figure 4.11: Accuracies of DNN models according to the number of neurons in three hidden layers

the target terrain (orientation-1) and (ii) facing the body towards the opposite side of the door (orientation-2) as shown in figure 4.12. That is orientation 1 and 2 differ by 180°.

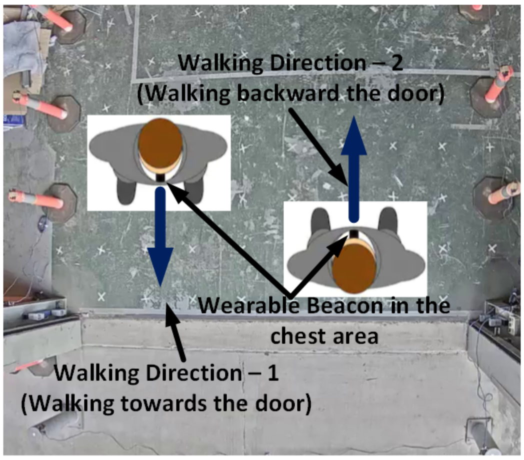


Figure 4.12: Explaining two walking direction of the target person relative to the test-bed

Receiver placement was another important factor as previously explained in section 3.4. Data was collected 10 receivers arranged as in figure 4.14 and the data was derived when the number of receivers were 4, 6 and 8. Receivers were arranged in both bounded type and linear arrangements as in figure 4.13. Figure 4.14 shows the top view of RF receiver arrangement in real world when the number of receivers was 10.

The floor was marked with a grid in which a cell is 50 cm × 50 cm as shown with the red markers in figure 4.14. The first data set was collected by standing on the red markers. Next more data collecting points were marked within a cell as shown in fig 4.15(b), 4.15(c) and 4.15(d). Here all the markers are 25 cm apart horizontally and vertically from each other.

There were four datasets collected by standing at grid positions given by figure 4.15(a), 4.15(b), 4.15(c) and 4.15(d) by facing at orientation-1 explained above. These datasets are referred to hereafter as Dataset-1 (figure 4.15(a)), Dataset-2 (figure 4.15(b)), Dataset-3,(figure 4.15(c)), and Dataset-4 (figure 4.15(d)) and these four datasets were used for analysing the effect of data collection position density on the localization accuracy in section 5.4.

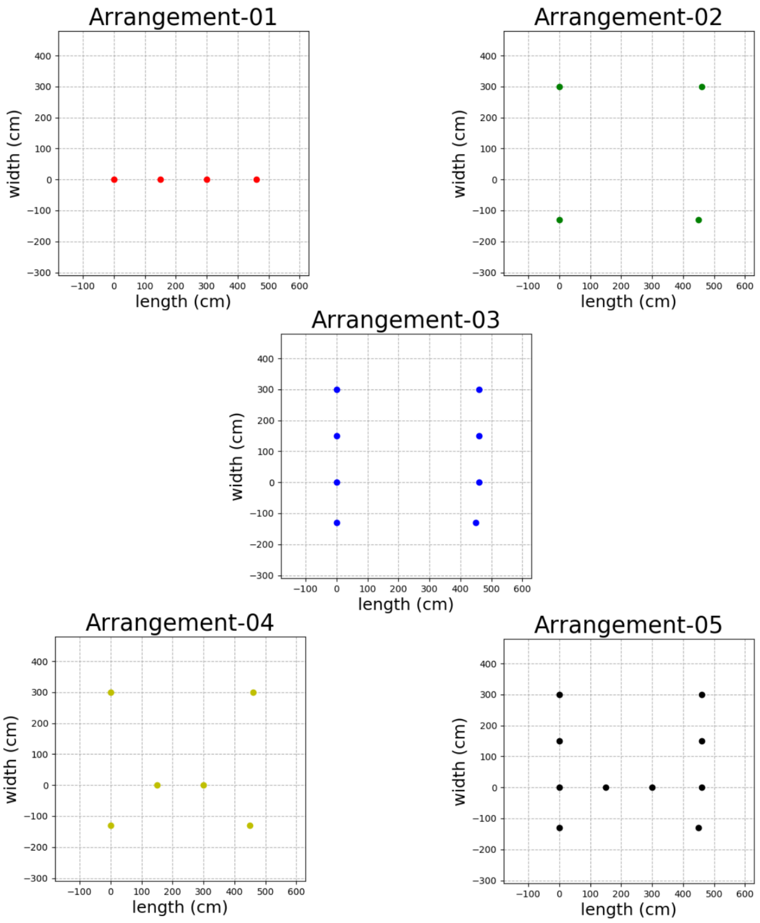


Figure 4.13: Receiver arrangements

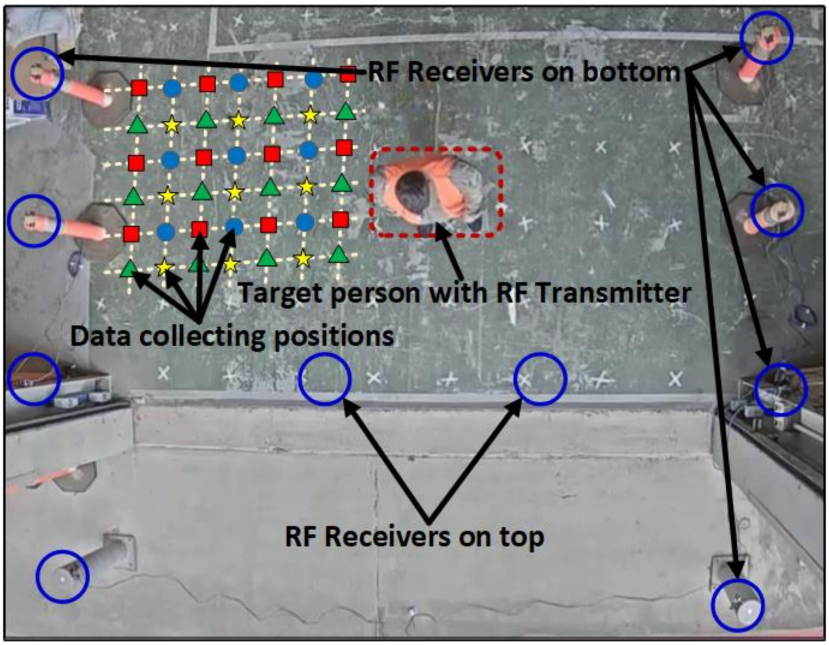


Figure 4.14: Top view of receiver arrangement for real RSSI data collection

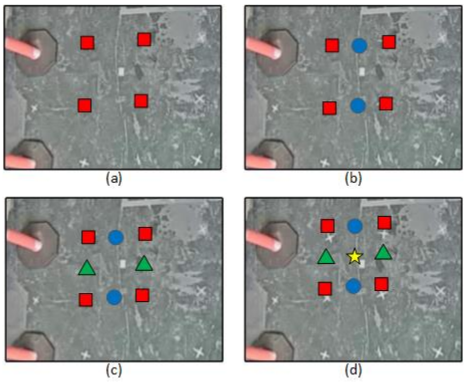


Figure 4.15: Subset of position coordinates

There were 2000 RSSI arrays collected in each of these datasets. These RSSI arrays were equally distributed among the data collecting positions in each dataset.

4.6 Recurrent Neural Network approach for analysing Temporal-RSSI data

This problem is analyzed as a sequential ML data analysis problem. The movement of the target person can be modeled as a sequentially varying-parameter corresponding to RSSI data arrays.

A walking path contains multiple position coordinates and relevant RSSI arrays. Those position coordinates change sequentially over the time in a walking path. RSSI data were recorded including temporal data as mentioned in 4.4.2 and walking paths of the target person were recorded as mentioned in 4.4.3

A walking path was selected with a size of 19-foot-steps and each step having a distance of 25 cm. Two neighbouring walking paths were separated by a gap of 25 cm from each other. Thus it resulted in 17 different walking paths inside the target terrain. Camera supervised position coordinates were used to construct time domain-based RSSI data related to walking paths. Those coordinates were corrected by using manually marked position coordinates.

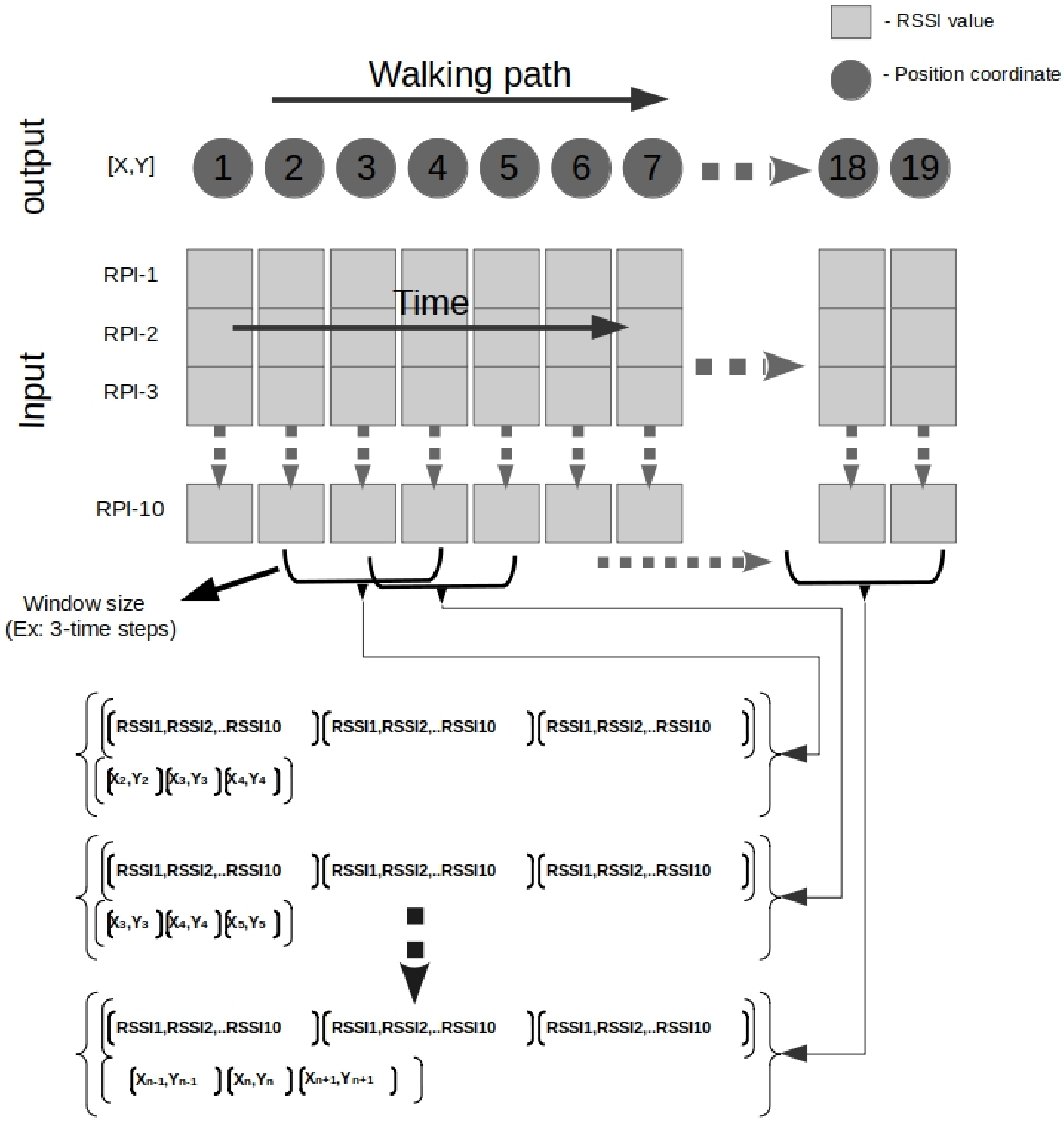


Figure 4.16: Temporal RSSI data extraction method for RNN

Sequentially filtered RSSI arrays are required to train RNNs. Figure 4.16 shows the basic method of preparing time domain-based RSSI data to feed RNNs. Here we demonstrated a system that has a window of three time steps with one footstep per time step. Window size implies the number of time steps that are fed to RNN in one training iteration. Figure 4.16 describes the ascending order of feeding data into RNN with the window overlap in every walking path. One training data packet includes three RSSI arrays and three neighbouring position coordinates. Considering consecutive two training data packets, the RSSI array and its position coordinate denoted by the second element must be used as the first element of the second training data packet as explaining in figure 4.16.

One element of a particular training data packet consists of Ten RSSI values as inputs and two-position coordinates as outputs fed into RNN. A data packet consists of three such elements. Therefore, this problem can be considered as a multiple inputs and multiple output type RNN problem. There are three types of vanilla recurrent neural network; simple (RNN), gated recurrent unit (GRU) and long short term memory unit (LSTM). The main difference among GRU, simple RNN and LSTM is that a GRU/Simple-RNN has two gates, namely reset and update gates whereas an LSTM has three gates namely input, output and forget gates. The an LSTM cell remembers values over arbitrary time intervals and the three gates regulate the flow of information into and out of the cell. Therefore, LSTM has more capability to handle sequential-sensitive data compared to other RNNs as mentioned in section 2.2.1

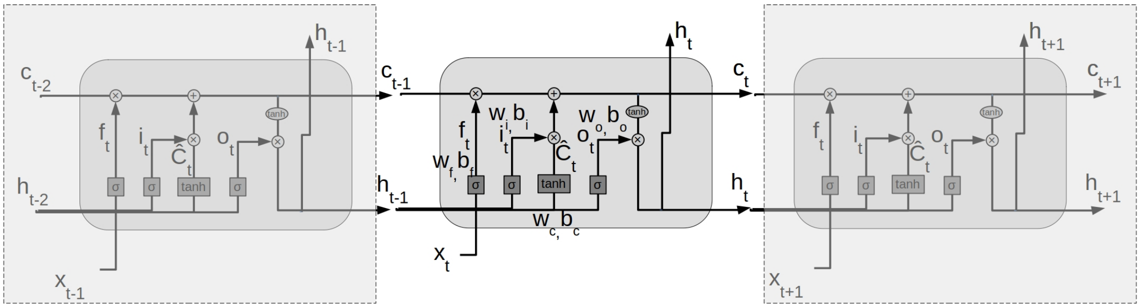


Figure 4.17: Basic structure of the standard LSTM network

Figure 4.17 describes the basic structure of the standard LSTM units, where x_t is the input at time step t, h_t is the hidden state at time step t, C_{t-1} is the memory cell state at time step $t-1$, w_f, w_i, w_c, and w_o are the weights, b_f, b_i, b_c, and b_o are the biases. LSTMs use the tanh activation function for the activation of the cell state and the (σ) Sigmoid activation function for the node output.

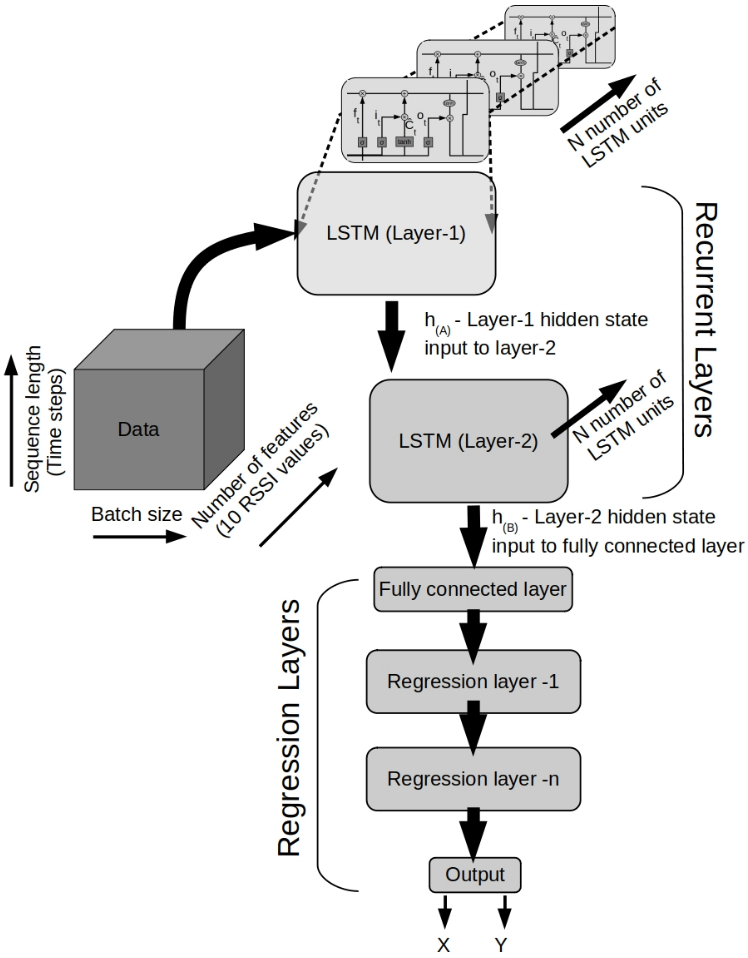


Figure 4.18: Block diagram representation of stacked-LSTM layers combined with fully connected regression layers in proposed Deep-RNN network

Prepared data set as mentioned in figure 4.16 were fed into the LSTM layer as shown in figure 4.18. Results of different batch sizes and different time steps and their performances would be discussed in section 5.7. Multiple LSTM layers (Stacked LSTM) and fully connected regression layers are proposed for a test to optimize the localization accuracy as mentioned in section 2.2.1. Suitable parameters and results obtained for the proposed Deep-LSTM network is mentioned in section 5.8

4.6.1 Preparing the datasets for RNN based analysis

Camera-based position coordinates and manually marked position coordinates were used to construct the sequential RSSI data that represent a walking path as mentioned in section 4.4.3.

A single walking path was defined by 19 position coordinate points based on manually marked points on the floor of the target area. Also, 17 different walking paths were defined based on alongside these manually marked points. Walking paths were constructed based upon two walking directions as mentioned in section 4.5.1. Hence, 1003 different walking path data were collected for Orientation-1 and 1089 different walking path data for Orientation-2 as shown in figure 4.12. These two data sets were named RNN-forward and RNN-backward respectively.

At the beginning, simple, single-layer LSTM units based RNN network has been trained for RNN-forward data set. After that, results of GRU units based RNN network has been compared with LSTM networks for the same data set. Research showed higher accuracy for LSTM.

Results were obtained by comparing the accuracy of stacked RNN networks with that of Deep-RNN networks for a given data set. Deep-RNN was identified as the suitable RNN structure for the given RSSI sequential data. Next it was tried to identify walking direction by feeding both data sets collected for two-directional walking paths, namely RNN-Forward and RNN-Backward.

The number of time steps (window size or sequential length) in a given data set also affect the accuracy of RNNs. Therefore, different RNNs were trained and tested for different RSSI time steps. The time steps 2,3,5 and 10 are used to train different RNNs. The accuracies are compared in section 5.8 to identify the optimum RSSI time steps.

4.7 Summary

An entrance to a warehouse was selected for the test bed with similar characteristics of an extremely noisy environment for RF signals. Propagation of RSSI signal in ideal and noisy conditions were analyzed using equations 3.1 and 3.2. A simulation was designed to represent the selected target area and to generate RSSI arrays corresponding to position coordinates. The simulation was aimed at finding the feasibility of using machine learning for analysing RSSI data and to identify internal ML based and external factors affecting localization accuracy.

A testbed was built to capture real world RSSI data in the selected cluttered environment to track a person in real time who moved through the door way area from a safety zone to a hazardous zone. Raspberry Pi-3 micro computers were configured as receivers and Kontakt-ioTough Beacon TB15-1 modules were used as transmitters. A central server was configured and the fixed receivers were connected to the server with Power Over Ethernet. All RF receivers were connected to a centralized server and data processing and predictions are announce by this central computer. RSSI readings from all the receivers were collected at the server referred to as RSSI arrays annotated by positions and timestamps. Receivers were time synchronized using NTP to annotate RSSI arrays with timestamp with reference to a common time frame for all receivers. The camera-based system was used additionally to manual position coordinates collecting. It was possible to estimate Link Quality by counting the number of non zero elements in the timestamped RSSI arrays. RSSI arrays were also annotated with position coordinates that were manually fed.

The Number of RF receivers and their arrangement, body orientation of the target person and the RSSI data collecting position density were identified as external factors. These parameters have been changed to find the suitable structure for achieving high localization accuracy in a given environment. Five RF receiver arrangements, two body orientations and four position densities were considered in designing the experiments. The internal factors of the model were DNN architecture, learning rate and batch size. A regression type DNN with RSSI arrays as inputs and the position coordinates as outputs was designed with 3 hidden layers having all neurons with ReLu activation function.

Regression type RNNs were used to optimize the walking path localization accuracy for time-domain based RSSI data. LSTM and GRU based RNN networks were compared by their localization accuracy for recorded temporal RSSI data. Further, a stacked LSTM network was implemented and their parameters were optimized in order to improve localization accuracy. Finally, DNN and RNN combined (Deep-LSTM) NN was implemented to analyse body orientation based temporal RSSI data.

Chapter 5

RESULTS AND DISCUSSION

This chapter presents the results obtained for the following experiments using the testbed in section 4.1:

1. The relationship between RSSI readings and distance between transmitters and receivers
2. Feasibility of using DNN for analysing RSSI data
3. Effect of the number and arrangement of RF receivers
4. The effect of position coordinate density for RSSI based localization accuracy
5. Effect of body orientation on RSSI based localization accuracy
6. Improving tracking and localization accuracy in realtime using DNN predictions
7. Finding best neurons ratio in hidden layers and optimum learning rate for RSSI data
8. Compare the accuracy of LSTM based RNN network witn GRU based RNN network
9. Finding the best Deep-LSTM structure to improve the localization accuracy compared with DNN localization accuracy
10. Finding suitable time-steps and implement the body orientation of the target person by a single Deep-LSTM network compared to Multiple-DNNs

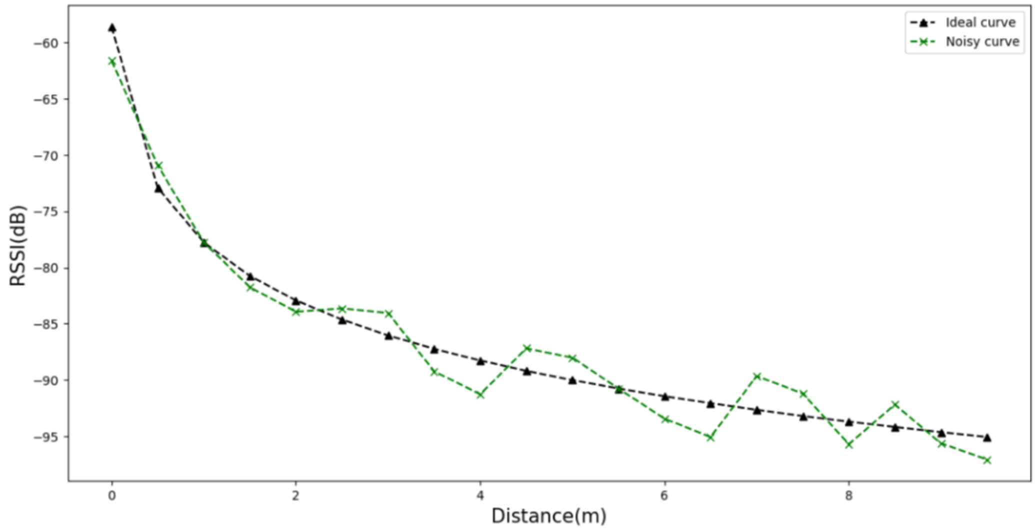


Figure 5.1: Variation of RSSI value with distance for ideal (equation 3.1) and noisy environments (equation 3.2)

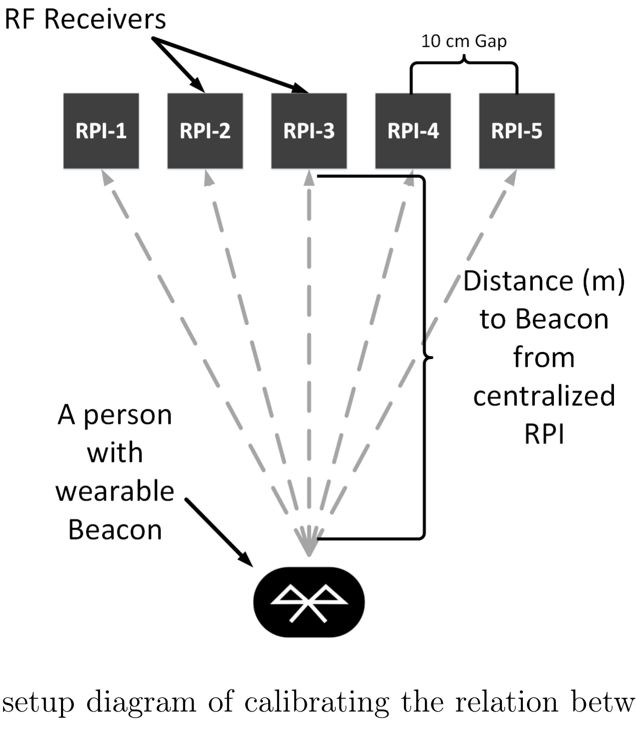


Figure 5.2: Test setup diagram of calibrating the relation between RSSI vs Distance

5.1 The relationship between RSSI readings and distance between transmitters and receivers

A simulation was developed to explore the RSSI signal behaviour with distance between a transmitter and a receiver as already mentioned in section 4.3. Figure 5.1 shows the the simulated results when a single pair of transmitter and receiver is used for ideal and practical scenarios. In ideal scenario, the RSSI variation with distance between the transmitter and the receiver usually adopts the logarithmic loss model according to equation 3.1 as mentioned in section 3.2. The black curve in figure 5.1 represents the ideal relationship between RSSI readings vs distance. However, practically there is environmental noise and signal attenuation as explained by equation 3.2. A random noise was added in the range of ±3 dB as explained in section 4.3. Data points calculated for the noisy environment are represented by green color cross marks in figure 5.1. It can be concluded that RSSI data follows the logarithmic model of propagation against the distance even in noisy environments.

A simple test was conducted at the beginning to analyse the relationship between the RSSI signals at the receivers and the distance of the between the transmitter and the receivers when the transmitter is mounted on the chest of a person. Five fixed RPI devices were used as RF receivers placed along a straight line at a height of about 1.5 m to match the transmitter height. One BLE-Beacon was used as the RF transmitter configured to have an effective transmission range of 20 m, an advertising window of 350 ms and a transmission power of -77 dB at 1 m as previously shown in Table 4.2.

Figure 5.2 shows the test setup in which five RPIs were separated from each other by a gap of 10 cm. The target person faced his body towards the RF receivers. As already explained in section 4.4.2 all the RPIs were connected to a centralized server through POE cables. All programs were run on Linux based platform and written in Python 3.2.

Target person walked towards the RF receivers starting at a distance of 10 m along the normal from the transmitter to the line of receivers as in figure 5.2. RSSI arrays were recorded by standing at every 50 cm on the way. The target person stayed at each data collection position for 10 seconds. During this time period each RPI recorded about 25 RSSI readings per position. These 25 readings were averaged. Figure 5.1 shows these averages of each RPI against the distance of the transmitter.

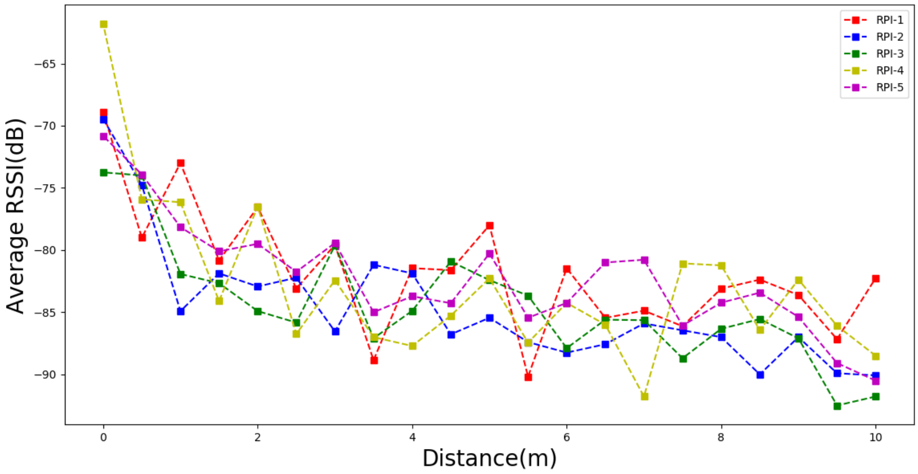


Figure 5.3: Average RSSI vs nominal distance between BLE-Beacon and five RPIs

The RSSI Vs Distance curve for each RPI in figure 5.3 shows a similar variation as in the simulated practical scenario given by the green curve in figure 5.1 except for the range of variation. In a lab environment researched in [45] the noise level has varied range of ±7dB and the average noise was ±3 dB whereas in figure 5.3 noise level varies in the range ±2 dB to ±15 dB. Average noise level for all readings of all RPIs was ±7 dB. Therefore this environment can be identified as an extremely noisy environment. It should be due to the fact that workshop activities were underway during the experiment with heavy metallic objects moving around. This experiment also verified that the terrain represent a cluttered indoor environment.

5.2 Feasibility of using DNN for analysing RSSI data

Using the simulation study explained in section 4.3 we explored how DNN can be applied to analyse RSSI data. The problem was solved as a regression type NN problem using a DNN having three hidden layers with each layer having 25, 10 and 5 neurons respectively. ReLU activation function and Mean Absolute Error loss function were used in every neuron. RSSI arrays were used as the input and the predicted position was the output. The predictions were identified as positive and negative as previously explained in section 4.5 referring to figure 4.8.

The simulated terrain was of size 420 cm X 450 cm. This terrain was divided into a grid of 5 cm × 5 cm cells thus giving 7560 positions. In the ideal scenario there was a unique RSSI array recorded per position. Therefore, A dataset consisting of 7560 ideal RSSI arrays was generated as explained in section 4.3 using equation 3.1. A simple regression model was used as an starting point to analyse this dataset and it resulted in an accuracy of 99.22% with a 50 cm threshold. It was concluded that ML based approach is feasible and the study was extended to analyse noisy data.

Noisy RSSI arrays were generated as explained in section 4.3 using equation 3.2 by obtaining 50 readings per position in a grid of 25 cm × 25 cm cells. The resulting 17000 noisy RSSI arrays were fed to the same DNN model above and an average validation accuracy of of 90.92% resulted for 50 cm threshold level. This simulation results indicate that RSSI based data can be successfully analyzed using DNN based approach for a better localizing accuracy.

5.3 Effect of the number and arrangement of RF receivers

This experiment was conducted to find the effect of the number of RF receivers and the arrangement of RF receivers in the target area on the localization accuracy. Four DNN models were created for 4, 6, 8 and receivers respectively. The DNN models differ only by the size of input layer because the size of RSSI array equals the number of receivers. Figure 4.13 shows the top view of RPI arrangements with their grid coordinate positions. Two of the RPIs in Arrangement-1,4 and 5 located at coordinate points (150,0) and (300,0) were mounted on top of the door as explained in Section 4.5.1. All the other RPIs were mounted on poles as shown in figure4.1 such that they lie on the same plane. The localization accuracies given by the DNN models when the RSSI data from five receiver arrangements, namely Arrangement-1,2,3,4 and 5 in figure 4.13 are given in table 5.1. Here the same DNN is used for the Arrangement-1 and 2 because the number of receivers is 4 in both arrangements. Arrangement-5 in figure 4.13 is similar to RPI arrangement in figure 4.14.

RPI Arrangements	Validation	Test
Arrangement-1	53.2%	47.08%
Arrangement-2	56.8%	51.98%
Arrangement-3	78.8%	74.13%
Arrangement-4	61.6%	58.31%
Arrangement-5	92.78%	81.78%

Table 5.1: Training and validation accuracies of DNN models for five RPI arrangements in figure 4.13

During the advertising window of 350 ms of the transmitter there were 40 RSSI values recorded at the receivers on average because a person stood for 30 seconds at each position coordinate as already explained in section 4.5.1. However, packets were filtered out according to the LQ factor with a threshold of 60%. Thereby a dataset of 14916 real RSSI arrays could be created for each receiver arrangement as explained in section 4.5.1. All the DNN models were trained using this number of real RSSI data. Training of five DNN models was stopped after about 73,000 iterations because overfitting occurred beyond this number of iterations. Figure 5.4 describes the validation accuracy changes over the training iterations of five RPI arrangement models. According to table 5.1, accuracies of DNN models increased when the number of RF receivers increased. Significant level of increase in the accuracy was visible for circular or bounded type arrangements. Also, arranging RF receivers in multiple planes is recommended according to the result to capture more LOS RSSI signals.

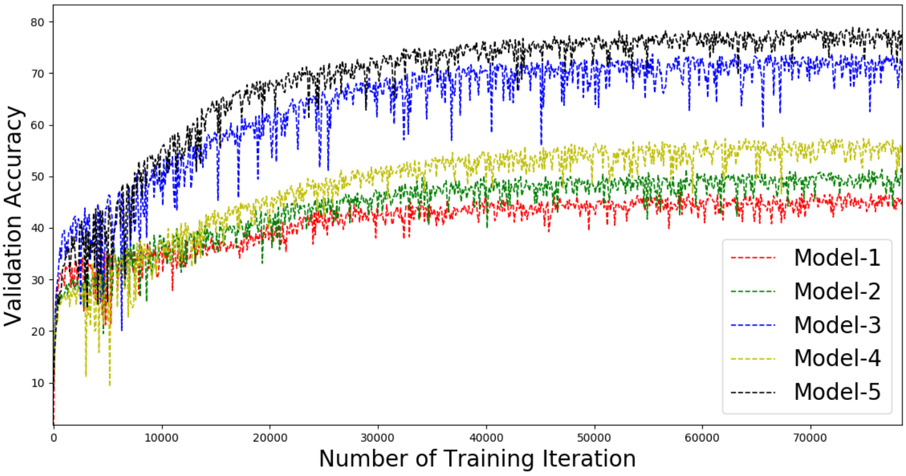


Figure 5.4: Validation accuracy Vs training iteration of five different RPI arrangements

5.4 The effect of position coordinate density for RSSI based localization accuracy

A set of real world experiments was conducted in the target terrain described in section 4.5.1 with the hardware testbed explained in section 4.4 and with Arrangement-5 as explained in section 5.3. The objective of this set of experiments was to study how density of positions of collecting RSSI data affect localization accuracy. There were four datasets collected as explained in section 4.5.1 such that position density increases from Dataset-1 through Dataset-4. A DNN model was used with three hidden layers with 40, 60 and 20 neurons respectively. The DNN was trained using these four datasets. The number of RSSI arrays in training data was constant at 2000 as previously mentioned in section 4.5.1. Validation data set was constructed by using all the datasets. Table 5.2 shows the training, validation and test accuracies of DNN models for four position densities.

Position density	Training	Validation	Testing
Dataset-1	99.5%	60.36%	57.49%
Dataset-2	99.0%	66.77%	62.19%
Dataset-3	99.0%	69.07%	65.88%
Dataset-4	97.5%	69.78%	68.77%

Table 5.2: Localization accuracies of four DNN models for RSSI data position coordinate density

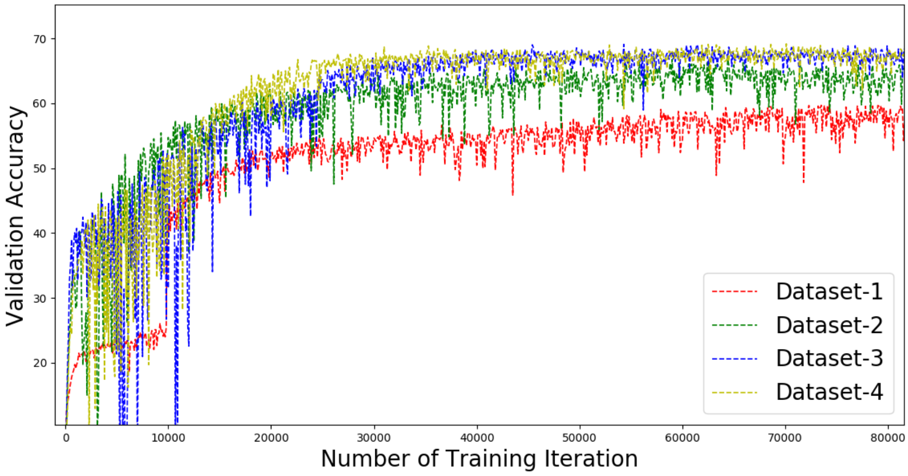


Figure 5.5: Accuracy of the DNN when RSSI data collection position density increased from Dataset-1 through 4

Figure 5.5 shows the training iteration vs validation accuracy of the DNN model when the position density was increased from Dataset-1 through 4. Validation accuracy was recorded for every 100 training iterations. Dataset-3 and Dataset-4 showed DNN overfitting scenario after about 70,000 training iterations. Therefore, the training was stopped after 60,000 training iterations in all four experiments. According to table 5.2 testing and validation accuracies are increasing when the RSSI point density is increased. Finally, the DNN trained with Dataset-4 was selected as the ML model. This DNN was trained using more RSSI data that is 14916 number of real RSSI data points. This number of data points were gathered in the same process as in section 5.3. In this case, training, validation and testing accuracies of 98.50%, 81.18% and 80.18% respectively resulted for 100 cm threshold level. Training, validation and test data sets were constructed by using 60%, 30% and 10% number of data points respectively from 342 position coordinate points as described in Section 4.4.3.

5.5 Effect of body orientation on RSSI based localization accuracy

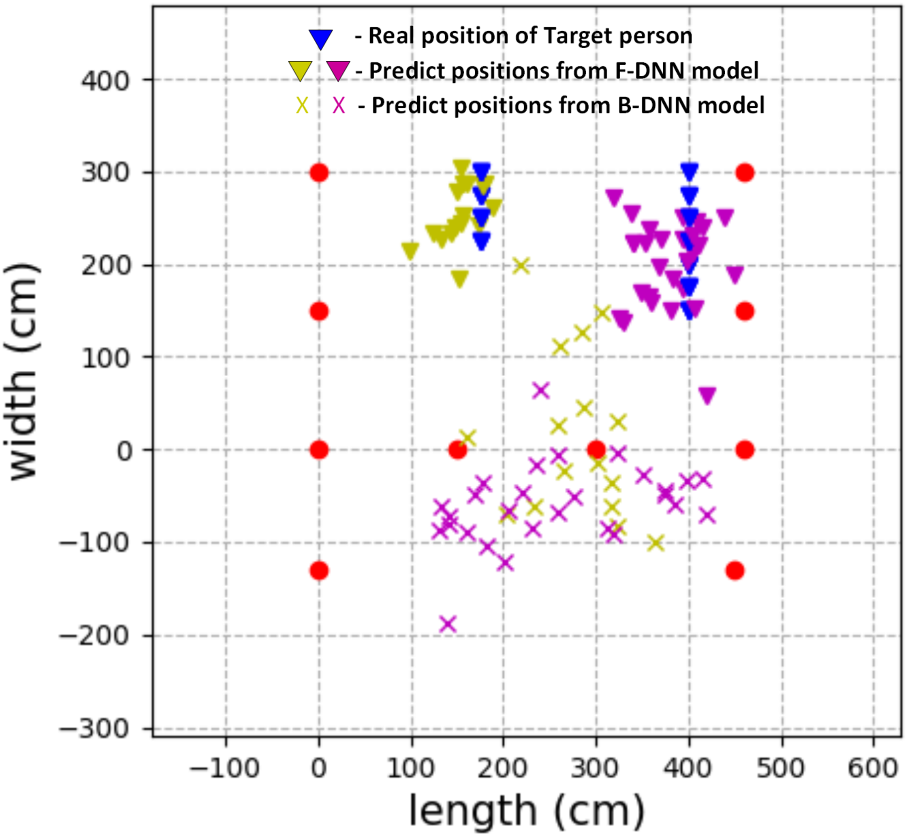


Figure 5.6: Prediction from Forward-DNN and Backward-DNN model for similar two walking path section

Body orientation of the target person is shown to be an important factor that affect localization accuracy as explained in section 2.2.2. An experiment was designed in section 4.5.1 to evaluate this effect. In summary, two RSSI datasets were prepared at two body orientations namely Orientation-1 (Forward Data) and 2 (Backward data) that are different from each other by 180°. A DNN with the same architecture as in experiment above in section 5.4 was trained with this data in order to detect the orientation of the target person.

The DNN model trained with Forward Data is referred hereafter as Forward-DNN and that trained with Backward Data as Backward-DNN. Forward-DNN model gives 81.18% test accuracy for 100 cm threshold level when validated with Forward Data. However, test accuracy reduced in Backward-DNN to 12.5% for 100 cm threshold level when validated with Forward Data. The same behaviour of accuracy is seen when the Backward-DNN was validated with Forward Data. This shows that there is a significant effect of RF signal attenuation through the body of the target person on the localization accuracy.

Figure 5.6 further verifies the effect of body attenuation when the person is walking. The figure shows two walking path sections of the target person marked with blue color triangles representing the real coordinate of the walks. The target person walked towards the door (Walking direction-1). Purple and yellow color triangles represent the predictions of the locations given by Forward-DNN model. Predicted locations given by the Backward-DNN model are represented by purple and yellow crosses in figure 5.6. The predictions were closer to the real path when the DNN was trained with the data pertaining to the same body orientation as the walking direction. There were 150 walking path sections tested each for the two body orientations in figure 4.12 thus resulting in 300 walking paths altogether. All uniformly showed scattered predictions when the DNN was trained with the data pertaining to the opposite direction of orientation as the walking direction. When the person is walking the RSSI data was simultaneously fed to both the Forward-DNN and Backward-DNN. The DNN that gave less scattered predictions always matched to the real orientation of the person in the 300 paths.

The above results can be used to detect the walking path based on the RSSI data received from a transmitter mounted on a walking person. The RSSI data can be input to both the Forward-DNN and Backward-DNN and see which DNN gives predictions closer to each other. Thereby, it can be concluded that the person was walking towards the same direction as the orientation of the person that the DNN was trained with.

5.6 Improving tracking and localization accuracy in realtime using DNN predictions

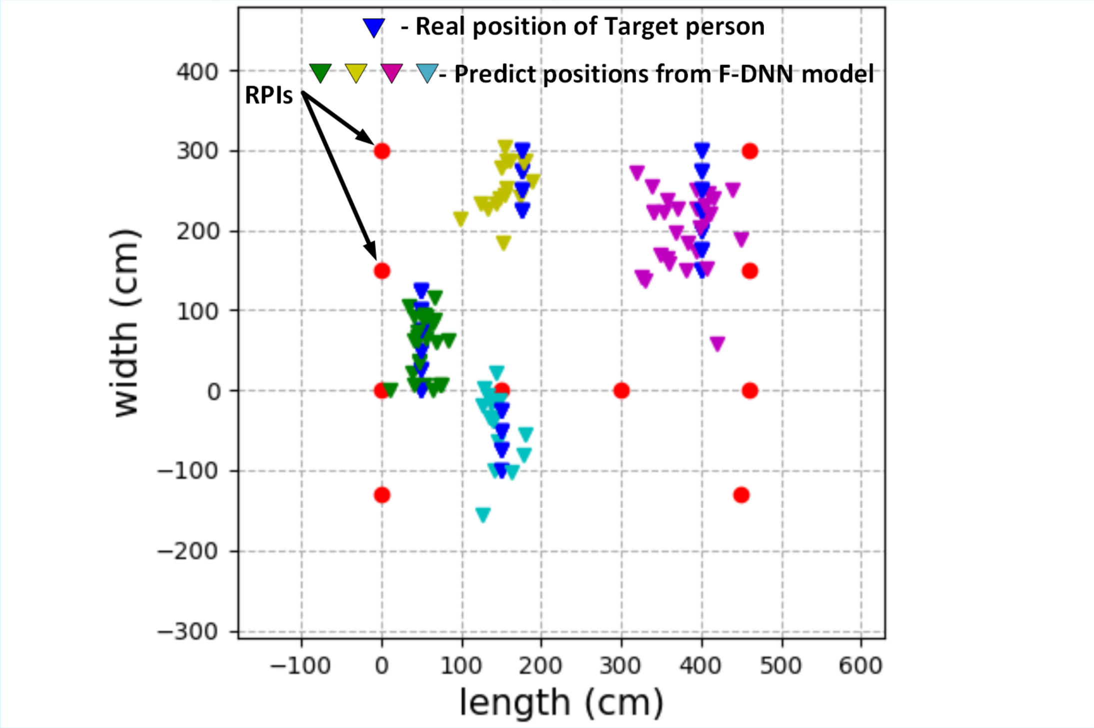


Figure 5.7: Four real paths and relevant predicted positions given by Forward-DNN model

In this experiment, a person is detected, tracked and monitored with time by the central server based on the RSSI data collected from fixed receivers when the person walk along a straight path wearing the transmitter. Here, only Orientation-1 and Forward-DNN explained in section 5.5 because static positions were localized with over 80% accuracy with this combination of data and DNN.

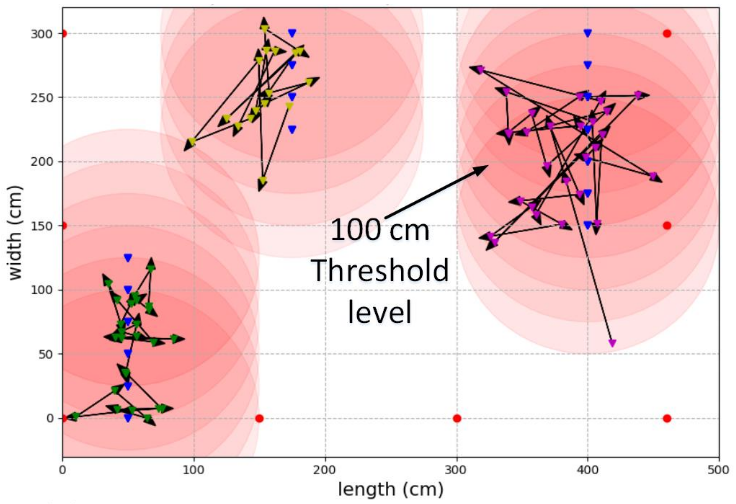
Figure 5.7 shows four test straight paths denoted by blue triangles. Predicted positions of each path are marked with different color triangles. According to the figure, the predicted positions marked by yellow, green and light blue triangles are closer to the actual path. However, the positions marked by purple triangles are scattered about the actual path.

The predicted positions in yellow, green and purple in figure 5.7 were further analysed with respect to time. Here light blue and yellow predictions are scattered in a similar manner, therefore only one of them was selected. The predicted positions are plotted using arrows to indicate the order of predictions according to time in figure 5.8.

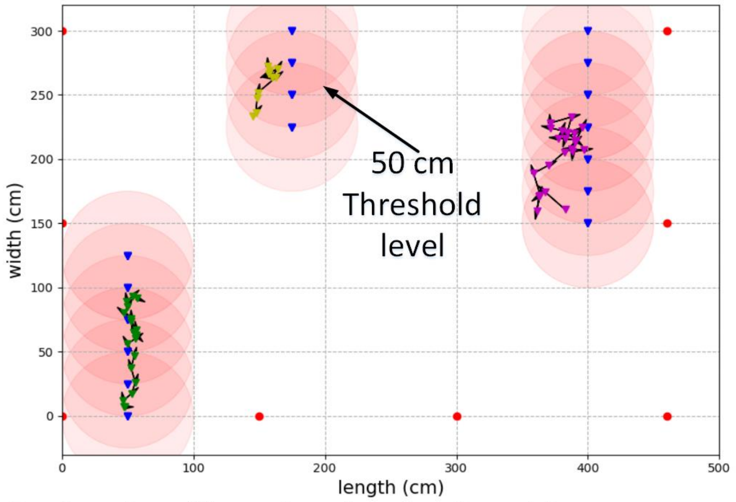
A path can be considered as a combination of static positions recorded with time. An orange shaded circle in figure 5.8 shows the threshold introduced in figure 4.8. The thresholds are marked for each position along the actual paths. Figure 5.8(a) represents the real-time prediction output of the three walking paths. When the threshold is 100 cm, all the predicted positions fall within the area marked by threshold circles. However, 100 cm is too large for a threshold to give an accurate prediction of a path. Therefore, a method was explored to reduce the threshold by considering the means of the predicted positions.

The time-based averaging method was used to derive a position closer to the path using realtime predictions in figure 5.8(a). The centroid of consecutive three positions was used to derive a predicted position in figure 5.8(b). A sliding window of size 3 was shifted by one position to calculate the next centroid. For example, the first centroid was calculated using realtime prediction 1, 2, and 3 and the second centroid was calculated using realtime prediction 2, 3, and 4. The derived path using these position centroids was within the shaded area of 50 cm threshold circles.

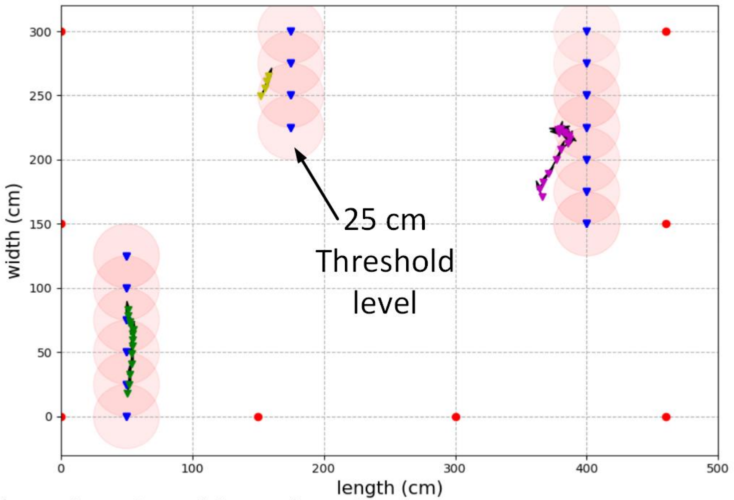
The above centroid calculation was extended to 6 consecutive positions and a sliding window of 6 positions shifted one position at a time. Figure 5.8(c) represents the position centroids using 6 positions. Here the threshold could be reduced to 25 cm for yellow and green color predicted positions. However, predicted path shrink in length.



(a) Real path vs predicted real-time path from DNN



(b) Real path vs filtered path using 3 positions per centroid



(c) Real path vs filtered path using 6 positions per centroid

Figure 5.8: Improving walking path accuracy using centroid of consecutive RSSI arrays over the time

Ideally BLE-beacon should emit 3 RSSI packets per second although some packets may be lost due to environmental effects. If more predictions are buffered for calculating the centroids it will take long time to give the first centroid and the centroid will shift farther to the actual starting position. The above experiment was conducted for walking at a average speed of 25 cm per second.

5.7 Improving tracking and localization accuracy using time-domain filtered RSSI data

In this section, we present the test results obtained for sequential-RSSI data by using RNNs. We used the Arrangement-5 RF receiver configuration mentioned in section 4.5.1 and used the RNN-Forward data set mentioned in section 4.6.1.

First, a single layer LSTM network was tested. Different LSTM units were added and tested for localization accuracy. After that, a stacked LSTM network was trained and tested for localization accuracy. Different LSTM layers and number of LSTM units have varied to optimize the localization accuracy. Finally, fully connected regression layers have added to the stacked LSTM network as shown in figure 4.18 in Section 4.6.1.

At the beginning, we trained a single layer LSTM RNN network with 2 unit output dense layers. We changed the LSTM units and tried to find out the suitable number of LSTM units for a given RSSI data set. Table 5.3 represent the accuracies of trained LSTM networks with different LSTM units in a single LSTM layer. Accuracies were compared with the average threshold level for the given test data set as shown in Table 5.3.

Increasing LSTM units have resulted in an accuracy improvement. However, increasing LSTM units took longer time to train an RNN network. Also, increase in LSTM units caused RNN model stuck in a local minimum. Average 100 to

500 range LSTM units were selected and those numbers performed the highest accuracies in less training time in the LSTM network.

Number of LSTM units, Accuracy	Threshold level (cm)	
50	87.15%	51.23
100	87.70%	49.01
500	89.04%	42.8
1000	89.73%	41.77

Table 5.3: Localization accuracies and resulted threshold levels of four LSTM models for single layer LSTM model architecture

Stacked-LSTM networks have trained and accuracies were compared to identify suitable stacked-LSTM layers and the ratio of their LSTM units for given RSSI data set. Table 5.4 represent the resulted accuracies of those LSTM networks. Increase in LSTM layers and LSTM units have not improved the accuracies. RNN structure of three LSTM layer network with 500 to 100 LSTM units in each layer showed the highest accuracy. Accuracies and the average threshold level were compared for the given test data set as shown in the table 5.3.

Number of LSTM layers	LSTM units in each layer	Accuracy	Threshold level (cm)
3	(50,50,50)	87.95%	48.9
3	(100,100,100)	89.85%	40.31
3	(500,500,500)	90.12%	41.43
5	(100,100,100,100,100)	89.02%	46.17
5	(500,500,500,500,500)	90.65%	40.43

Table 5.4: Localization accuracies and resulted threshold levels of five stacked LSTM models for select suitable number of LSTM layers and units for RSSI data

Further, we analyzed the accuracy differences of LSTM and gated recurrent unit (GRU) based RNN networks to find the best RNN structure. Accuracies of the RNN network with three LSTM layers including 500,500,500 LSTM units and the RNN network with three GRU layers including 500,500,500 GRU units were compared. LSTM network showed 90.02% localization accuracy for 41.43 cm threshold level. GRU network showed 88.92% localization accuracy for 46.5 cm threshold level.

Finally, regression layers were added into stacked LSTM network and this improved the localization accuracy to 94.44% for 20.33 cm threshold level. We used three hidden layer DNN structure as in section 4.5. Hence, Deep-LSTM network contains three LSTM layers with 500,300,100 LSTM units and three regression layers with 120,160,50 neurons gave the highest accuracy for the given sequential RSSI data set (RNN-Forward). We used test data sample from RNN-Backward data set and predictions were calculated by this RNN network (Those data were not used for training this Deep-LSTM network). Localization accuracy of 65.81% resulted for 177.07 cm threshold level due to the RSSI body attenuation effect.

5.8 Implementing RSSI body attenuation effect using single RNN network and improving accuracy by analyzing the time steps

A Deep-LSTM network with above mentioned NN structure (Deep-LSTM network contains three LSTM layers with 500,300,100 LSTM units and three regression layers with 120,160,50 neurons) has trained for two data sets (RNN-Forward and RNN-Backward) as mentioned in section 4.6.1. Those data sets were randomly shuffled and the final data set contained walking paths along two walking directions. A localization accuracy of 93.81% resulted with 27.19 cm threshold level for three time-steps in RSSI data arrays.

A walking path consists of 19-time steps. Therefore, we selected 2,3,4,5,7,10, and 15 times steps, which can uniformly separate 19 consecutive time steps for the extraction of sequential RSSI data in each walking path. Table 5.5 shows the resulted accuracies and threshold levels for different Deep-LSTM networks with different time steps.

Number of time steps	Accuracy	Threshold level (cm)
2	92.41%	33.10
3	93.81%	27.19
4	94.78%	23.16
5	94.42%	22.25
7	96.09%	17.21
10	96.29%	15.27
15	96.15%	17.58

Table 5.5: Localization accuracies for different time steps based LSTM

Overall, localization accuracies were slightly increased when RSSI time steps increased. Threshold level also decreased in considerable range compared to localization accuracy when the time-step increased up to 4-time-steps. Hence, we select the time step as the 4 for final Deep-LSTM model and altogether 28229 different sequential-RSSI training data (these data contains both walking directions) were used to train the Deep-LSTM model.

Figure 5.9 shows the prediction output of 4 step size Deep-LSTM network. Four consecutive LSTM predictions (Prediction-1,2,3 and 4) were used to construct the walking path in figure 5.9. Red shaded circles represent the 25 cm threshold level for real position coordinates. Real position coordinates were marker by blue triangles (walking towards the door) and predictions from Deep-LSTM models were marked by purple triangles. Red dots represent the position coordinates of RPIs as arranged in a real testbed scenario. Black arrows in prediction samples (Prediction-1,2,3 and 4) in figure 5.9 show the sequential changes of the target person in each LSTM prediction step.

Deep-LSTM is able to predict both walking directions of the target person. Predicted one Deep-LSTM output has an average 95% test accuracy for 20 cm threshold level. However, a constructed path using multiple Deep-LSTM outputs showed that the highest accuracy level almost tally with real walking paths.

Figure 5.10 shows four different walking path sections that are representing both walking directions. Blue triangles represent real position coordinates and triangles are pointing towards where the target person walked as mention in figure 5.10. Red shaded circles represent the 25 cm threshold level reference to real position coordinates. However, some walking paths contained negative prediction points those are marked and pointed as outlier predictions as shown in figure 5.10.

Overall, predicted walking paths can be identified as similar to their real walking paths using multiple prediction outputs from Deep-LSTM network. The predicted walking paths from Deep-LSTM also showed less threshold level compare to DNN based predicted walking paths.

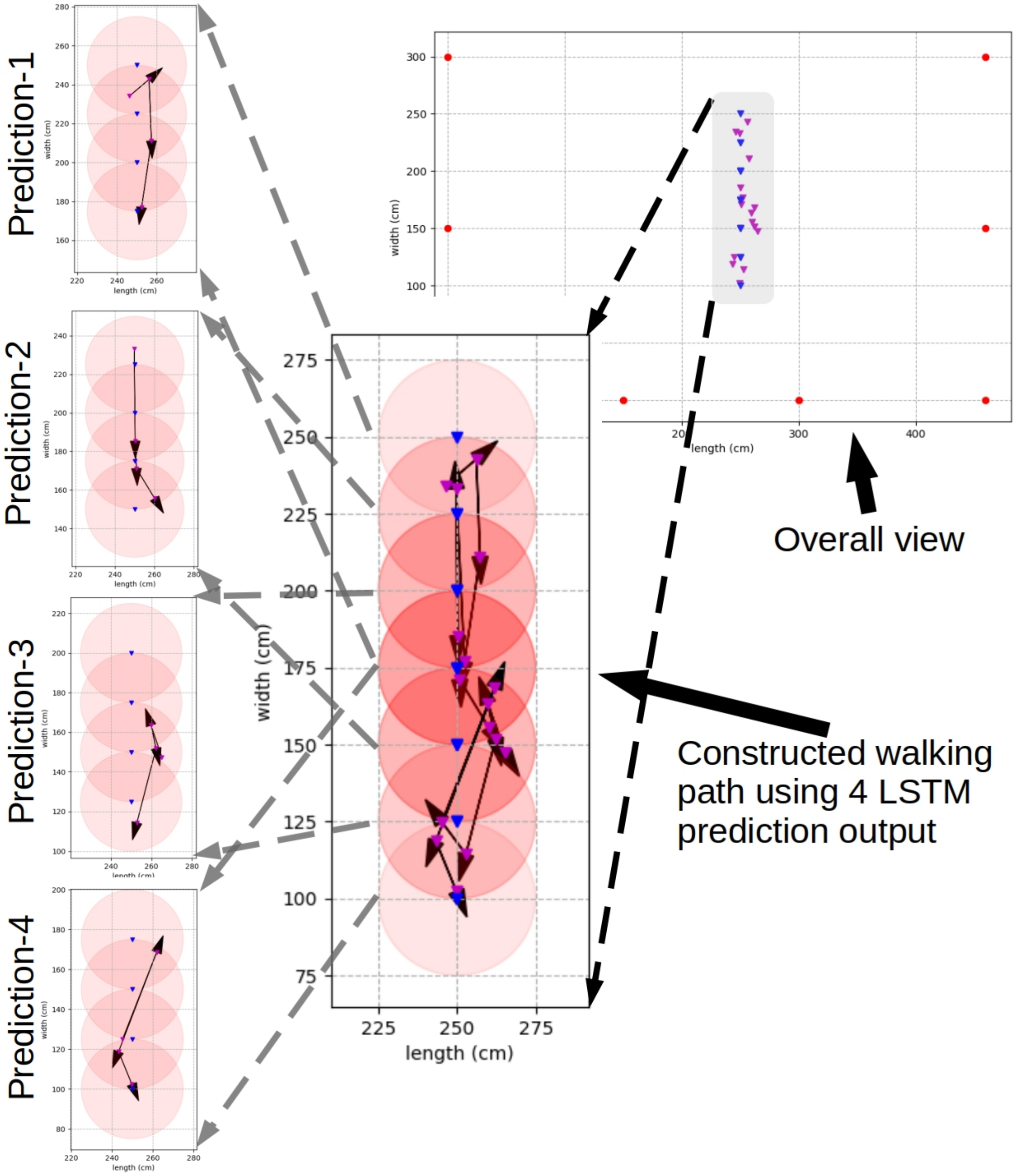


Figure 5.9: Constructing a walking path using prediction outputs from Deep-LSTM networks

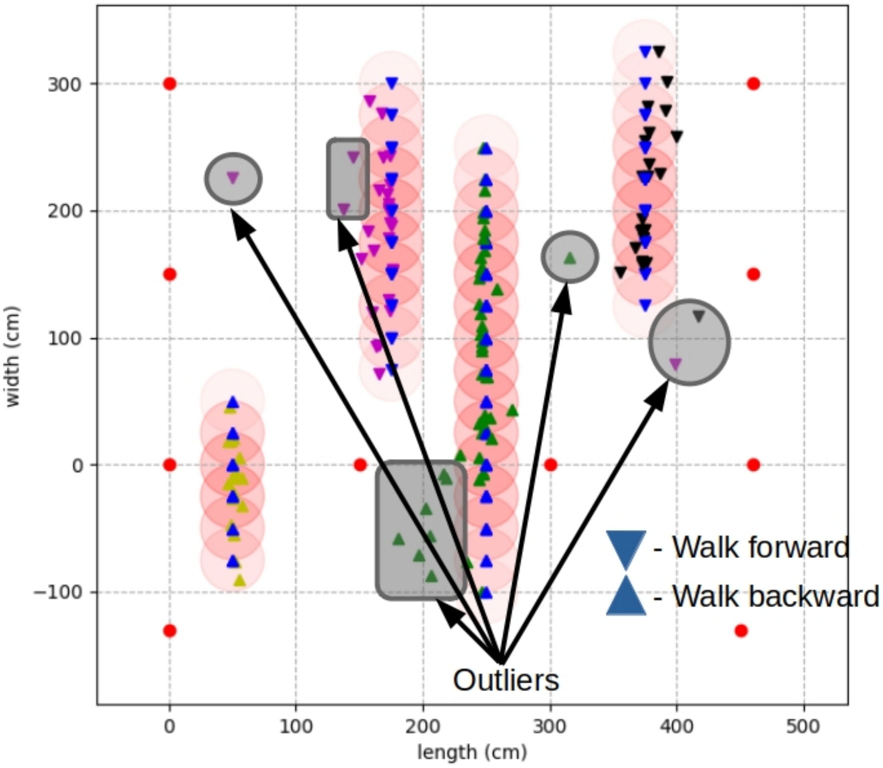


Figure 5.10: Plotted walking path predictions for two walking directions by the Deep-LSTM model

Chapter 6

CONCLUSION

This research was aimed at exploring the use of RSSI of RF signals for localizing a person by uniquely identifying the person and to track and centrally monitor multiple persons in an industrial application with high safety, security and privacy concerns. The scenario considered in this study was where a worker enters a hazardous zone from a safe zone through a doorway. Vision based localization was impossible in this scenario due to high privacy and the vision was obstructed by larger objects moving around.

A test setup was prepared in 420cm by 450 cm doorway in a large warehouse called W-block situated in CSIRO - Pullenvale Site in Australia which had characteristics of an extremely noisy environment for RF signals. A test bed was created using A Kontakt-io Tough Beacon TB15-1 module as RF transmitter, Raspberry Pi-3 combine with POE module as RF receivers and these are low cost, widely used and affordable components. According to literature three models of RF based localization approaches were identified and it was decided to use the Model-1 approach. In this approach the receivers are fixed in the environment and the transmitter is carried by the target person. A machine leaning based approach specifically DNN and RNN were devised to analyse RSSI data because literature revealed that DNN and RNN gave high localization accuracies in the presence of noisy RSSI data.

Experiments were carried out to explore how RSSI varies with distance between transmitters and receivers using both simulations and real world measurements. It was found that the RSSI varies in slightly in a logarithmic manner with a noise variation of in the range of ±2 dB to ±15 dB and ±7 dB on average in the test bed. Thus it was verified that the target terrain was extremely noisy in comparison to terrain classifications in the literature. According to the simulation study it was found that DNN and RNN can be used to analyse RSSI data because it gave and accuracy of over 90% in localizing a person within a threshold of 50 cm.

There were several factors affecting RSSI based localization accuracy according to the literature; (i) number and arrangement of RF receivers (ii) position coordinates density of collecting RSSI data and (iii) body orientation of the target person who carries the transmitter. There were 4, 6, 8 and 10 number of receivers placed in both bounded and linear arrangement and also at different planes. The receiver arrangement with the highest number of receivers (i.e. 10) in bounded type placement and with two receivers mounted at a higher elevation gave the highest accuracy. The elevated receivers were able to capture more LOS RF signals. The terrain was marked with a grid of 50 cm $\times$ 50 cm cells and RSSI data was collected when the person was standing in different locations within a cell. Accordingly there were four RSSI datasets collected with different data collection position densities. The DNN gave better predictions when it was trained with the dataset that had the highest position density. Further, Deep-LSTM model improved the walking path localization accuracy using sequential RSSI data.

Two body orientations were used in experiments and they were 180° different from each other. One orientation was when the person faced the door (forward) and the other was opposite side (backward). Two datasets were collected when the person was oriented forward and backward with the transmitter mounted on his chest. It was found that the orientation of a person was predicted with an accuracy over 81.18% when the DNN was trained with the dataset having the same orientation. For example, when a forward looking person was predicted by a DNN trained with forward looking data (Forward-DNN) it predicted accurately. However, when the same DNN was used to predict a backward looking person the accuracy was reduced remarkable by about 70%. When the predicted positions were plotted with the actual walking path, it was found that Forward-DNN gave highly scattered predictions when the person walked towards the backward direction. The scatteredness of predictions given by Forward-DNN and Backward-DNN was used to predict the orientation of the person.

The target person who walked at an average speed of 25 cm/s was tracked along a straight path. Realtime predictions were scattered within a threshold of 100 cm. In order to reduce the threshold, an averaging mechanism was used. Centroids were calculated by buffering the consecutive predicted position with respect to time. The centroids fell within a threshold of 50 cm when centroids were calculated for every 3 consecutive predictions. Most of the paths could be tracked within a threshold of 10 cm when the centroids were calculated for every 6 consecutive predictions. However, centroid based predictions shrink the predicted path length.

RNN based walking path localization approach was capable of identifying the walking directions compared to the Multiple-DNN based approach motioned above. Deep stacked LSTM network showed 94.78% walking path accuracy for average 25 cm threshold level. This is around 10% of accuracy improvement compares to Multiple-DNN based results. The number of time steps is also a useful measurement to predict walking direction using Deep-LSTM network. However, 150 number of test walking paths in walking direction-1 and 150 number of test walking paths in walking direction-2 were successfully identified by the pre-trained Deep-LSTM model.

However, collecting data for a DNN model is easier than collecting data for an RNN model in the given target terrain. Synchronized camera-based position coordinate capturing system was used to collect RSSI data in different walking paths. The target person walked at 25 cm/s average speed in collection of data for RNN based analysis. Practically RSSI values were not recorded at some position coordinates of a walking path and camera-based system was used to manually filter those types of RSSI data.

Finally, this research was able to uniquely identify, localize, detect body orientation and track the walking path of a person. Since person is uniquely identified and RSSI data is MAC addressed this work can be extended to localization of multiple persons. The research was successful in applying machine learning and according to the findings we recommend to use Deep-RNN for noisy sequential RSSI data in cluttered environments.

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