Inferring Activities of Daily Living of Home-Care Patients Through Wearable and Ambient Sensing

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STATEMENT OF ORIGINALITY

I, Mathangi Sridharan, confirm that the research included within this thesis is my own work or that where it has been carried out in collaboration with, or supported by others, that this is duly acknowledged below and my contribution indicated. Previously published material is also acknowledged at the end of the thesis.

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TO MY FAMILY

Abstract

There is an increasing demand for remote healthcare systems for single person households as it facilitates independent living in a smart home setting. Much research effort has been invested to develop such systems to monitor and infer if the person is able to perform their routine activities on a daily basis. In this research study, two different methods have been proposed for recognizing activities of daily life (ADL) using wearable and ambient sensing respectively. The thesis presents a novel algorithm for near real-time recognition of low-level micro-activities and their associated zone of occurrence within the house by using just the wearable as the lone sensor data. This is achieved by gathering location information of the target person using a wearable beacon embedded with magnetometer and inertial sensors. A hybrid three-tier approach is adopted where the main intention is to map the location of a person performing an activity with pre-defined house landmarks and zones in the offline labeled database. Experimental results demonstrate that it is possible to achieve centimeter-level accuracy for recognition of micro-activities and a classification accuracy of 85% for trajectory prediction. Furthermore, additional tests were carried out to assess whether increased antenna gain improves the ranking accuracy of the fingerprinting method adopted for location estimation. The thesis explores another method using ambient sensors for activity recognition by integrating stream reasoning, ontological modeling and probabilistic inference using Markov Logic Networks. The incoming sensor data stream is analyzed in real time by exploring semantic relationships, location context and temporal reasoning between individual events using a stream-processing engine. Experimental

analysis of the proposed method with two real-world datasets shows improvement in recognizing complex activities carried out in a smart home environment. An average F-measure score of 92.35% and 85.75% was achieved for recognition of interwoven activities using this method.

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Table of Contents

List of Figures

List of Tables

List of Algorithms

List of Abbreviations

AAL	Ambient Assisted Living
ABox	Assertion Component
ADL	Activities of Daily Living
AI	Artificial Intelligence
AP	Access Points
BiLSTM	Bidirectional Long Short Term Memory
BLE	Bluetooth Low Energy
CASAS	Center of Advance Studies in Adaptive System
CQELS	Continuous Query Evaluation
C-SPARQL	Continuous SPARQL
DTW	Dynamic Time Warping
ECG	Electrocardiogram
FM	Frequency Modulation
FOL	First Order Logic
GPS	Global Positioning System
HMM	Hidden Markov Models

IoT	Internet of Things
IPS	Indoor Positioning System
LIDAR	Light Detection and Ranging
LOS	Line of Sight
LSTM	Long Short Term Memory
MCMC	Markov Chain Monte Carlo
MEBN	Multi Entity Bayesian Network
MFV	Magnetic Field Vector
MLN	Markov Logic Network
MM	Magnetic Matching
NBT	Naïve Bayes Tree
NLOS	Non Line of Sight
OWL	Web Ontology Language
PCA	Principal Component Analysis
PDR	Pedestrian Dead Reckoning
PMC	Product Moment Correlation
PR-OWL	Probabilistic Web Ontology Language
RADAR	Radio Detection and Randing
RDF	Resource Description Framework
RF	Radio Frequency
RFID	Radio Frequency Identification

RMSE	Root Mean Square Error
RNN	Recurrent Neural Network
RP	Reference Point
RSSI	Received Signal Strength Indicator
SCRRF	Skip Chain Conditional Random Field
SRL	Statistical Relational Learning
SWRL	Semantic Web Rule Language
TBox	Terminological Component
TV	Television
USB	Universal Serial Bus
UWB	Ultra Wide Band
WSU	Washington State University

Chapter 1

Introduction

This chapter presents the motivations of this thesis, the research objectives, the main contributions and the structure of the thesis.

1.1 Need for Remote Monitoring and Self-Care Systems

Routine activities such as eating, dressing, bathing, toileting are commonly referred to as *Activities of Daily Living (ADL)* which people tend to do on a daily basis for normal self-care [2]. There has been a significant increase in the number of home-care patients requiring assistance through caregivers with their daily activities. The caregiver may offer home visits based on the patient's condition and help with managing their day-to-day activities. Providing such close monitoring and management is expensive and time consuming. In most cases, the caregivers are understaffed and have to deal with high caseloads and administrative duties that could limit their time spent with patients [3].

Part of the caregiver's job is to interact and gather information from the patient if they have been performing their daily activities and then report back to the clinician regarding their progress. However in most cases, the collected information may be incorrect as the patients may not entirely tell the truth or forget to report information. This method of manual collection of data is quite laborious and puts extra burden on the caregivers. Advancements in cheap sensing technology and communication systems has helped improve quality of life by developing applications for various domains. Therefore, trying out alternatives such as setting up a smart sensing system at home that requires less monitoring by caregivers is the right way to move forward. Patients are embracing the new technology, which will enable them to live independently in the comfort of their own homes.

Commercially available smart devices and copious amount of research studies on smart living in homes have helped to design systems to look after the elderly and people suffering from other medical conditions such as depression, Parkinson's disease, Alzheimer's disease and dementia [4],[5],[6]. This research aims to address the above-discussed issues through development of smart monitoring solutions that use minimal sensing methods to understand, learn and interpret the daily activities of a person at their own homes. The results of the proposed system can be extended in developing an application to cater specifically for a health condition or delivering automated prompts to remind the home occupant to do their daily activities, which is beyond the scope of this thesis.

1.2 Research Motivation

Technological advancements in location based services have led to them being used as a solution for recognising low-level activities carried out by a person in an indoor environment [7], [8]. *Simple* or *Low-level activities* are simple activity steps or actions that cannot be decomposed any further. For example – sitting on the couch, standing, eating dinner, drinking tea, sleeping and so on. A collection of low-level activities makes up a *complex* or a *high-level activity*. Examples of a complex activity may include preparation of breakfast, which involves several low-level activities such as opening the fridge, using the microwave or toaster, using the kettle and so on. It may be possible to deduce the low-level activities if the locus of the person performing them is identified. Based on this hypothesis, the thesis tries to tap into the potential of using an indoor positioning system to derive low-level activities based on location context.

A combination of different sensing methods may be used to monitor high-level activities. Despite the presence of advanced sensing systems, recognition of complex activities may prove a challenging task as the low-level activities may be *concurrent* or *interleaved* in nature. The recognition of two activities happening at the same time through an observed activity sequence is called a *concurrent* activity. An activity is said to be *interleaved* if it is paused for a short duration and is resumed again after execution of another activity. A reliable system needs to be in place to handle the data complexity in a real-time scenario. Furthermore, it is not always feasible to have access to training data while setting up a monitoring system. The thesis tries to work around these issues and discusses two main models using an indoor positioning system for low-level activities and a hybrid ontology and Markov Logic Network (MLN) model for complex activities.

1.3 Research Questions

This thesis provides an overview of using different sensing technologies coupled with different computation techniques to model a real-world activity recognition problem, which are discussed in detail in the next chapters. In doing so, it aims to answer the following research questions:

1. **How to address the stability issues of an indoor positioning system for achieving fine-grained positioning accuracy?**

   Indoor positioning has been commonly used for monitoring and tracking user movement. However they are mostly restricted to the use case of room level monitoring as the wireless signals are highly unstable. The thesis attempts to answer this question through experimental testing done in Chapter 4. A possible solution of hybridising two different wireless technologies – *Bluetooth low energy (BLE)* and *magnetic field data* along with a novel algorithm is devised to predict low-level activities and walking trajectories derived from the resulting location context.

2. **What are some of the key parameters that affect the performance of an indoor positioning system using Bluetooth location fingerprinting?**

   Care has to be taken while designing an indoor positioning system for a domestic environment. Due to the presence of strong Non Line of Sight (NLOS) conditions, it is important to focus on choosing the right equipment and establish the data collection method before deployment. Important parameters such as deciding the number of receivers to be deployed, deciding the average length of walking routes to maintain in a training database, effect of receiver coverage density on position accuracy are discussed in Chapter 5. The experiments done in Chapter 5 helps in refining the performance of the BLE fingerprinting system. A detailed analysis is presented by evaluating these factors experimentally in a real-world apartment.

3. **How to tackle the challenge of recognising complex activities without the requirement of training data in a real-world setting?**

   Though there are several research works on activity recognition, a vast number of studies assume that the subject carries out only one activity at a time, which is rather unrealistic in a real-world setting. Chapter 6 aims to address this problem by using a probabilistic logic method such as Markov Logic Network (MLN) along with a domain ontology to exploit the inter-relations between the participating sensors, activities, location and objects in an unsupervised way. Additionally, well-defined C-SPARQL queries are formulated for deducing start and end times of a sensor event from raw unseen streaming data to explore the temporal relationships between different activities occurring together at the same time.

1.4 Contributions of this Thesis

Two different sensing methods that use contrasting models for activity prediction in a smart home are explained in this thesis. In the first half of this thesis, a novel hybrid supervised data-driven approach is adopted with wearable sensing for low-level activity recognition. Whereas, in the latter half of this thesis, unsupervised probabilistic reasoning techniques are integrated with static knowledge-driven methods for complex activity recognition using object-tagged and ambient sensors. In particular, the thesis identifies the following contributions:

1. Discovering low-level activities and their associated zone of occurrence by gathering useful location context information through wearable sensing for a domestic home environment with strong NLOS conditions.

2. Development of a novel sequence based algorithm for simple activity recognition using location-based techniques that requires less training data.

3. Prediction of walking trajectories of the home occupant moving between different areas of interest in a small household using just a wearable and without relying on data from other modes of sensing.

4. Investigation of factors that can help improve the performance of bluetooth location fingerprinting systems employed for fine-grained low-level activity recognition and route prediction.

5. Handling uncertainty using Markov Logic Networks over continuous incremental RDF sensor streams through exploitation of domain knowledge modeled using ontology.

6. Recognition of complex activities carried out in an interwoven manner in real time using an unsupervised approach.

1.5 Limitations of scope

This thesis focuses on evaluating the research questions posed above to address few problems that are particularly challenging or lacks sufficient investigation in the field of activity recognition. With the allowed time for PhD research, few key aspects surrounding ADL recognition for healthcare were selected for investigation and experimental analysis in this thesis. Further work on other aspects listed below was not possible in this project due to time constraints. In particular, the following limitations apply.

1. Both the data-driven and knowledge driven techniques discussed in the thesis using wearable and ambient sensing methods respectively were tested only in a single home user environment. Although, a multi-user scenario has not been tested in this thesis, it is possible to differentiate between two individuals through different device ID's (MAC address) of the wearable for the indoor localisation approach suggested in Chapter 4. However the effect of interference from multiple human bodies on the beacon signal is not studied

and may affect the positioning performance. In the case of ambient sensing systems, multiple people may perform individual or joint activities together such as preparing a meal or cleaning the house. Individual activity patterns can be studied in depth to help distinguish between persons carrying out the same activity. The model developed in this thesis is not sophisticated enough to identify such user patterns and may not cope with recognition of joint activities performed by two or more individuals.

2. The algorithms developed for indoor positioning for tracking user activities are designed with two-dimensional data co-ordinates and were tested experimentally in one-bedroom flats. Its suitability for multi-floor homes or large spaces is questionable and requires further development and testing. Using the same indoor positioning system described in Chapter 4 for a multi-floor environment may fail to distinguish between floors as the system was not calibrated to account for vertical localisation. In the case of the ambient sensing system, discussed in Chapter 6, using the same model in a multi-floor level home is likely to not have any major impact on the performance and can be used as it is without making any additional changes.

3. Chapter 5 considers a few important factors that affect the performance of the deployed indoor positioning system described in Chapter 4 for tracking the user activities and trajectories. However, there may be other factors such as receiver placement, receiver orientation, interference from human bodies and impact of certain building properties such as wall thickness on the localization accuracy that are not discussed in this thesis. In particular, the coverage area of the receivers may be reduced if the receiver placement

and orientation of the antenna is not directed properly. Furthermore, the presence of thick walls may weaken the beacon signal due to heavy attenuation leading to performance degradation.

4. The thesis does not develop an end product that is designed for a specific health condition, but in general suggests methods that aids in the process of effective ADL recognition. There are still many practical challenges involved for fingerprinting in particular and for the C-SPARQL-MLN model that need to be addressed such as data management and performance issues such as latency, interoperability. The model needs to be fine-tuned for it to be used by a suitable application specific user interface. The discussed methods can be further expanded into a complete end user health application with the guidance of a relevant clinician.

5. Activity recognition systems deployed in a private space such as a home environment should also consider the necessary privacy aspects involved. Although the data handled in Chapters 4 and 5 is processed locally, data encryption is not performed at any time, which may be a cause of concern for the end user. When used as an end user application, control can be given to users on how much information is shared. With respect to personal privacy, visual sensing was not considered as a sensing option in the thesis. This topic is beyond the scope of this study and the thesis does not discuss such feature at any point.

1.6 Thesis Outline

The structure of the remainder of the thesis is outlined below. Each chapter aims to address parts of the research questions posed above. The logical progression of work is illustrated graphically in Figure 1.1.

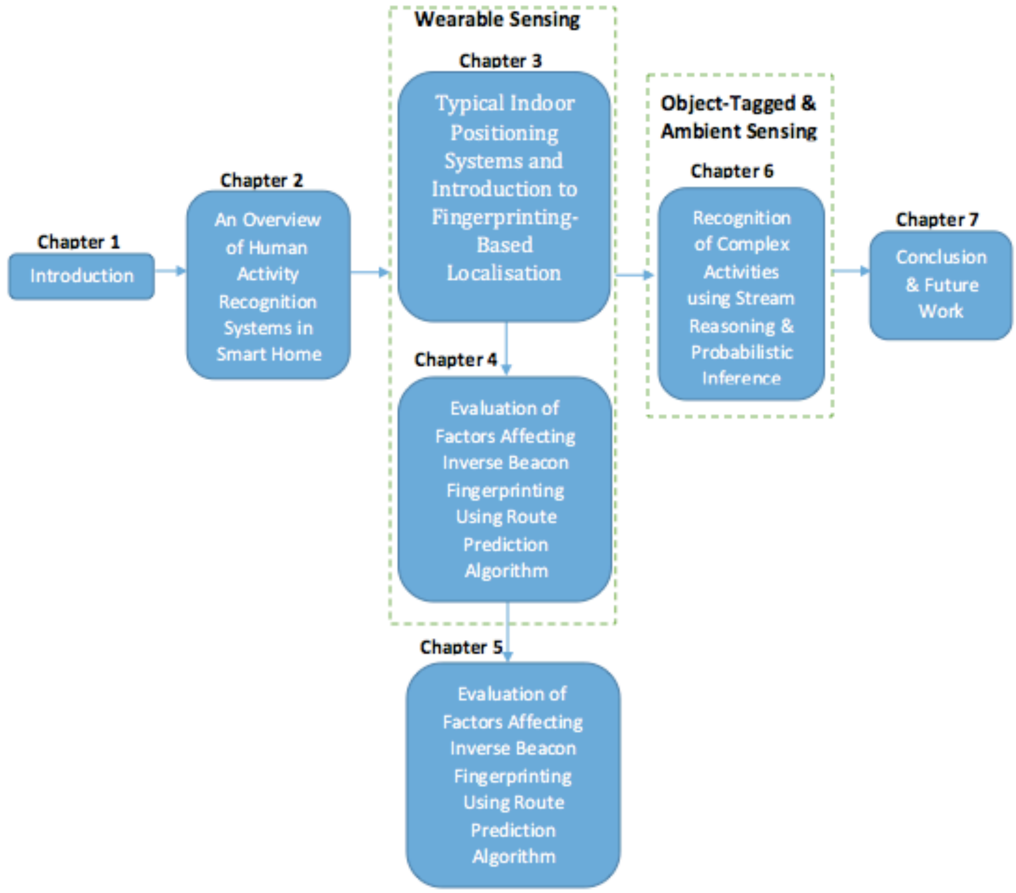


Figure 1.1: Thesis Progression

Chapter 2 presents an overview of the existing methods and techniques involved for each step in the process of activity recognition described with relevant examples from state-of-the-art works. The chapter also discusses the applications of smart home monitoring for healthcare and highlights the challenges faced by existing ADL recognition systems.

Chapter 3 presents an introduction to the indoor positioning system using different technologies and discusses the process of indoor location fingerprinting. It also explains the design process of the indoor positioning system employed in Chapters 4 and 5 highlighting the hardware setup, data collection process and design of the fingerprinting test beds.

Chapter 4 presents an approach for detection of low-level activities and walking trajectories using a hybrid indoor positioning algorithm through wearable sensing. The suggested approach applies fingerprinting techniques by integrating different technologies such as Bluetooth Low Energy (BLE), Magnetic Field and inertial sensors for accurate low-level ADL recognition assessed in two different homes.

Chapter 5 provides a detailed analysis on relevant factors that may affect the outcome of the indoor positioning method described in Chapter 4. The experiments conducted in this chapter will aid in the setup and choosing the number of equipment required for the home environment.

Chapter 6 outlines the approach of combining a knowledge-driven model with a probabilistic logic method and provides a detailed analysis of its benefits. It demonstrates the use of stream reasoning framework on real-world continuous data with probabilistic inference using Markov Logic Networks by making use of the domain knowledge represented using ontology.

Chapter 7 summarizes the developed methods and results obtained from the work carried out in this thesis, and outlines possible avenues for further research.

Chapter 2

An Overview of Human Activity Recognition Systems in Smart Home

The use of technology to support remote monitoring and self-care is transforming the healthcare industry and empowering patients to better manage their own health. However there are still various barriers to consider for it to be transformed into actual implementation. Efforts have been taken by a number of research studies to improve these areas of concern.

This chapter aims to provide an up-to-date summary of various state-of-the-art systems in activity recognition for smart homes. The three basic building blocks of any ADL recognition system are discussed in the first section. A detailed outline regarding state-of-the-art techniques applied in each of these three stages are introduced. It also presents the related work of activity recognition systems designed in specific for healthcare applications. The chapter concludes by providing an overview and a critical analysis of the related work.

2.1 Three Phases of Human Activity Recognition

Various techniques in activity recognition to support remote healthcare have been devised by exploiting pervasive computing technologies in the smart home domain. It is important for every individual to perform day-to-day activities such as brushing teeth, bathing, eating and other instrumental ADL's for their overall wellbeing. The ability to perform ADLs is used as a measurement of a person's functional status by a number of healthcare professionals. It therefore becomes necessary to monitor these routine activities to determine the progress and next level treatment for patients. Furthermore, monitoring the patients at their own homes through installation of remote healthcare systems provides a sense of independence and comfort to them.

Reliable ADL recognition involves choosing a sensing system that collects information about activities being currently executed, filtering the useful data from the raw sensor data obtained from the sensing system and using a computation model to infer activities done by a person. The process of ADL recognition can be divided into three main phases - *Feature Detection*, *Feature Extraction* and *ADL Prediction using a suitable model*. A glimpse into different techniques introduced at each stage is presented in the following sections.

2.2 Feature Detection

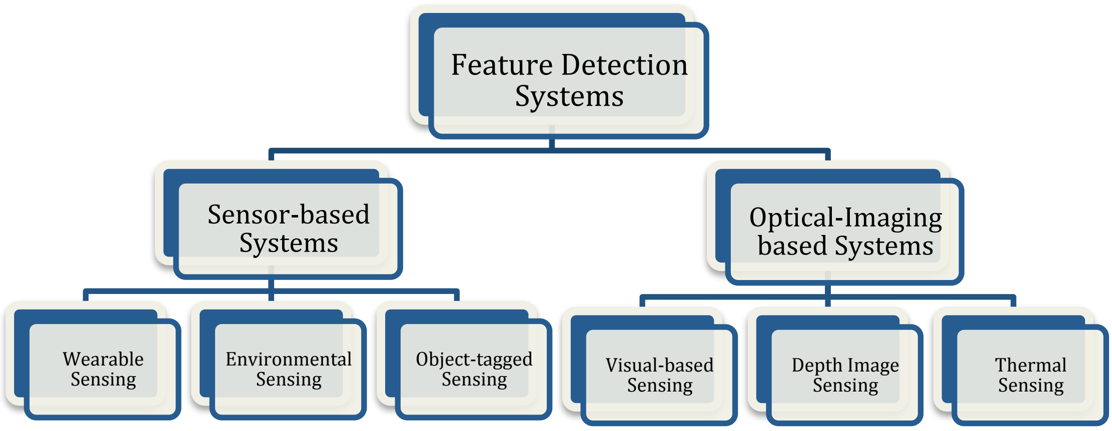


Figure 2.1: Types of Feature Detection Systems

The first step for ADL recognition is capturing relevant contextual information to infer the activity carried out by the home occupant. Deploying reliable monitoring systems is crucial as it reflects on the accuracy of the deployed activity recognition framework. Based on the type of observed data collection method, feature detection approaches can be broadly classified into *optical imaging* and *sensor-based systems* (Refer to Figure 2.1). A brief discussion of different techniques involved in feature detection are critically analyzed in this section.

2.2.1 Optical Imaging based Systems

In this section, we give a brief overview of various optical based systems ranging from visible imaging to thermal based sensing in the field of human activity recognition.

2.2.1.1 Visual-based Sensing

Visual-based systems include cameras or surveillance systems to monitor the person's actions in their homes. These systems have been a popular choice for data collection among the research community as it was one of the initial approaches used for activity recognition. Application of computer vision techniques on the captured data can recognize a variety of fine-grained activities [9], [10], [11]. The main challenge in these systems is extracting feature representations from videos to develop a robust human recognition model [12]. Tran et al. [13] adopted a deep learning architecture called C3D for classifying actions captured through video which extends a conventional 2D-CNN with a third convolution direction over time. The performance was evaluated using three public video databases and demonstrated that the developed structure was designed such that extracted features model appearances and motion simultaneously. Another study developed a similar model using two streams of 3D CNN. The features from the appearance and motion estimation stream were concatenated respectively to feed as input to a softmax layer to infer the activity classes. The main drawback however is the privacy involved with visible sensing methods. These solutions were identified as too intrusive in a smart home environment according to a recent study. The results showed that camera based medical monitoring in a private space such as a home had the lowest acceptance rate at 13.46% [14].

2.2.1.2 Depth Image Sensing

Lately the use of depth sensors has been gaining popularity for improving accuracy. Devices such as Kinect can be used capture human motion and record the 3D co-ordinates. A fall detection system designed by Mettel et al. [15] used a single Microsoft Kinect depth camera installed on the ceiling. The system used a combination of static detection to check if the person was lying on the floor with the dynamic motion detection of the fall. The use of a single depth sensor however resulted in performance degradation, which as per the author could be overcome by integrating multiple installations of the depth sensor. In another study, the authors have used Kinect-based sensors along with video cameras for data capture to enable them to function effectively under all lighting conditions [16]. [17], [18] and [19] have used a combination of standard web cameras and Kinect sensors for gathering activity information during all times of the day in their research study.

2.2.1.3 Thermal Sensing

Thermal infrared imaging is particularly useful when the human subject is indistinguishable from the background due to appearance and lighting conditions. These passive sensors measure infrared radiations emitted by warm objects as a thermal image. One such study makes use of thermal infrared imagery for spatio-temporal gait representation, called the Gait Energy Image (GEI), for human repetitive activity recognition [20]. GEI represents human motion sequence in a single image while preserving temporal information unlike other studies, which consider gait as a sequence of templates. Another study by Hevesi et al [21] leveraged a low-cost sensor array of 8*8 thermal sensors for recognizing different activities ranging from opening a refrigerator, oven or showering and also usage of electric appliances. The system claimed to track people within 1m accuracy range. A 16*16 thermal sensor array was used in [22] to recognize basic activities such as sitting, standing, walking etc. and abnormal activities such as fall detection. The authors used a deep learning based approach for extracting spatio-temporal representation. Thermal infrared sensing serves as a way to reduce the privacy concern caused by cameras in a household space by not revealing too much private information.

Despite the existence of several optical imaging systems designed for activity recognition, the acceptability of such systems are still questionable [23]. As per the study in [23], the end user is likely to accept a monitoring system that is less intrusive and vigilant regarding the data collected.

2.2.2 Sensor-based Systems

A wide range of sensor-based options is available to monitor the behavior of the person with their associated environment. Advancement in sensor technology and low cost has further encouraged many researchers to opt for a sensor-based approach for activity recognition. They can be further classified into three categories based on the method of deployment, which are *wearable*, *environmental* and *object-tagged sensing*.

2.2.2.1 Wearable Sensing

Wearing different types of sensors around the body is another popular method for collecting data about body condition and surroundings. They have been extensively used in the recognition of human physical movements. Devices ranging from accelerometers to wearable ECG sensors have also been used for monitoring patients at home when they suffer from disorders such as heart attack, anorexia, bulimia, Parkinson disease, Alzheimer's disease, depression and so on [4], [5],[6] and [24]. In [25], a combination of sensors meant for activity sensing, ambient environment sensing and location context sensing is integrated into a wrist-worn smart wearable device. Bluetooth low energy beacons are deployed in the surrounding infrastructure to notify the wrist worn wearable whenever in range, thereby estimating the location proximity.

Recently, micro-sensors that come in the form of body patches have been developed to monitor the body's physiological parameters. They are little less than one millimetre thickness and their usage is expected to increase by 40% in the next ten years [26]. These sensors that are termed as bio-stamps looks like a tattoo or sticker and have the capability to monitor chemicals in sweat, measure blood pressure, skin hydration, temperature and so on [27], [28] and [29]. Apart from micro-sensors, there has been increased research interest in the development of implantable medical devices. These minute sensors use RFID and can be implanted into the human body or are attached to certain internal organs for monitoring health parameters [29].

One notable disadvantage of this type of sensing is that they may easily be misplaced or the patient may forget to wear resulting in inferior performance of the monitoring system. Technical issues such as size, ease of use and battery life is another concern.

2.2.2.2 Object-Tagged Sensing

This method is also commonly referred as *dense sensing* which involves attaching sensors to objects of daily use. Activities are recognized based on the person's interaction with the object. Low-cost low-power object sensors are readily available which makes them suitable for deployment in intelligent pervasive environments. Furthermore, they are easy to install, require minimal maintenance and supervision, and do not have to be worn or carried. A change in status of an object-tagged sensor provides a strong indication of an activity being undertaken by the person. Displacement sensors, pressure mat sensors or contact switches are some of the commonly used sensors for tagging objects that simply report a value of zero or one at each time step when used. For instance, the activation of pressure mat sensors placed on the bed can strongly suggest the action of relaxing or sleeping.

The dense sensing paradigm has been deployed in different smart homes for ambient assisted living (AAL) [30], [31] and [32]. A major drawback of this type of sensing is that it bounds the person to use tagged-objects for recognition of activities. The lone use of object-tagged sensing method may not be suitable for recognizing all types of activities that do not require device interaction.

2.2.2.3 Environmental Sensing

Environmental or Device-free sensing has been gaining popularity over the past few years since users are not required to wear or tag the objects while performing an activity. The sensors are deployed in the surrounding environment to capture data for ADL recognition. A number of radio frequency (RF) based device free approaches have received significant attention for human presence detection and activity monitoring by capturing the data through deployment of RF tags in the surrounding environment requiring no participation from the user.

Different wireless technologies such as RFID [33]-[34], Wi-Fi [35]-[36], ZigBee [37]-[38], FM radio [39]-[40], microwave [41], RADAR [42], LIDAR [43] are commonly used for this type of sensing. However, the system may malfunction when reading from multiple receiver tags at once due to signal collision. The data captured by the sensing equipment may also be subjected to other forms of interference from the environment causing the injection of noise into the data. Various noise removal and anti-collision algorithms need to be formulated for effective activity recognition. Care needs to be taken to reduce the computational cost and complexity of the system through introduction of such algorithms.

Each category discussed above has its own share of pros and cons. The suitability and performance of the sensing method depends on the activities to be assessed and its end application. One or more sensing methods may also be used in combination with each other to yield acceptable results. In Chapters 3 and 4, wearable sensing method is used along with RF technology for low-level activity recognition and in Chapter 5, movement sensors and object-tagged sensors are used for detecting the human presence and capturing the human-object interaction respectively. Use of different computation methods in addition to employing two different sensing paradigms in this dissertation provides an overall insight into various techniques that can be adopted for AAL.

2.3 Feature Extraction from the Data Collected

Feature extraction or feature engineering is an important phase in activity recognition systems since the features extracted from the raw sensor stream influences the final outcome. This is also one of the most challenging phases in an ADL framework as it is quite difficult to determine useful information from continuous raw sensor data in a dynamic environment. It involves extracting important features through domain-specific expertise to train a machine-learning algorithm and to create a suitable predictive model. In most cases, the raw data collected from sensors requires intensive feature engineering to produce a model with sufficient prediction accuracy due to the large scale input database. Feature engineering of such time-series data collected using sensors is essential to provide as much information as possible with an optimum cost computation algorithm [44]. For techniques adopting machine learning methods for inference, a number a learning methods are used to select the features relevant to the recognition problem [45].

The sensor training data is usually quite large and a number of statistical methods may be applied to derive useful information in the form of different features. The most important features are then selected using relevant feature reduction techniques to reduce the overall dataset dimension. Mahbuba et al. [44] conducted a comparative study of ML classifiers for human activity recognition by applying different feature engineering techniques. The motivation of the study was to portray the significance of the feature engineering stage with data mining and ML algorithms in the field of human activity recognition. Four different feature-engineering approaches were implemented and the selected feature set from each of the four approaches were used to train various ML models. The final results indicate that the Extra tree classifier feature set showed the highest accuracy on average for all the considered ML classifier models; out of which, Multi-layer perceptron model performed the best.

Zdravevski et al. [46] proposed an automated feature engineering method which selects the best feature sets for execution of AAL algorithms for robust activity recognition. The authors tested this approach on five publicly available datasets. Each of the datasets was subjected to segmentation by applying a sliding window approach followed by extraction of time and frequency domain features from raw sensor data and carry out feature reduction techniques respectively.

For a majority of activity recognition applications, sensor data needs to be pre-processed and segmented after data acquisition. Determining the length of the sensor event stream to be used for real or near-real time ADL recognition also poses a huge challenge. Research work in the area of sensor data segmentation is quite sparse. Sliding window technique is a method used to identify the length of the sensor stream for activity recognition from an un-segmented sensor sample. The size of the window may be determined by using different parameters such as time intervals, number of sensor events triggered, change in person's location and other parameters that may help filter out the useful information from the raw sensor data. The authors of [47] follow the approach of segmenting the sensor stream into individual windows based on time intervals between observations and movement of a person between different zones (e.g. moving between sink zone to toilet zone). The main drawback is that it might take a longer time to define the segmentation until adequate information is received. There is also the issue of segmenting the sensor stream if multiple events mapped to different activities occur simultaneously when ADLs are performed in an interwoven manner. Hence including temporal information and finding the start and end times of the observed events can help in complex activity recognition in the later stages.

[48] presents a novel strategy for dynamic sensor data segmentation that includes a computation based on sensor correlation and time correlation. Pearson product moment correlation (PMC) coefficient is computed between the sensor events to delineate the boundaries of the activity. The PMC value depends on the placement of the sensor and a suitable threshold value is selected to determine the sensor correlation. A high PMC value indicates that the sensors are located within each other's vicinity and are therefore likely to be triggered together or sequentially. For time correlation, maximum time span is set for each activity and are identified based on the functioning area. The final segmentation is done based on the results of the threshold parameters set for time and sensor correlation. This type of approach allows recognition of activities at near real-time. The researchers of [49] have used dynamic time warping approach for sensor segmentation and differentiating between a set of ten low-level kitchen activities such as chopping, coring, dicing, peeling and so on. This was done by analysing continuous sensor data recorded by accelerometers that were embedded into the kitchen utensils.

2.4 Models Used for ADL Prediction

Models developed for ADL recognition frameworks can be divided into two categories namely, *inductive* and *deductive* [50],[47]. The inductive or data-driven methods mainly involve making decisions based on generalization and learning from examples observed in a specific case. This method includes the different machine learning algorithms that are executed based on the available training examples. Whereas, deductive methods utilise contextual information along with semantic knowledge to reach a conclusion. This includes all the activity recognition models that are based on knowledge-driven techniques such as logic-based [51] and ontology-based [52] approaches. In most cases, a combination of inductive and deductive models is used together in an ADL recognition framework [53]. Relevant literature that use one or both these methods are discussed below.

2.4.1 Inductive or Data-Driven Approaches

User activity models are created from existing large training datasets by using data mining and machine learning techniques and using the learned models to infer activities [54] – [55]. Many models have been used for inference of ADL at home, out of which the most popular computational models include the Hidden Markov Models (HMM) and Bayesian Models. In [56], HMM's that employ Viterbi decoder are adopted for real time human activity recognition. Instrumented objects along with hand co-ordinate data are used to correctly determine the sub-goals of tea making task. Their approach makes it feasible to detect sub-goals that occur simultaneously by passing the extracted feature vectors through a set of parallel asynchronous HMM detectors, each responsible for detection of one of the sub-goals.

In another prototype, few off the shelf sensors were used to investigate a measure of interaction with everyday objects called "busyness" to develop a reliable and cost effective AAL system for the elderly to live independently [57]. In their case study of hot drink making activity, Principal Component Analysis (PCA) is used for data pre-processing to reduce the number of features and maximize the system performance. This reduced dataset is then subjected to cluster analysis based on K-means algorithm and then uses Average Silhouette Width's indexes to estimate the number of clusters. But this system fails to distinguish between different people and hence is not applicable for a multiuser environment. The wearable used in [25] incorporates Deep Learning Neural Network based data analytics into its design that ensures fine-grained ADL recognition at home. It makes use of stochastic gradient descent algorithm with 2 hidden layers for training the neural network. The model also performed a 5-fold cross-validation to determine the number of neurons in each of the hidden layers. The final results indicate that a choice of 100 and 800 neurons in the hidden layers provide a reasonable 89.38% cross validation accuracy in their test experiment.

In [48], a number of popular algorithms such as Naïve Bayes, Bayesian network, C4.5 decision tree, Naïve Bayes tree (NBT) and HMM were assessed and compared to find the best recognition rate. The hybrid algorithm, NBT demonstrated improved recognition performance, but it was pointed out that the choice of algorithm might not be the single deciding factor for improving the precision rate. Support Vector Machines (SVM) and Artificial Neural Networks (ANN) are most commonly used discriminative approaches [58]. In [58], the authors use an SVM classifer on two existing datasets to resolve problems in activity recognition. The developed model is compared against 1-Nearest Neighbour classifier. The authors noticed that the SVM classifier performed poorly on imbalanced training sets.

Employing deep learning models to recognise complex activities has been gaining immense popularity. The authors of [59] have used a hybrid deep machine learning approach to recognise concurrent and interleaved ADL's. A two phase approach wherein a Bidirectional LSTM (BiLSTM) model to recognise concurrent activities and a Skip-Chain Conditional random field (SCCRF) model to identify interleaved activities were devised. The experimental analysis performed on two public datasets yielded an average accuracy of 93%. Another study [60] implemented four deep learning classifiers using BiLSTM to recognise complex activities with an average accuracy of 95%. However both these studies and other machine learning approaches require extensive training data to provide reasonable results.

The main advantage of data-driven methods is their ability to model uncertainty, which is important for real world deployments. However, they suffer from cold start problem, as copious amounts of training data are required for reliable activity recognition [50].

2.4.2 Deductive or Knowledge-Driven Approaches

Different types of knowledge-based approaches have been developed for recognising constituent tasks from sensor event data. The ADL's may be modelled as a set of goals and sub-goals to represent simple tasks. For Example: In [61], An ADL for "Make Breakfast" has "Enter Kitchen", "Prepare Food", "Cleaning", "Leave Kitchen" as their sub-goals. These sub-goals can be further divided into its sub-components. In this case, "Prepare Food" has the sub-goals "Prepare Toast" and "Prepare Tea". Researchers of [47], [62]-[63] use a hierarchical framework for identification of different ADL's where ADL's are at the top of the hierarchy and sensor events form the lowest level. In [62]-[63], ADL recognition is divided into two levels where the lower tier is responsible for task recognition from different sensor events and the higher tier carries out recognition of activities from the tasks recognised in the lower tier. The higher tier comprising of different ADL's were modelled using a plan representation language called Asbru.

Using ontologies for activity recognition has garnered interest as they facilitate portability, interoperability and reuse for different applications [64]-[65], [50]. Moreover they can capture and encode rich domain knowledge in a machine understandable way. The ontology model when combined with contextual information can help decrease data misinterpretations.

In [66], the authors carry out ontology based activity recognition by using a model which consists of the user's context such as human posture, location, sensor and so on. With the added information regarding the posture data, the authors were able to solve some of the ambiguous cases and distinguish between final activities through ontological reasoning. The researchers of [52] developed an ADL framework that is purely knowledge driven based on an ontology model. Their purpose of the study was to experimentally evaluate the effectiveness of the ontology approach using a smart home activity dataset. The preliminary results highlighted that the ontology-based approach without temporal information underperformed when compared to the data-driven techniques. However when the model was extended with temporal reasoning, the performance was comparable with techniques such as HMM. The authors of [67] create a knowledge-driven framework for situation awareness and human activity understanding in multi-sensor environments. The framework relies on ontology design patterns and standards such as SPARQL that can be reused with different individuals or environments. In [68], a rule-based method was proposed for offline and online ADL recognition that was implemented using Jess rule engine for a smart home environment. The developed system uses a bottom-up multi-level reasoning approach to recognize complex activities.

Compared to the data-driven approach, knowledge-driven approaches do not suffer from cold start problem as they use generic domain knowledge rather than data for activity modeling, but are weak in handling uncertainty.

2.4.3 Hybrid Approaches

The main idea of hybrid-based activity recognition approaches is to solve the drawbacks of data-driven and knowledge driven methods through combined usage of both the methods in a single system. [53] combine statistical inference techniques with ontological activity modeling and recognition. Similarly in [69], the authors proposed the AGACY Monitoring hybrid model by integrating the background knowledge with the data-driven method for recognition of activity instances and hence were able to support the inherent uncertain nature of sensor data.

Different probabilistic techniques such as Dempster-Shafter theory [70], Markov Logic Networks (MLN) [71]-[72] and Bayesian networks [73] are used along with ontology-based approaches in order to handle uncertainty. In [71], probabilistic ontology based activity recognition of complex activities is carried out through use of MLN models containing formula weights. The authors used a hybrid location based sliding window approach to intelligently segment the data based on the zone where sensors were triggered. MLN rules were formulated using object sensor mappings from the ontology and formula weights were assigned based on the observed training data. The authors were able to achieve an average F-measure of 96%. Riboni et al. [72] also used Markov logic network models to recognise concurrent and interleaved activities using an unsupervised approach. The study relied on ontological reasoning to derive necessary conditions about sensor events and semantic correlations. The start and end times of the activity instances were decided based on these sensor correlations.The final activity recognition on the candidate activity instances were performed using MAP inference based on the MLN model defining sensor events and semantic constraints. An average F-measure of 78% was achieved using this model.

2.5 Privacy Issues in Human Activity Recognition

Though activity recognition using the latest smart devices and technology presents innumerable benefits, privacy breach when dealing with software, data collection and sensing methods is a cause of concern. Privacy infringement in ADL recognition systems may take place in various forms. For example: unintentional exposure of personal information from photos or images recorded by the surveillance system, information leakage during data pre-processing and analysis, extracting data related to user behavior or location details from raw data and so on. It is therefore necessary to implement suitable measures to protect human related privacy while handling sensitive data for the purpose of activity recognition. The authors in [74] and [75] proposed complete data isolation by carrying out homomorphic encryption (HE) to prevent information leakage. Similarly sensitive areas in images or videos are encrypted in the study conducted in [76]. Another interesting privacy-preserving solution is to capture anonymized images or videos by using different modified pictures of the same person [77]. Garcia et al. [78] proposed edge computing over central computing to prevent risk of hacking and delay in data transmission. The data is thus immediately analyzed and processed locally near to the user's device rather than sending it to a central data center such as the cloud. Few studies have proposed adversarial trainings to suppress the information disclosure for preserving privacy in deep learning and neural network approaches [79], [80]. This type of machine learning technique supplies deceptive input such that sensitive information is eliminated while maintaining sufficient information to predict the user's activity. Another option is to implement differential privacy by injecting noise in order to prevent information disclosure in machine learning methods [81], [82]. Based on the model adopted for activity recognition, a suitable privacy preserving solution can thus be implemented.

2.6 Applications of ADL systems for Healthcare

There has been some significant amount of work done in the area of activity recognition at home designed specifically for elderly monitoring, treatment of health disorders [4], [5], [6] and for overall wellbeing. Figure 2.2 illustrates some of the common healthcare applications developed for smart homes. A number of research projects have been dedicated for healthcare in smart homes [83],[84]. The project "Aging in Place" was developed to assist seniors to live independently at their own homes [83]. The popular SPHERE project helped people by predicting falls, strokes and to detect periods of depression or anxiety using computer-based therapy, in addition to analyzing human eating behavior [84].

There are few proposed systems that deal with depression treatment by monitoring the person's daily activities at home [86]. One such proposal is Help4Mood that was mainly framed for people suffering from major depression [86],[87]. This system makes use of non-intrusive sensors along with an interactive virtual agent, which compiles changes in activity pattern and reports it to the clinician. Data is collected using a smartphone as well as wearables. In addition to these sensors, parameters such as sleep time, sleep quality and physiological measurements such as heart rate and breathing are measured using an under-mattress sensor and a watch that works on the SimpliciTI protocol. Based on the incoming data from the

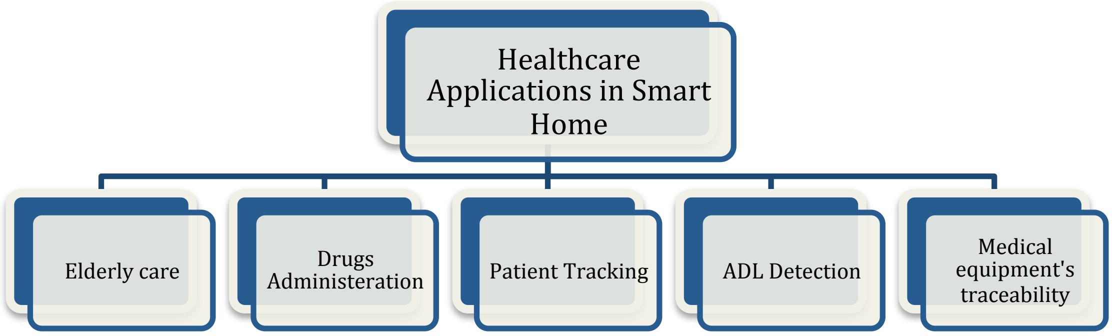


Figure 2.2: Healthcare Applications in Smart Homes. Adopted from [85]

sensors, the developed virtual agent (VA) prompts the user to carry out helpful activities and alerts the clinician if necessary. ICT4Depression project incorporates the use of biosensors and comprises of interactive self-management modules and intelligent reasoning system integrated through an innovative mobile solution called Moodbuster [87]. A number of therapeutic modules that deals with goal setting, exercise therapy, medication therapy and feedback modules about the level of mood are also present. These modules help the patient in doing their daily routine activities by sending reminders in addition to updating itself by prompting user for mood ratings.

2.7 Challenges of Existing Activity Recognition Systems

Although significant research has been done in the field of activity recognition, there are still some open issues that need to be addressed.

2.7.1 Complex Activity Recognition

Most of the existing work in ADL recognition concentrates on recognizing only one activity at a time. But in a real world scenario, a person may carry out activities concurrently i.e., multiple activities at the same time. For example, a person can talk in phone and watch TV at the same time. A majority of the existing works on ADL recognition have been used only for simple activity recognition and does not deal with handling concurrent and interleaved activites [88], [89]. A number of data-driven models such as [59] are designed for complex activity recognition. However they require extensive training data to achieve reliable results. Very little research has been done in this area. The thesis attempts to address this issue in Chapter 6 through probabilistic inference and reasoning.

2.7.2 Real-Time Recognition

It is a challenge for many existing systems to cope with the high volume and continuous incoming data from heterogeneous sources and carry out the ADL recognition with less latency [90]. Real time recognition is vital in many smart home health care systems. Dynamic segmentation techniques has been studied in various research works such as [91], [48], [92] for real time recognition. In [92], authors use a semantic segmentation technique on real time streaming data and separate them into multiple dynamic threads for inferencing. The activity was then predicted using the domain knowledge encoded in an ontology. In this thesis, a stream reasoning approach is introduced in Chapter 6 to help process large amount of sensor data against the knowledge base with high throughput.

2.7.3 Security

Security is one of the important open issues that needs to be addressed in ADL recognition. Relevant security measures to ensure data protection, privacy and accessibility needs to be researched. As highlighted in Chapter 1, this thesis does not discuss this aspect. However methods such as homomorphic encryption discussed in Section 2.5 can be implemented to prevent information leakage [75], [74]. Use of visual based sensing methods can be quite invasive. Personal privacy can be preserved by introducing features to anonymise the person appearing in images or videos as in [77]. In this thesis, data is processed locally near to the source (in Chapter 4) and only non-invasive modes of sensing are used.

2.7.4 Minimal Sensing

Home-care patients opt for a minimal sensing environment with an ADL recognition system [93]. The complexity of the recognition algorithm may increase when more number of sensors are used [94]. Hence efforts have been taken to reduce the sensing equipment used in Chapters 4 and 5 by using just a wearable and few receivers. Similarly, minimum number of sensors from a real-world public dataset has been chosen in Chapter 6. Despite the minimal sensing environment, the developed models in these chapters perform well without compromising on the accuracy of the predicted activities.

2.7.5 Requirement of Extensive Training

A number of studies that implement data-driven approaches propose solutions that require extensive training data [59], [56], [54]. The performance of such systems are largely dependent on the quantity and quality of training data. However, amassing massive training data in a real-world setting is not feasible and practical. In this thesis, efforts have been taken to reduce the amount of training required for the data-driven approach discussed in Chapters 4 and 5. Furthermore, Chapter 6 tackles this issue by using an unsupervised approach to carry out probabilistic inference when combined with an ontology.

2.7.6 Multiple Subjects

It is necessary to design an ADL recognition system to handle situations with multiple subjects in a smart home setting. For example, multiple people carrying out kitchen or living room activities .The different challenges and opportunities involved in multi-user activity recognition is discussed in [95] However, the work done in this thesis is not tested experimentally for such scenarios and may need further development and investigation.

2.7.7 Variability

Variability refers to the same activity being performed by different persons or same activity performed at a different pace and order. An activity recognition system needs to be robust enough to deal with the issue of variability as it may otherwise lead to performance degradation. The real-world dataset used in Chapter 6 consists of data recorded for eight different ADLs performed by twenty one participants in no specific order or time. Also, in Chapters 4 and 5, experimental analysis was conducted on data recorded by two different participants. Despite the complexity involved, the proposed systems were able to overcome the issue of variability and produce good results.

The next chapter provides a formal introduction to different indoor positioning systems and the process of indoor location fingerprinting. Chapter 3 describes the design details implemented in Chapters 4 and 5 and will serve as a base for understanding the concepts presented in both these chapters.

Chapter 3

Typical Indoor Positioning Systems and Introduction to Fingerprinting-Based Localisation

Indoor Positioning Systems has been an actively researched topic in the past years due to the growing demand to provide location-based services for various applications indoors. Traditional techniques such as fingerprinting is still used in many studies due to its many benefits. The first half of the chapter presents a short introduction to existing indoor positioning systems followed by describing the indoor location fingerprinting approach. The experiment design details regarding the hardware setup, data collection process and design of the fingerprinting test beds is explained in the second half of the chapter.

3.1 Introduction to Indoor Positioning Systems

The demand for indoor positioning systems (IPS) has increased in recent years in order to provide support to a range of pervasive applications like indoor navigation, proximity based applications, elderly person monitoring, asset tracking and indoor emergency systems. The Global Positioning System (GPS) that has been widely used for outdoor positioning, fails to provide adequate support for indoor localization due to the high attenuation of the satellite signal caused by roofs and walls inside buildings [96]. As a result, this has opened up research on alternative methods that are reliable and capable of achieving higher accuracy. Over the past few years, researchers have developed indoor positioning systems that are based on different mediums. An overview of the common technologies used for indoor location estimation is illustrated in Figure 3.1.

Radio Frequency (RF) based systems such as Wi-Fi, Bluetooth, Radio Frequency Identification (RFID) and Ultra-Wide-Band (UWB) are the some of the most popular technologies used in existing IPS due to the widespread prevalence of hardware and existing networks [97]. Indoor positioning using Wi-Fi based on the IEEE 802.11 standard is a popular choice due to the wide scale deployment of wireless LAN infrastructure in buildings. It has the advantage of using previously deployed access point infrastructure and provides extended coverage over several meters [98][99]. Existing localization systems that use Wi-Fi as the medium, apply either the timebased, angle-based or Received Signal Strength Indicator (RSSI) based technique. RADAR, the world's first Wi-Fi signal-strength based indoor positioning system uses RF fingerprinting and implements nearest neighbor algorithm to estimate the user's location [100]. Its median accuracy was in the range of 2 to 3 m. Bluetooth is another widely used wireless technology that operates in

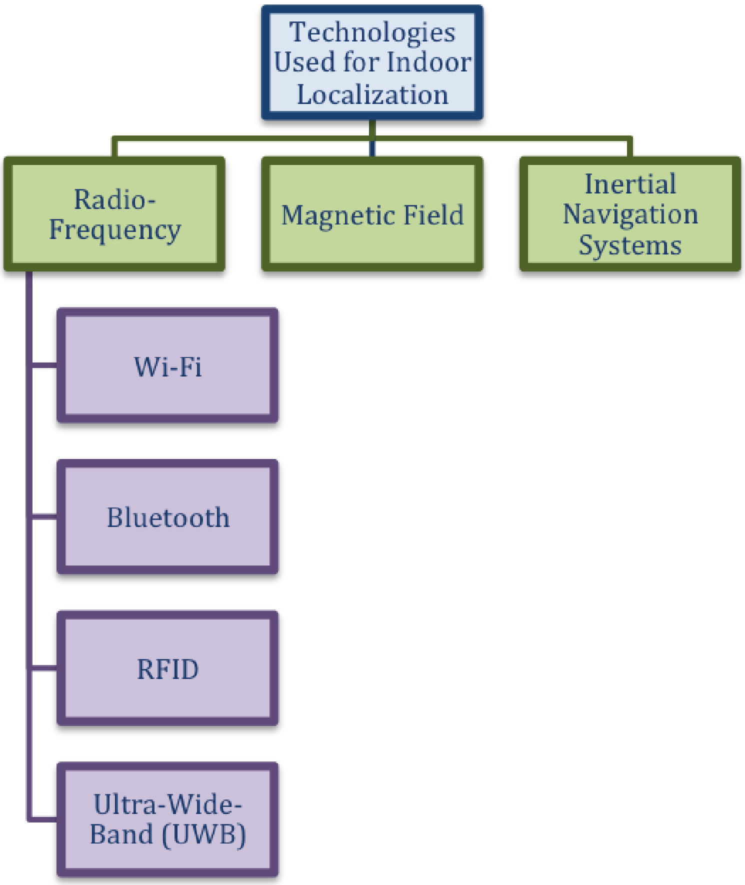


Figure 3.1: Different Technologies Used for Indoor Location Estimation

the 2.4 GHz band and is based on the IEEE 802.15.1 standard. Similar to Wi-Fi, a number of consumer devices are equipped with Bluetooth radio transceivers and is readily available. Increasing number of IPS utilise Bluetooth Low Energy (BLE) ever since the introduction of iBeacon protocol. The protocol was first introduced by Apple [20] and since then, various other vendors have designed compatible low-cost beacons that implement BLE wireless technology. RFID technology has also been used for locating assets or people in an indoor environment. RFID compatible hardware is inexpensive and is relatively simple to use and easy to maintain. The authors of [101] and [102] use Time of Arrival (ToA) and RSSI techniques for RFID based location systems. Their work highlights the issue of high power consumption, delay in receiving response and the need for higher density of nodes to improve accuracy. When a radio signal is transmitted, it can take multiple paths including the direct path to reach the receiver. UWB technology, which uses very narrow pulses, will be able to distinguish these individual signals as they arrive at the receiver. This ensures finding the direct path component in the multipath signal leading to high precision measurement of time of flight of the signal.

Apart from these technologies, magnetic field based positioning systems have garnered extensive interest amongst the scientific community due to the fact that they are not prone to multipath degradation and can operate in obstructed Line of Sight (LOS) conditions [103],[104]. The anomalies in the ambient magnetic field, which are formed due to distortions caused by the surrounding structural steel elements, form the main basis for building magnetic maps for indoor localization [103],[105]. In comparison with Wi-Fi or Bluetooth Low Energy (BLE), the magnetic field has low sensitivity to changes in surrounding environment (movement of people or furniture) and therefore, has the capability to generate the same magnetic fingerprint over time [104]. However an extensive reference database consisting of continuous samples of magnetic signatures is required to improve the accuracy and uniqueness of the mapping.

Another viable technology used for indoor location estimation is the use of inertial sensors at high sampling rates to obtain position and orientation information. This process is often referred to as *dead-reckoning*. These sensors are compact, low cost, lightweight and most of them are integrated into smartphones. A major drawback with these systems is that a small deviation in orientation measurement could lead to large errors in position estimation and hence may require frequent calibration.

Each of the above-discussed technologies has its share of limitations. The positioning accuracy of RF based systems is largely dependent on the location fingerprint created by the radio signals being reflected and attenuated by objects through which they pass. In a dynamic, realistic scenario the layout of the environment will change; For example, furniture being moved which will change the reflection and attenuation characteristics from those when the training data was collected, which may reduce accuracy. On the other hand, UWB systems perform well in Non-Line-of-Sight (NLOS) conditions achieving a positioning accuracy of the order of 20cm. But most of these systems are commercially expensive when compared to other technologies and in some cases, the signals may be blocked by large metallic objects [106]. The decrease in accuracy of Wi-Fi based positioning caused by user movement and presence of obstructions remains a main concern [107]. Zhao *et al.* compared the positioning accuracy of BLE and Wi-Fi in a similar test bed environment and the results showed that BLE outperformed Wi-Fi by around 27 percent [108]. BLE devices are low power consumption devices which allows them to be continuously powered from batteries from months to years [109]. This makes them a suitable candidate to be deployed in places where WiFi access points would be difficult to power. Furthermore, the usage of iBeacon technology is expected to increase in the coming years with the release of Bluetooth 5. Technologically advanced Bluetooth 5 has improved speed, broadcast messaging capacity and increased range contributing to better localisation performance.

Having considered the advantages and disadvantages, of various technologies, Bluetooth RSSI and magnetic field data were opted as the main technologies for the indoor localisation system discussed in Chapter 4.

3.2 Introduction to Indoor Location Fingerprinting

Radio Frequency (RF) fingerprinting techniques using different wireless technologies are often considered to be suitable for indoor localization since they provide better performance when compared to triangulation [110] - [111]. It is based on the signal strength measurement and involves two stages; the offline training phase and the online positioning phase. In the offline phase, a detailed site survey is performed where sufficient number of RSSI samples are collected and recorded at known locations to construct a training database (also known as a radio map). During the online positioning phase, the gathered RSSI samples from one or more receivers are compared against the radio map using deterministic or probabilistic methods to estimate the target's location. As a result, the radio map accuracy is crucial to the success of the system.

Factors such as number of training positions (also addressed as reference points in this thesis), measurements at each position and the labeling format of the received signal data are important parameters to be considered before the training stage. Increased space between reference points reduces granularity and may lead to high positioning error. On the other hand, the surveyor needs to cover more training positions when the space between the reference points is less making it more laborious. It is also important to collect sufficient number of samples at each position for providing a detailed location fingerprint. Lastly, the RSSI data sample at each reference point needs to be labeled using a suitable identifier (For example: Cartesian co-ordinates, latitude and longitude or any user-defined label). One of the limitations associated with fingerprint-based systems is the labour-intensive construction of the training database. However, methods with reduced workload have been introduced recently such as implementation of crowd sourcing techniques to train the system automatically [112]-[113] or incorporating robots to do the survey process [114]-[115].

When a target user needs to be positioned in an indoor space, the positioning algorithm is invoked with the incoming RSSI values at the receiver end. The algorithm matches the online RSSI sample against the training database, performs necessary computation and returns the closest match as the position estimate of the target user. The performance of the system is not only dependent on the accuracy of the constructed radio map, but also on the algorithm used to match the online sample against the training database. One of the main challenges in this phase is to decide the length of the online sample to be matched against the radio map. A suitable segmentation technique needs to be employed based on the requirement of real-time or offline positioning.

Fingerprinting using Wi-Fi has been quite popular and well established as it can make use of the existing infrastructure containing access points (AP). RADAR, the world's first Wi-Fi signal-strength based indoor positioning system uses RF fingerprinting and implements nearest neighbor algorithm to estimate the user's location [100]. Its median accuracy was in the range of 2 – 3 m. As an alternative to Wi-Fi, many studies have used the fingerprinting technique with other technologies like BLE [109], [116] and magnetic field data [117]. The authors of [116] conducted a detailed study of BLE fingerprinting using 19 beacons investigating the choice of key parameters such as beacon density, transmit power, transmit frequency and also performed a quantitative comparison with WiFi fingerprinting. The results of their study indicate that BLE beacons performed better when compared to WiFi, with the former achieving $<$4.6m error in the worst case scenario with reduced beacon density and the latter achieving <8.5m error for an established WiFi network in the same space. In [117], the authors constructed the fingerprint database with magnetic field values using smartphones. The magnetic field data along with its extracted features was fed into four Deep Neural Networks (DNN) to get a probability map of the user's location. After applying suitable post processing methods, the authors were able to achieve good results with an average distance error of 2.5m by using only the magnetic field data.

BLE RSSI along with magnetic field strength are used as the main indicators of location estimation using the fingerprinting approach in Chapters 4 and 5 of this thesis. The training database is constructed separately for BLE RSSI transmitted by the beacon as well as for MFV readings for the purpose of fingerprinting.

3.3 Inverse Beacon Positioning

Most of the existing positioning systems employ a set of fixed beacons at known locations and a moving receiver such as a mobile phone. However, using multiple receivers at fixed positions to track a moving beacon is better suited for use cases such as monitoring a person or asset tracking [118]. This type of technique is commonly referred to as the *Inverse Beacon Positioning* method. The implementation is based on the principle that the RSSI signal decays with the increasing distance between the beacon and the receiver.

A similar setup was followed in [118], where the positioning computations were performed by multiple fixed sniffers implemented on Raspberry-Pis and a cloud based central server, while the testing was done using a smart phone carried by the user. The benefits of this type of implementation include power efficiency of the user device making it suitable for long-term tracking services. Furthermore, the use of a wearable eliminates the issue of device diversity encountered by using different models of smart phones and is also a better choice for developing monitoring applications at home.

This type of approach was opted for BLE fingerprinting in Chapters 4 and 5 of this thesis. A wearable beacon is used and multiple Raspberry-Pi receivers are placed at fixed points to determine the location of the resident. More details regarding the hardware, initial configuration, data collection process and information regarding the fingerprinting test beds followed in Chapters 4 and 5 are mentioned in the upcoming sections.

3.4 Setting up the Indoor Positioning System

3.4.1 Hardware Considerations

The indoor positioning system is composed of a set of Raspberry-Pis that function as receivers and a transmitting wearable beacon with embedded sensors known as MetaMotionR manufactured by MbientLab [119]. The wearable allows on-chip logging or streaming of sensor data and it comes enclosed in a waterproof casing with a rubber clip. Amongst the multiple onboard sensors present in the wearable, the magnetometer, the built-in step detector module and the beacon functionality is utilised.

The MetaMotionR wearable is powered by a rechargeable 100mAH lithium-ion

3.7V battery that can last for about 1.5 weeks on a single battery charge. Other wearables from MbientLab that use a coin cell battery can also be worn that may be more suitable for elderly monitoring applications, in which case the battery can last up to 1 year. The power consumption of the MetaMotionR wearable ranges from 20μA to 20mA @ 3.0V.

The sampling frequency or sampling rate, f_s, is the average number of samples obtained in one second (samples per second), thus $f_s = 1/\mathrm{T}$. In this study, the sampling frequency of the beacon is set at 10Hz (f_{s1} = 10Hz) and the magnetometer sampling frequency is set at 10Hz (f_{s2} = 10Hz), such that the battery life of the wearable is effectively prolonged while maintaining sufficient accuracy. If f_{s1}=10Hz, then nearly 10 samples are acquired approximately per second from the beacon. This is averaged to 1 reading per second during data pre-processing. After a preliminary coverage analysis, the beacon was configured with a transmission power of 0 dBm. This intermediate power allows covering all the areas of the house without too much spectral overlap between beacons.

3.4.2 Hardware Setup and Placement

The optimum number of receivers required depends on the area of the space to be measured and the number of obstacles present in that particular space. The number of receivers needs to be distributed uniformly throughout the property with the intention that every part of the house falls within the coverage area of the wearable beacon at any given position (Refer to Section 4.5.4 in Chapter 5 to decide the number of optimal receivers required for a given environment). The beacon is clipped on to the shirt collar such that it is positioned at chest level at all times. A majority of the receivers were deployed at a height of approximately 1.5 m from the floor and were alligned to provide maximum scope for detection by the beacon in the horizontal plane. Their placement in the experimental test bed was decided based on the activities to be monitored. For example: In order to monitor kitchen related activities, it is necessary to place the receiver in close vicinity and in line of sight view while using common kitchen objects such as microwave, kettle, stove and so on. Easy access to a power supply was another important factor for deciding the placement of the receivers. In places such as a bathroom where there is a lack of a power supply source, the Raspberry-Pis were powered up by an external battery pack. Furthermore, a detailed study into the key parameters for setting up the BLE fingerprinting system is discussed in Chapter 5

3.4.3 Data Collection Software Setup

A python script was written as part of the data collection module setup in each of the Raspberry-Pi receivers. A master-slave approach was used to collect and combine the beacon RSSI data from all the Raspberry-Pi receivers. One of the Raspberry-Pis was programmed as the master and the rest of the receivers were assigned as slaves. An issue with time synchronization may occur when the RSSI collection process is not in sync amongst the Raspberry-Pi receivers. In this case, the collected data is invalid and provides inaccurate results. In order to overcome this scenario, the master Raspberry-Pi stands out as the time broadcaster. Each of the slave devices will set their own time based on the master Raspberry-Pi's time. This is achieved by assigning the master device as the NTP server. The time synchronization process happens each time the Raspberry-Pis are booted up and this service works as a thread in the background keeping the time uniform amongst all the devices in the local network.

All the Raspberry-Pis collect beacon RSSI data along with their respective timestamp and save it locally. The collected raw data was then sent to the master Raspberry-Pi every few minutes during the training stage, which is responsible for combining and sorting the amassed RSSI data into a single file. As part of the sorting process, the master Raspberry-Pi averages out the RSSI value if there are multiple readings in the same second or performs linear interpolation if there are missing readings per second between records. The magnetometer sensor readings and step counter data with the corresponding timestamp are simultaneously transmitted from the wearable to the master receiver. The final processed data consisting of the beacon RSSI, magnetometer and step detector readings are used as input for Algorithm 1 described in the next chapter. The same data collection software was also used during the testing phase. Based on the application and end user requirement, the rate of frequency of transferring the raw data to the master receiver can also be adjusted. For example, data to be transferred could be sent every few seconds rather than minutes from the slave Pis to the master Pi for applications that require near-real time positioning.

3.4.4 Data Collection Process

Stickers with Cartesian co-ordinates were marked on the floor of the experimental testbed measured using a laser distance meter for ease of collecting measurements during the training stage. These were used as the reference points for the radio map and were spaced 0.5m apart since it is equivalent to the distance travelled with each step while walking at a normal pace. A number of walking routes and stationary positions were chosen to reflect regular domestic human behavior to provide the most realistic scenario for testing. Sequence based fingerprinting approach was followed in this study which involves creating the fingerprinting database with sequences of collected data samples for each label that are incremental in time. This type of fingerprinting technique is explained further in detail in the next Chapter. It is important to note that cartesian co-ordinates were included in the fingerprint training database only for the purpose of evaluating various performance metrics for the developed model. It is sufficient to annotate the data samples using just the key locations of interest and commonly used paths inside the house during the ground truth collection for the training database. With all of the hardware in place and the physical location measurements complete, a fingerprint map was built by collecting the RSSI values of the beacon detected at each Pi and magnetometer readings at different reference points based on the routes or positions to be measured.

For the construction of the training database, measurements were made at relevant reference points along commonly used walking routes (For example: bedroom to bathroom, couch to front door and so on) and fixed positions (For example: couch, bed, dining area). The readings were collected at these reference points for a period of 30s in all possible orientations to ensure that the interference from signals passing through the human body was taken into account. The training database size and overhead in this case is considerably less when compared to other existing data collection methods as limited samples at required reference points (for selected positions and routes) are amassed for a short duration of 30s, making the calibration stage undemanding. Furthermore, the beacon RSSI and MFV samples from the wearable were collected simultaneously at all times. A simple mobile application was developed to record the corresponding timestamp and ground truth label (see Figure 3.2) during the training and testing phase.

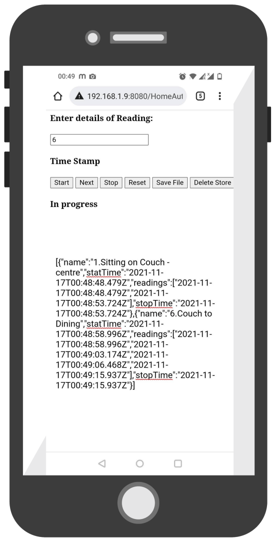


Figure 3.2: The Annotation app used for recording the ground truth labels

3.4.5 The Fingerprinting Test Beds

Details regarding the test beds - Trial Home-1 and Trial Home-2 used in Chapters 4 and 5 of this thesis are presented here. Both the test beds are one-bedroom apartments and the measurements were collected in realistic conditions in an inhabited flat with large pieces of furniture and equipment. Two different individuals carried out the experimental study in their respective flats; one of them being the thesis author[1]. Separate training databases were maintained for beacon RSSI and MFV

[1]The researchers who performed the experiments completed the QMUL Research ethics questionnaire application. Based on this, an ethics approval was not required for the study.

readings respectively in each test bed. A detailed description of each trial home is presented below.

3.4.5.1 Trial Home-1

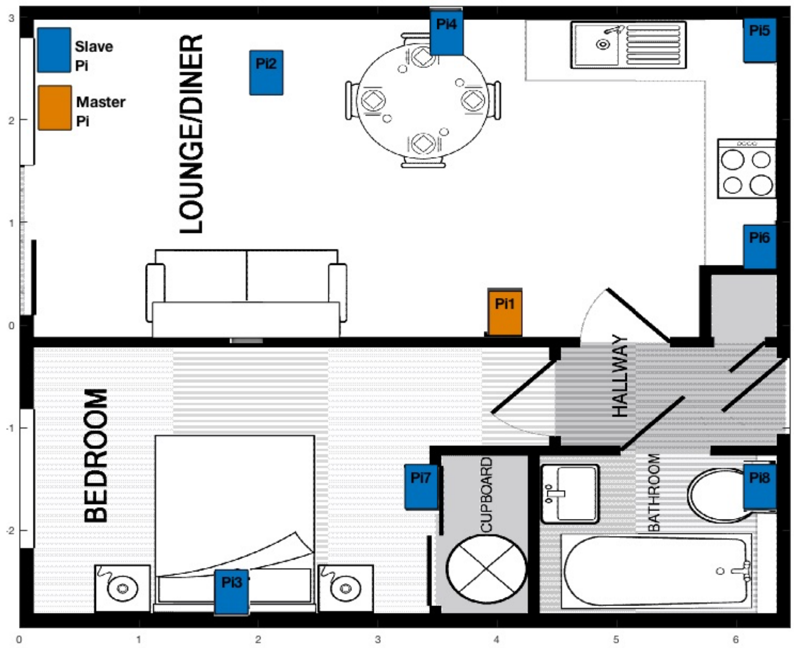


Figure 3.3: Layout of Trial Home-1

This one-bedroom apartment space which measures 6.45m by 6m has a living area, 1 kitchen, 1 bedroom, 1 bathroom and is occupied by a single person. Raspberry Pi 2 Model B devices (Quad Core CPU 900 MHz, 1 GB RAM, Linux) each fitted with a Bluetooth USB dongle were used as receivers in this test bed. The leftmost corner of the lounge was selected as the origin and all other reference points were measured relative to it. To provide comprehensive Bluetooth coverage of the entire house, a total of eight Raspberry-Pi receivers were deployed in Trial home-1 (see Figure 3.3). It was observed that all the eight receivers were detected at any given reference point in Trial home-1, which was our intention so as to provide maximum coverage and present an ideal case scenario to get good results. In total, there are 68 reference points in the collected fingerprint database identified with their respective Cartesian co-ordinates and a user-defined label. Data collection took place over a period of 10 days at different times of the day.

3.4.5.2 Trial Home-2

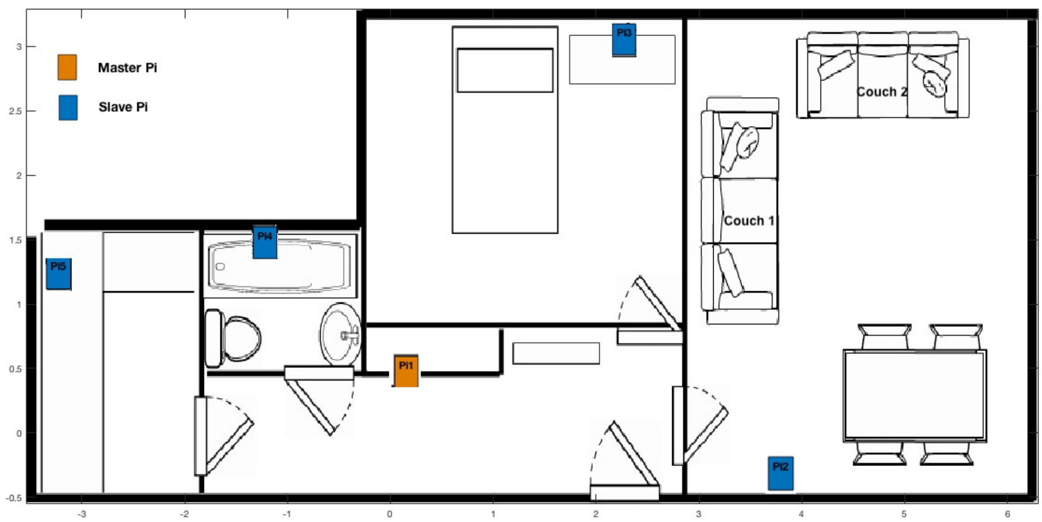


Figure 3.4: Layout of Trial Home-2

This test bed is also a one-bedroom apartment with floor area measuring 10.57m x 4.44m. The entirety of the property was chosen to be used for the analysis. Five Raspberry-Pi receivers were deployed in Trial home-2. The number of receivers to be deployed was decided based on some of the parameters discussed in Chapter 5. Similar to Trial home-1, the receivers were equally distributed throughout the flat and the their placement was chosen as per the activities to be monitored. Figure 3.4 illustrates the layout of Trial home-2 along with the placement of the master and the slave Raspberry-Pi receivers. The location of the master Pi was considered as the origin and all other points were measured relative to it using Cartesian co-ordinates in Trial home-2. It was decided to deploy lesser number of receivers when compared to Trial home-1 for evaluation purpose. These receivers were fitted with external BLE dongles of different antenna gain -1dBi and 5dBi to investigate if an increased antenna gain helps in maintaining the same level of accuracy with reduced number of Raspberry-Pi receivers.

To avoid the possibility of differing performance characteristics between different Bluetooth chips, each Raspberry-Pi 3 Model B receiver (1.5 GHz 64-bit quad core ARM Cortex-A72 processor, 1GB RAM) was equipped with a Sena UD100-G03 Bluetooth USB dongle that supported interchangeable omnidirectional antennas (1dBi and 5dBi gain antennas). The on-board Bluetooth in the Raspberry-Pi Model 3 devices was disabled while carrying out the experiments.

88 points were required to cover the entire property with reference points spaced at 0.5m from each other. The construction of the radio-map and the MFV fingerprint database during the training stage was carried out for both the 1 dBi and 5 dBi antennas separately. The data collection was done over a week with measurements made on different days and at different times of the day.

Table 3-A provides a summary of the two test beds.

3.5 Chapter Summary

Chapter 3 introduced the different types of indoor positioning systems with relevant literature. It also explains the concept of location fingerprinting in an indoor positioning system. Furthermore details regarding the experiment design such as the hardware setup, data collection process and description about the fingerprinting test beds are explained in detail and included here to better understand the concepts presented in Chapters 4 and 5.

Table 3-A: Summary of the Fingerprinting Test Beds Used in Chapters 4 and 5

Parameters	**Trial Home-1**	**Trial Home-2**
Training area	6.45m * 6m	10.57m * 4.44m
Surveyed space	Entire Home (1 bedroom, 1 living area, 1 kitchen, 1bathroom)	Entire Home(1 bedroom, 1 living area, 1 kitchen, 1bathroom)
No. of Floors	1	1
No. of surveyors	1	1
Time taken for Data collection	10 days	1 week
Database Annotation	Done by the surveyor with annotation app	Done by the surveyor with annotation app
Tx and Rx Devices	MetaMotionR beacon, Raspberry Pi	MetaMotion R beacon, Raspberry Pi with external antennas
No. of Receivers	8	5
Additional Receiver Antennas	Not Used	5dBi and 1dBi omnidirectional antennas
Distinct positions (No. of Reference points in database)	68	88 (Each for 1dBi and 5dBi respectively)
Space between 2 adjacent reference points	50 cm	50cm
Fingerprint Metric	BLE RSSI, Magnetic Field Strength	BLE RSSI, Magnetic Field Strength (Chapter 4), Only BLE RSSI (Chapter 5)
Beacon Fingerprint database size	9916	With 1dBi antennas: 14386 With 5dBi antennas: 14151
MFV Fingerprint data size	13020	8071
Fingerprint Type	Point based + Sequential	Point based + Sequential
Label Type	Cartesian (metre scale) + user-defined label based on house landmarks/routes	Cartesian (metre scale) + user-defined label based on house landmarks/routes
Training Time at each RP	30s (in each orientation)	30s (in each orientation)
Beacon Transmission Power	0dBm	0dBm
Beacon Advertisement Interval	100ms	100ms
Beacon Sampling Frequency	10Hz	10Hz
Magnetometer Sampling frequency	10Hz	10Hz

The subsequent Chapters (Chapter 4 and 5) present details regarding the proposed work done on recognising low-level activities using hybrid indoor positioning. Chapter 5, in particular describes few key parameters that affect the performance of the BLE fingerprinting system.

Chapter 4

Prediction of Micro-Activities and Walking Routes through Wearable Sensing Using Location Estimation Techniques

A common mode of sensing for ADL recognition is by detecting human object interaction through ambient and infrastructural sensors. Additionally, collection of location information of the resident in their homes can assist in the ADL recognition process by providing context information and can help reduce the number of installed infrastructural sensors.

In this chapter, a method for recognition of low-level activities and prediction of walking routes using location estimation techniques through wearable sensing is elaborated. The chapter starts with introduction to hybrid indoor positioning systems, a short survey of related work that use location information for activity recognition followed by necessary background and definition concepts. Sections 4.5 and 4.6 provides details regarding the system architecture and description of the algorithm. The evaluation results investigated in the experimental test-bed using the proposed approach are presented in Section 4.7. In Section 4.8, the findings of several aspects of the proposed method are analyzed and discussed.

4.1 Introduction to Hybrid Indoor Positioning Systems

BLE based inverse beacon positioning method was opted in this study due to its inherent benefits. However, beacon signals that are mainly suited for proximity based positioning are often erratic and do not contribute to fine-grained positioning when used as a solo solution [120]. BLE is known to work best when combined with other technologies. Similarly, magnetic field matching, when used as an independent IPS solution, may not be enough for accurate positioning as only three parameters are considered, which increases the probability of having the same fingerprint in different locations [107],[120]. Such drawbacks can be overcome by hybridizing the positioning information coming from different technologies. Prior research suggests that implementing hybrid technologies for indoor localization has proved advantageous since they exhibit sufficient positioning accuracy [121],[122].

To address concerns of low accuracy, BLE signals may be supplemented with other technologies such as Wi-Fi or magnetic field data to produce more accurate localisation. Since magnetic field is unlikely to be affected by changes such as furniture movements and remains fairly constant over time when compared to

Wi-Fi, the former remains a sensible choice to be used along with BLE system.

In this chapter, a novel algorithm is proposed to find the locus of the target user and track their movement between different zones of the house using the MetaMotionR wearable (described in Chapter 3) embedded with beacon, magnetometer and other onboard sensors.This is achieved by the collaborative use of BLE technology with inertial sensors to reduce the search space for magnetic field sequence matching.

4.2 Related Work

Different sensor technologies have been used for carrying out activity recognition. Some works such as [123],[124] rely on smartphones for monitoring activities. The authors of [123] use just a single smart phone to identify simple and complex activities. Their experiments yielded a classification accuracy of above 90% for simple activities, but drops to 50% for complex activities. Using smart phones may not be suitable in most patient or elderly monitoring applications as it forces the resident to carry their bulky phones with them at all times. Other works depend on object-based sensing methods for recognizing different activities [125],[126]. Instrumenting most of the daily-use objects with sensors increases the deployment cost and is not a practical solution for a home environment.

An overview of recent work on ADL recognition systems, where location information is used for identification of low-level or complex activities, is presented here. Torres et al. carried out experiments with a smart phone in seven different urban flats to study whether the Wi-Fi fingerprinting approach is feasible for in-home monitoring applications [124]. Their results provided an average accuracy of

89%. In [127] and [128], the authors implemented a BLE fingerprinting approach using beacons for monitoring of nursing home residents and for detecting frailty in older adults based on indoor localization habits, respectively. However, all these systems were designed to predict simple activities based on the user's location with just room-level accuracy. Other studies have used location as one of the parameters alongside other sensing methods to predict multiple complex ADL's [126][129]. The authors of [129] use positioning sensors along with power meters for real time recognition of routine activities in a smart home. The system achieves an overall classification accuracy of 79.39%. In [126], multiple events from binary sensors, a capacitive smart floor and a wearable beacon with an accelerometer are combined together in a real-time segmentation-free approach to predict 24 different personal activities in an apartment. Such systems predict a high number of ADLs, but increase the deployment cost and sensing complexity. Failure to track user movement between different zones of the house is also a major drawback in the above-discussed solutions. This may provide inconsistent results due to missing sensor readings which may prove costly in an end user application.

4.3 Sequential Fingerprinting Method

Locating a person inside a home requires contextual and useful information related to their inherent surroundings, which can be mapped easily to an activity recognition framework. Using just the global coordinate system for location mapping inside a house for such applications is impractical. The Received Signal Strength Indicator (RSSI) collection process during the training stage is much less strenuous when a sequence of RSSI samples can be collected along a known pathway as opposed to dividing the house floor plan into a grid like pattern and collecting data over random discrete points. Prior research suggests that position estimation using sequential RSSI values along a path is less variant when compared to point based prediction methods [113]-[130]. RF fingerprinting performed in this way is known to be more resilient to changes in the surrounding environment because the sequential values collected along a pathway have a distinct signature and consequently, this approach is more suitable for beacon fingerprinting to account for its high signal variability. The authors of [113] and [130] have used sequences of RSSI data for radio map creation, but importance has not been given to the inclusion of key locations and routes that reflect a person's daily routine inside their homes. It is rather helpful to create a system, which integrates various key elements of a home such as couch, dining area, sink, stove, bed and so on into the fingerprint collection database. The RSSI and MFV samples were collected for conditions when a person is performing an activity with minimal movement (e.g., sitting in the dining area or couch) and when a person walks along a certain path both in the forward and reverse directions (e.g., bedroom to bathroom, bathroom to bedroom).The focus of the developed system is not in finding the (x,y) coordinates of the target, but determining whether the target is present at certain defined locations of interest or moving along certain defined paths. Even if the location of the objects are changed in the future, it is sufficient if the user collects 30s of data samples at the new location of interest for updating the training database. Incase of adding a new walking route to the training database, the user has to collect 30s of data samples at random points along the walking route spaced around 50cm apart (approximate distance between consecutive steps) in the forward and reverse directions. Since cartesian co-ordinates are not required for recording the ground truth in this study, it is much simpler for the user to record the ground truth labels using the names of the key locations and routes through the developed mobile app in Fig. This makes the entire calibration phase simple and easily adaptable for any changes in the environment.

Initially a hybrid two-phase approach for recognition of landmarks and routes in a complex indoor environment using a wearable and a smartphone was developed [131]. This has been further improvised using a single wearable coupled with inertial sensing to get better results in both the trial homes.

4.4 Background And Definitions

The necessary background knowledge, along with the definition of several important terms, concepts and notations used in this Chapter are presented below.

4.4.1 Micro-activities, Routes and Zone

Definition 1. There are certain unique locations of interest inside a home where the home occupant tends to spend a considerable amount of time carrying out a daily routine activity. The study identifies these locations and collects data samples for the training database. Location is one of the key indicators in identifying the activities performed by the user. Based on this logical assumption, The thesis refers to these points of interest as **micro-activities**. The activities performed at these unique locations are simple or atomic activities that cannot be decomposed any further. For example: sitting on the couch, sitting in the dining area or sleeping on the bed activities cannot be split any further. The focus of the chapter is to find the locus of these simple activities pre-defined in the training database and assumes that if the location of the person is estimated to be at any one of these points, the person is performing a micro-activity associated for that respective location. The terms **micro-activities** and **low-level activities** have been used interchangeably for the remainder of the thesis. Combination of several micro-activities derived from location context can be a part of a high-level complex activity such as preparing breakfast, watching TV and so on. Furthermore, the results of this study can also be used in combination with other sensing methods such as ambient sensing to identify a complex activity.

Definition 2. In addition to micro-activities, the thesis also recognises pre-defined **walking routes** to account for the transition when a person moves between different landmarks inside the house. In other words, **walking route** is the trajectory followed by the home occupant between two points of interest where a micro-activity takes place. The walking routes have been further categorised as short routes (less than 5 steps) and long routes (greater than 5 steps) based on the average number of steps a person takes in order to differentiate routes of varying lengths covering the same reference points. All the routes present in the training database are labelled as either *Micro-Activities/Short Routes* or *Long Routes* based on the resulting step count measured using the built-in step detector module in the wearable.

Definition 3. Each house is divided into different sections such as *Lounge, Kitchen, Bedroom, Bathroom and Hallway* where a person carries out a specified set of activities. These sections are referred to as **Zones** in this study. The proposed model monitors the movement of the person within each zone as well between different zones.

4.4.2 Modelling the BLE Fingerprint Database

Definition 4. (A **beacon RSSI profile** ($RSSI_i$) are individual RSSI values observed at position (L_i) from n nearby receivers. $L_i = (d_x^i, d_y^i)$ corresponds to a specific point marked by its two-dimensional Cartesian label (used only for performance evaluation in this study). In this study, a set of Raspberry-Pis is used as the receiver of the beacon signal. The RSSI profile measured at any given point is represented by:

$$RSSI_i = \{Pi_{RSS_1}, ..., Pi_{RSS_n}\} \tag{4.1}$$

where $Pi_{RSS_1}, ..., Pi_{RSS_n}$ are the individual signal strength of n Raspberry-Pi receivers.

Definition 5. The **beacon RSSI fingerprint database** ($RSSI_{DB}$) is modeled as:

$$RSSI_{DB} = \{RSS_{S_1}, \ldots, RSS_{S_K}\}(1 \leq k \leq K) \tag{4.2}$$

where RSS_{S_k} represents the collective beacon fingerprint measurement for an individual micro-activity or walking route identified by $S_k(1 \leq k \leq K)$ with K being the total number of micro-activities and routes in the database. For any given S_k, N training samples are present where each sample is an individual fingerprint B_i.

A **beacon RSSI fingerprint** (B_i) is a combination of RSSI profile $RSSI_i$ measured at location L_i, labeled by its corresponding route or micro-activity S_k. It is represented by:

$$B_i = [L_i, RSSI_i, S_k](1 \leq i \leq N) \tag{4.3}$$

For cases where S_k is a walking route, the training examples will be a sequence of RSSI values recorded at their corresponding position co-ordinates along the considered walking path. The database may contain duplicate values of L_i as

X	Y	Pi$_{RSS1}$	Pi$_{RSS2}$	Pi$_{RSS3}$	Pi$_{RSS4}$	Pi$_{RSS5}$	Pi$_{RSS6}$	Pi$_{RSS7}$	Pi$_{RSS8}$	Micro-Activity/Route
5.296	-0.647	-60	-79	-86	-75	-76	-81	-74	-82	Main Door to Bedroom Door
5.296	-0.647	-57	-75	-85	-69	-84	-89	-76	-79	Main Door to Bedroom Door
5.296	-0.647	-55	-74	-79	-72	-77	-85	-79	-82	Main Door to Bedroom Door
1.811	1.046	-72	-84	-81	-90	-74	-78	-81	-76	Couch to Main Door
1.811	1.046	-78	-89	-83	-91	-69	-78	-84	-77	Couch to Main Door
1.811	1.046	-70	-85	-84	-92	-69	-82	-87	-92	Couch to Main Door

Figure 4.1: RSSITrainingDatabaseSample

several RSSI readings are captured at the same position. Sample data of the training database ($RSSI_{DB}$) is presented in Figure 4.1.

4.4.3 Magnetic Field Vector (MFV) Sequence Matching

Definition 6. The **Magnetic Field Vector,** MFV_i profile represents the magnetic field strength in x, y, z direction observed at position co-ordinates $L_i = (d_x^i, d_y^i)$. It is represented by:

$$MFV_i = \{MFV_x, MFV_y, MFV_z\} \tag{4.4}$$

Definition 7. Similar to $RSSI_{DB}$, the **MFV training database (**MFV_{DB}**)** is populated with sequential three-dimensional vector readings modeled as:

$$MFV_{DB} = \{MV_{S_1}, \ldots, MV_{S_K}\}(1 \leq k \leq K) \tag{4.5}$$

where MV_{S_k} represents the collective magnetic field measurement for each micro-activity or walking route identified previously as $S_k (1 \leq k \leq K)$. Each **MFV fingerprint** (M_i) observed at position co-ordinates $L_i = (d_x^i, d_y^i)$ for a given micro-activity or route S_k is represented by:

$$M_i = [L_i, MFV_i, S_k](1 \leq i \leq N) \tag{4.6}$$

where N is the number of training samples observed for individual S_k.

Definition 8. The **Dynamic Time Warping (DTW)** technique is used as the distance measure to compute the similarity between two MFV sequences. DTW is a well-known algorithm to measure the similarity between two sequential series of different lengths that vary in time or speed. It has widespread application in image processing, speech recognition, data mining, robotics, manufacturing and other classification techniques [132]. The DTW distance measure has an innate advantage over Euclidean distance for time series measurement as the latter fails to provide a correct measure when there are small distortions in the time axis. DTW is more robust for comparing MFV sequences as it allows a one to many mapping (compression and stretching the time axis) of one or both the sequences to obtain a suitable alignment. An iterative procedure is performed for all the eligible routes, which involves constructing a matrix between the offline and measured magnetic sequence to find the warping path that minimizes the overall cost function. This is calculated using the dynamic programming approach given by Eq(4.7).

$$\begin{aligned} DTW(n,m) = d(q_n, c_m) + \\ min\{DTW(n-1, m-1), \\ DTW(n-1, m), DTW(n, m-1)\} \end{aligned} \tag{4.7}$$

where $d(q_n, c_m) = (q[n] - c[m])^2$ is the squared distance between the sample points. $Q = \{q_1, q_2 \ldots .. q_N\}$ and $C = \{c_1, c_2 \ldots .. c_M\}$ are the online and offline magnetic sequences of length N and M, respectively. Squared Euclidean distance is selected to calculate the cost measure in Eq(4.7) as it provides better accuracy in comparison with Euclidean or Manhattan distance measures. The final predicted route is the one with the least distance measure, which implies a high similarity between the measured sequences.

Definition 9. $RSSI_{Online}$ and MFV_{Online} are the respective online beacon and magnetic sequences collected using the wearable for prediction of location context of the target user using the reference $RSSI_{DB}$ and MFV_{DB}. The task is to find the label S_K using the algorithm described in Section 3.6.

4.5 Main Contributions of this Chapter

The main contributions of this chapter is two-fold.

- A novel algorithm is proposed using a wearable for recognition of low-level micro-activities and their associated zone of occurrence within the house. The resulting outcome helps in providing useful location context information for discovery of complex ADL's. This method is particularly useful in developing monitoring applications for home-care patients and also for sheltered accommodation, which are typically studio or one-bedroom apartments. In order to demonstrate and verify the accuracy of the proposed system, extensive experiments are conducted in two different home environments under strong Non-Line of Sight (NLOS) conditions.

- In addition to recognizing the micro-activities, the proposed algorithm is capable of predicting accurately the movement of a person between different points of interest within a room and also between different zones of a house without relying on data from other infrastructure-based sensors.

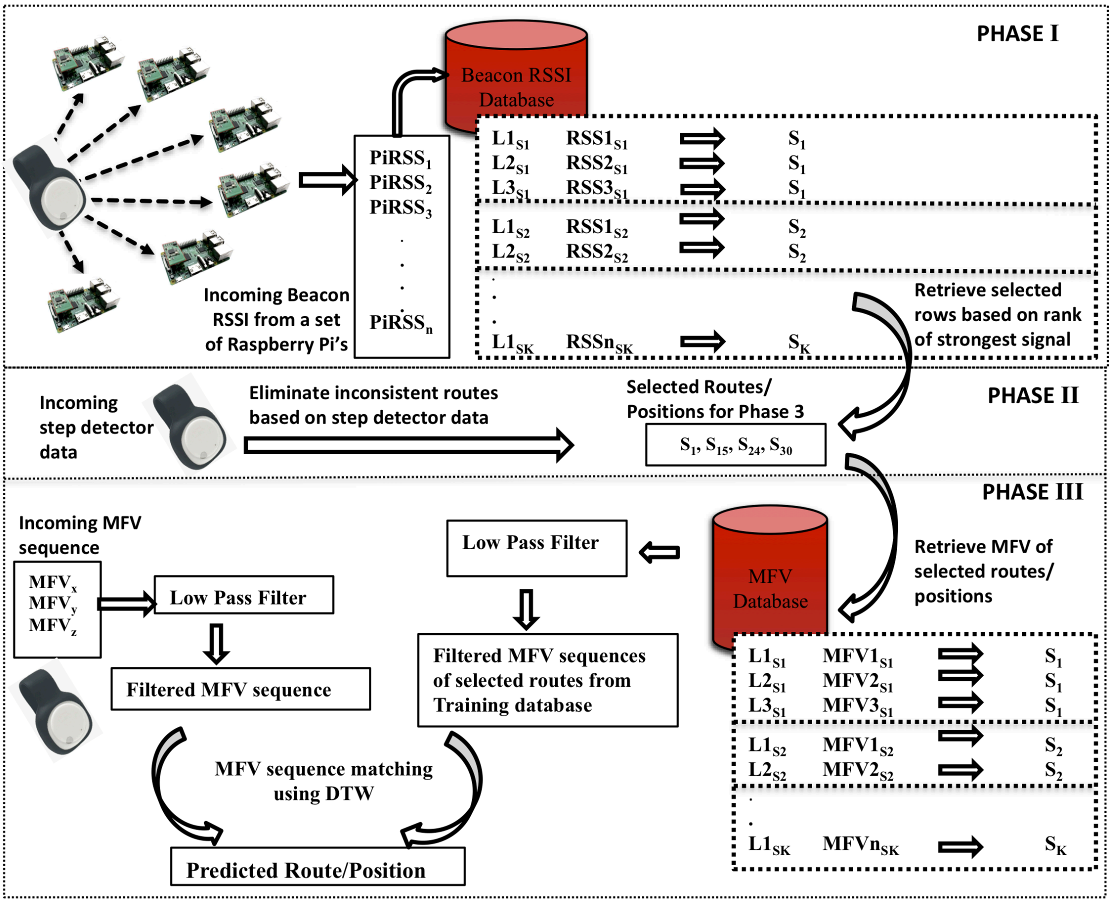


Figure 4.2: Schematic Diagram of the Proposed System

4.6 Algorithm For Detection Of Micro-Activities And Walking Routes

The proposed algorithm constitutes three main phases for prediction of micro-activities and walking routes. It follows a data-driven approach as the method relies on the training data collected using the wearable and their respective ground truth labels expressed in terms of different micro-activities (location of interest) and routes within an indoor environment. Figure 4.2 illustrates the overall system architecture. A brief description of the three phases involved in the positioning algorithm is given below and their respective pseudocode is shown in Algorithm 1.

Algorithm 1 Route Prediction and Detection of Micro-Activities

Inputs: $RSSI_{Online}$ and MFV_{Online}, $stepCount$
Output: $R \leftarrow$ Predicted Walking Route or micro-activity
for i = 1: $sizeof(RSSI_{DB})$ **do**
    $A \leftarrow$ Sort $RSSI_i$ in descending order
end for
for i = 1: $sizeof(RSSI_{Online})$ **do**
    $B[i] \leftarrow$ Get corresponding label S_k for matched $RSSI_i$ in $RSSI_{DB}$ after sorting in descending order
    $occ[i] \leftarrow$ Compute frequency of occurrence of matched S_k in $B[i]$
end for
$C \leftarrow$ Sort B based on $Sum(occ)$, $groupCount$ incase of ties, where $groupCount$ = no. of routes grouped by occ
$D \leftarrow$ Retrieve top 10 or less S_k from C
if $stepCount \geq 0$ && $stepCount \leq 5$ **then**
    $selectedS_k \leftarrow$ All Micro-activities & Short Routes applicable in D
else
    $selectedS_k \leftarrow$ All Long Routes applicable in D
end if
$MFV_{Train} \leftarrow MFV_i$ of $selectedS_k$ from MFV_{DB}
for i = 1: $sizeof(MFV_{Train})$ **do**
    $R \leftarrow findBestS_k(MFV_{Train}(i), MFV_{Online})$; //Predict S_k label using DTW
end for
return R

4.6.1 Description of the Positioning Algorithm

4.6.1.1 Phase I - Route Selection Using Beacon RSSI Fingerprinting

The offline collected RSSI training samples and the online measured sequences are initially sorted based on their strongest beacon signal strengths. An individual rank matrix for the training and online data is then created, where each row contains the Raspberry-Pi identifier arranged in order of the strongest signal (Refer to Figure 4.3). Both these ranked datasets are compared against each other to find similarities between them and a list of corresponding matched S_k labels

Raspberry Pi ID Rank based on strongest RSSI signal								WalkingRoute
4	5	6	1	8	7	3	2	'Sitting in the dining area - left side'
4	5	6	1	8	7	3	2	'Sitting in the dining area - left side'
4	5	6	1	8	7	2	3	'Sitting in the dining area - left side'
5	1	2	4	8	6	3	7	'Couch to Dining'
5	1	2	8	4	6	3	7	'Couch to Dining'
5	1	2	8	6	4	3	7	'Couch to Dining'
5	1	2	6	4	8	3	7	'Couch to Dining'

Figure 4.3: Representation of the Ranked Training Matrix from Phase I

are returned. The routes and positions for the next phase are selected based on the total number of occurrences of matched labels ($Sum(occ)$) and frequency of occurrence for each position co-ordinate over the entire length of the measured test sequence ($groupCount$). The number of highest ranked positions/routes considered for Phase II depends on the accuracy of the Beacon RSSI fingerprinting method. An optimal count is chosen such that the correct position/route is part of the magnetic search area in the next phase. In this study, the maximum count is set to ten or less for selection from the resulting output of Phase I.

4.6.1.2 Phase II - Elimination of Inconsistent Routes from Phase I Using the Step Detector Module

Data from the step counter is used to identify if the selected routes from Phase I fall under *Type I* (Micro-Activities and Short routes (≤ 5 steps)) or $TypeII$ (Long routes (> 5 steps)) category. The number of steps is chosen as *five* in this case based on the sensitivity of the step detector module embedded in the MetaMotionR wearable. Since the distance between multiple micro-activities considered for classification is only few cms apart, the threshold value to distinguish them from long routes is set to *five*. This threshold value to detect steps can be varied based on the type of wearable used. Based on this classification, extraneous routes are excluded and only the relevant routes are carried forward to the next phase. Micro-activities and short routes have been grouped together as there is a likelihood that the step detector may produce false positives or false negatives when small strides between 'kettle to sink' or 'fridge to microwave' are considered. This is especially true in a kitchen scenario when the objects of interest such as kettle, stove, sink, microwave are very close to each other and transitional changes between two stationary positions near different objects/landmarks need to be taken into consideration. Inclusion of the step counter assists in improving the accuracy by easily eliminating the overlapping routes in an indoor space. For example, *Couch to Dining* is a short route that overlaps with the longer route *Couch to Main Door*. Results from the step detector help in differentiating and choosing the applicable route for that particular instance. It is also beneficial for the next phase as it further reduces the magnetic matching searching space. This helps in improving the overall time complexity since the DTW technique that is used in the next phase is known to be a computationally expensive algorithm. Depening on the requirement, the step detector can be configured in 3 modes: Normal/ Sensitive/ Robust.

4.6.1.3 Phase III - Magnetic Matching (MM) using DTW

The magnetic signatures of the selected routes from Phase II are alone considered from the MFV training database and consequently, the overall efficiency is likely to improve as the search space for MFV fingerprinting is significantly reduced. A low pass filter is applied to smooth the noise of the magnetometer sensor data before calculating the similarity measure. *Nearest Neighbor Dynamic Time Warping* algorithm that makes use of the dynamic programming approach given by Eq(4.7) is used to compute the similarity between two MFV sequences. The pseudocode for the 1-Nearest Neighbor DTW is presented in Algorithm 2.

Algorithm 2 1-Nearest Neighbor DTW

Inputs: $MFV_{Train} \leftarrow$ MFV of $selectedS_K$ from MFV_{DB}, $MFV_{Online} \leftarrow$ MFV of Online sequence

Output: $Reference\_MFV$

```
best_so_far ← ∞
Reference_MFV ← MFV_Train[1]
for i = 1: sizeof(MFV_Train) do
    DTW_distance ← DTW(MFV_Train[i],MFV_Online)
    if DTW_distance < best_so_far then
        best_so_far ← DTW_distance
        Reference_MFV ← MFV_Train[i]
    end if
end for
return Reference_MFV
```

4.7 Experimental Study

The suggested approach is assessed in two different test environments (Trial home-1 and Trial home-2) where the main aim is to map the target's location with the pre-existing routes and positions(micro-activities) in the reference database. $RSSI_{DB}$ and MFV_{DB} contain data samples for a total of 40 micro-activities and walking routes (24 micro-activities/short routes + 16 long routes) in Trial home-1 and a total of 36 micro-activities and routes (18 micro-activities/short routes + 18 routes) in Trial home-2.

In order to evaluate the performance of the proposed algorithm, the whole dataset was split into training set and testing set (hold-out method). The split was done in such a way that from the measurements obtained at each reference point, the first 70% samples ordered in time was allocated to the training set, while the remaining 30% samples was allocated to the test set. Apart from this, test data samples for some of the micro-activities and routes in both the trial homes were collected multiple times separately on different days and times from the original dataset. This unseen new data was collected randomly at regular walking pace which may or may not cover the same reference points used during the training stage. These test data samples are referred to as *Test Dataset-2* and the test set from the hold-out method is referred to as the *Test Dataset-1* for the remainder of the chapter. This type of dual testing provides an in-depth evaluation of the proposed framework.

The performance of the proposed method : *BLE-MMDTW (BLE aided magnetic matching using DTW with step detector)* was mostly compared when the same algorithm was used without step detector results - *BLE-MMDTW (without step detector)* and also with the sole use of magnetic data samples matched using DTW method (*MMDTW*). Sequence-based inputs of varying lengths require specialized classifier algorithms as they are different from other supervised learning problems. The order of the observations and the temporal context must be preserved when training models and making predictions. The accuracy of the proposed algorithm is not compared against well-known machine learning classifiers in this chapter as most of these models are not suitable for such complex sequence classification problems. Recurrent Neural Networks (RNN) using Long Short-Term Memory (LSTM) networks are one of the few state-of-the-art techniques known for sequence classification [59]. In particular, Bidirectional LSTM's are used when there is a need to preserve information about the complete input sequence at each time step. These models have the capability to take sequences as input both in the forward and reverse directions and perform much better than unidirectional LSTM's. Benchmark comparison of the developed model is done against the state-of-the-art *Bidirectional LSTM* model in this study.

Micro-activities and short routes are grouped together for performance evaluation and long routes are evaluated separately using the proposed model. Much of the evaluation was done in Trial home-1. Similar kind of experimental analysis were carried out in Trial home-2 too but with reduced receivers to check the efficiency of the proposed fingerprinting system.

4.7.1 Performance Assessment Of Recognition Of Micro-Activities and Short Routes in Trial home-1

4.7.1.1 Error Calculation Using Test Dataset-1

A list of the micro-activities and short routes considered in Trial home-1 is presented in Table 4-A.

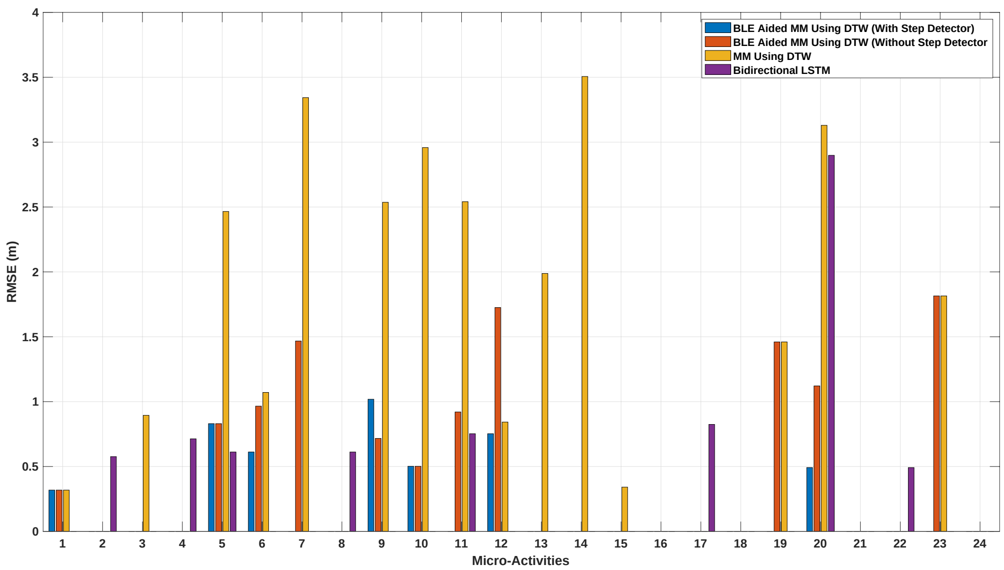


Figure 4.4: RMSE measure for recognition of 24 micro-activities using Test Dataset-1

The Root Mean Square Error (RMSE) is used as the main performance metric

Table 4-A: List of Micro-activities and Short routes considered in Trial home-1

Micro-activity/Short Route No.	**Name**
1	Sitting on Couch - centre
2	Sitting on Couch - left side
3	Sitting on Couch - right side
4	Sitting in the dining area - left side
5	Sitting in the dining area - right side
6	Near stove
7	Standing near sink
8	Near Kitchen shelf
9	Near kettle and fridge
10	Near Microwave
11	Near bathroom closet
12	Near bathroom washbasin
13	Shower area
14	Sitting in bed left side
15	Sitting in bed right side
16	Sleeping in bed
17	Near bedroom cupboard
18	Couch to Dining
19	Dining to Couch
20	Sink to fridge
21	Fridge to sink
22	Fridge to Microwave
23	Microwave to Fridge
24	From bed to cupboard in bedroom

for determining the standard deviation of the predicted locus of the micro-activities and short routes against the position co-ordinates of the ground truth. Figure 4.4 shows the performance comparison of the RMSE measure computed for the 24 micro-activities and routes using the proposed BLE-MMDTW method, BLE-MMDTW (without step detector) method, MMDTW method and Bidirectional LSTM method.

A *paired T-Test* was conducted between the RMSE values of BLE-MMDTW and MMDTW methods and between BLE-MMDTW and BLE-MMDTW method (without step detector) respectively to check for statistical significance as all the

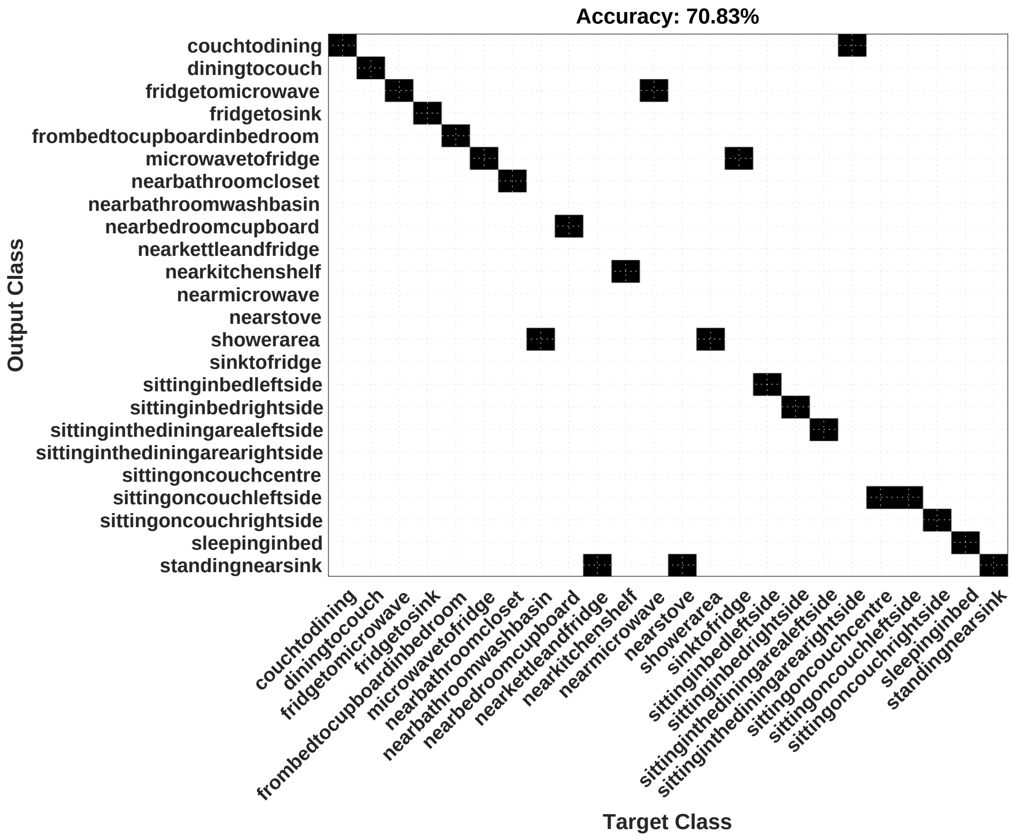


Figure 4.5: Confusion matrix for Micro-activities/Short Routes Using Test Dataset-1 in Trial home-1 for BLE-MMDTW model

three models were evaluated on the same dataset but with variations in the algorithm. The results of the paired T-Test provided a value of 0.0170 and 0.0003, which is less than the 0.5 significance level indicating a significant difference between the proposed method and the MMDTW method and BLE-MMDTW method (without step detector) respectively.

Out of the four models, the proposed BLE-MMDTW and the Bidirectional LSTM models have the least average RMSE of 0.18m and 0.31m respectively. The average RMSE of the other two models, BLE-MMDTW (without step detector) and MMDTW is 0.49m and 1.2m respectively. The Bidirectional LSTM model was designed using the following layers and parameters: a sequence input layer with 11

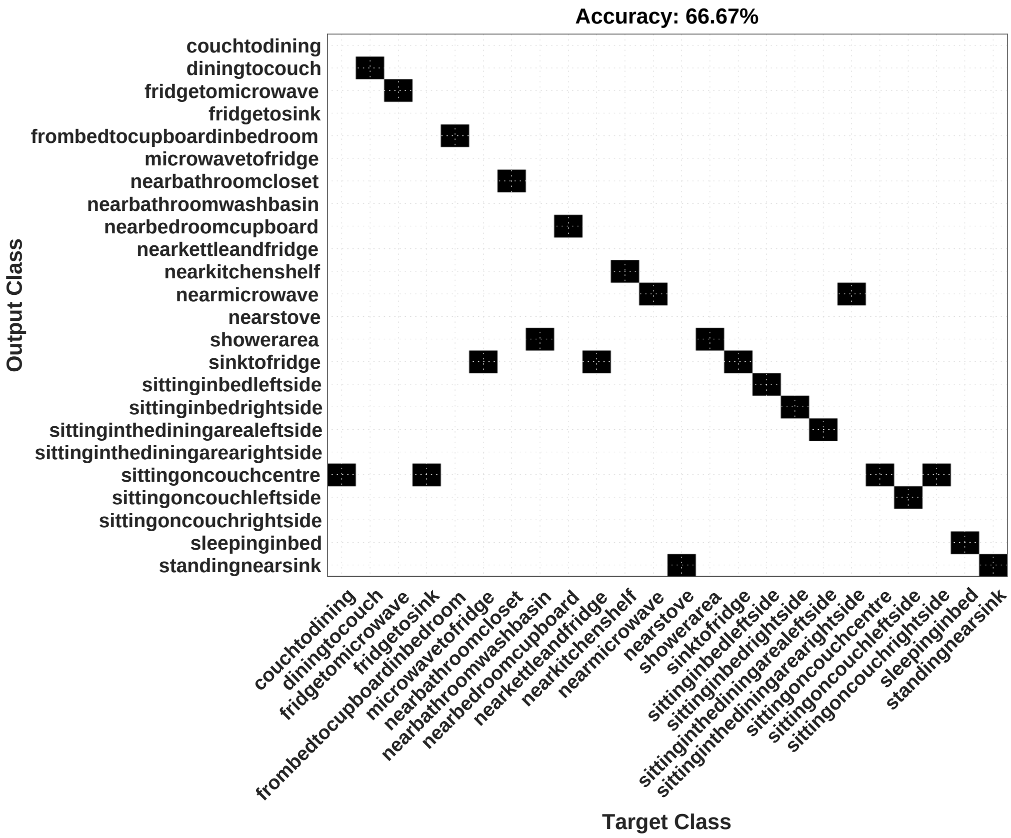


Figure 4.6: Confusion matrix for Micro-activities/Short Routes Using Test Dataset-1 in Trial home-1 for Bidirectional LSTM model

features, a bidirectional LSTM layer with 100 hidden units, a fully connected layer of size 24 followed by a softmax layer and a classification layer. The maximum epochs was set to 100 and the mini batch size was set to one as only a single observation for each of the 24 classes were present in the training set. The initial learning rate was set to 0.01 and was reduced by a factor of 0.1 every 5 epochs. The model uses Adaptive Moment estimation (adam) as the optimizer and cross-entropy as the loss function. In this case, Bidirectional LSTM model is the second best performing model with 16 output classes being correctly predicted.

The confusion plot for both the BLE-MMDTW method and Bidirectional LSTM method are show in Figure 4.5 and Figure 4.6 respectively. A total of 17 micro-activities/short routes were predicted correctly out of the 24 considered classes. For the wrongly classified micro-activities and short routes, it can be seen that the predicted outcome is very close to the actual ground truth. On closer inspection, all the wrongly classified labels have RMSE <= 1m with the "Near Kettle and Fridge" class having the maximum error of 1.01m. This is a good result for a multi-classifier problem with 24 different classes considering that the predicted output and the actual positions are only few centimeters apart. The proposed model will perform much better if only the object of interest involved in the micro-activity/short route is considered ignoring the seating direction. For example: using just the class "Couch" instead of having separate classes for left, right and center seating positions on the couch will greatly improve the results. The user can modify the class labels based on the level of granularity required for a given space.

4.7.1.2 Zone Based Classification Accuracy Using Test Dataset-1

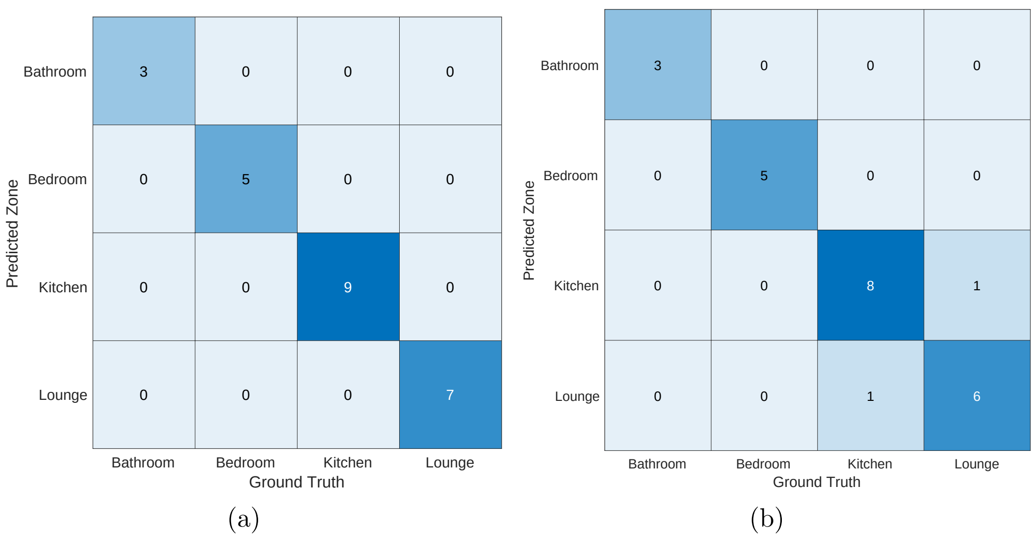


Figure 4.7: Confusion matrix for Zone-based recognition of Micro-Activities Using Test Dataset-1 (a) BLE-MMDTW Model (b) Bidirectional LSTM Model

In order to check the room level classification accuracy of the detected micro-activities, Trial home-1 was divided into five zones namely: *Lounge, Bedroom, Bathroom, Kitchen* and *Hallway*. None of the micro-activities and short routes listed in Table 4-A fall under the *Hallway* category in this particular case. The confusion matrix for zone based recognition of micro-activities and short routes using BLE-MMDTW(proposed) and Bidirectional LSTM models is shown in Figure 4.7(a) and Figure 4.7(b) respectively. The proposed method was able to classify all the 24 micro-activities/short routes correctly to their respective zones (100% accuarcy). For the Bidirectional LSTM model, *Fridge to Sink* and *Sitting in the dining area - right side* were wrongly predicted as *Sitting on Couch - centre* and *Near Microwave* and hence classified into the *Kitchen* and *Lounge* zones respectively resulting in a classification accuracy of 91.67%. The classification accuracy deteriorates to 58.33% when only magnetic samples are matched using DTW which highlights the significance of hybridising the positioning results of both beacon and magnetic data.

4.7.1.3 Error Calculation Using Test Dataset-2

Following are the micro-activities considered for evaluation with Test Dataset-2 in Trial home-1. Ten different test data samples were collected for cross-validation for each of the below mentioned micro-activity measured over different days.

1. Sitting on Couch - centre, 2. Sitting on Couch - left side, 3. Sitting on Couch - right side, 4. Sitting in the dining area - left side, 5. Sitting in the dining area - right side, 6. near stove, 7. Standing near sink, 8. Near Kitchen shelf, 9. Near kettle and fridge, 10. Near Microwave, 11. near bathroom closet, 12. near bathroom washbasin, 13. shower area, 14. sitting in bed left side, 15. sleeping in

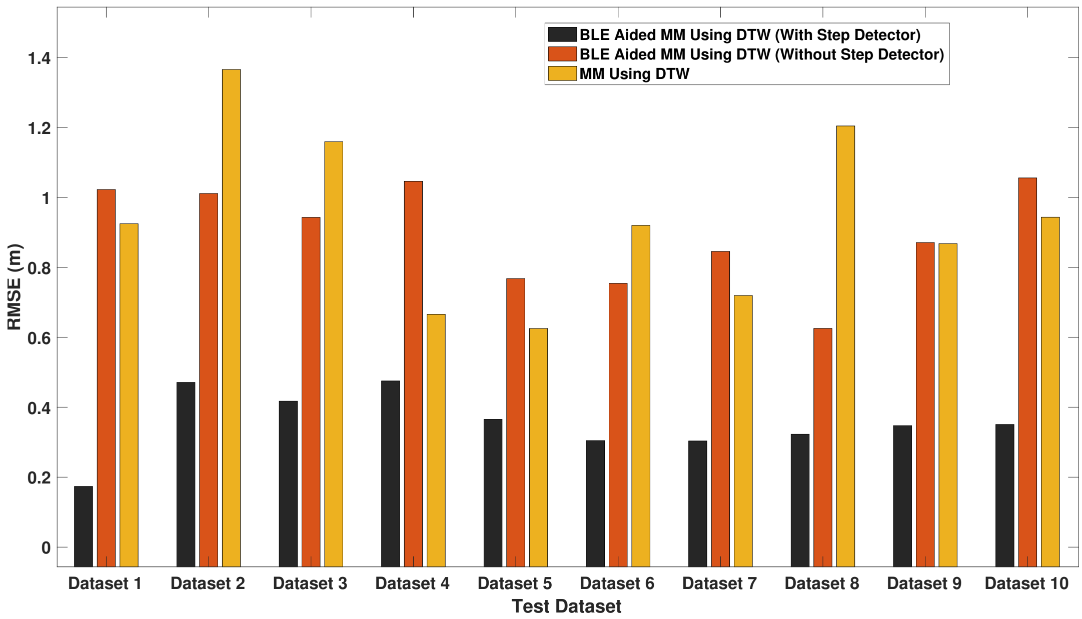


Figure 4.8: Average RMSE measure for recognition of micro-activities Using Test Dataset-2

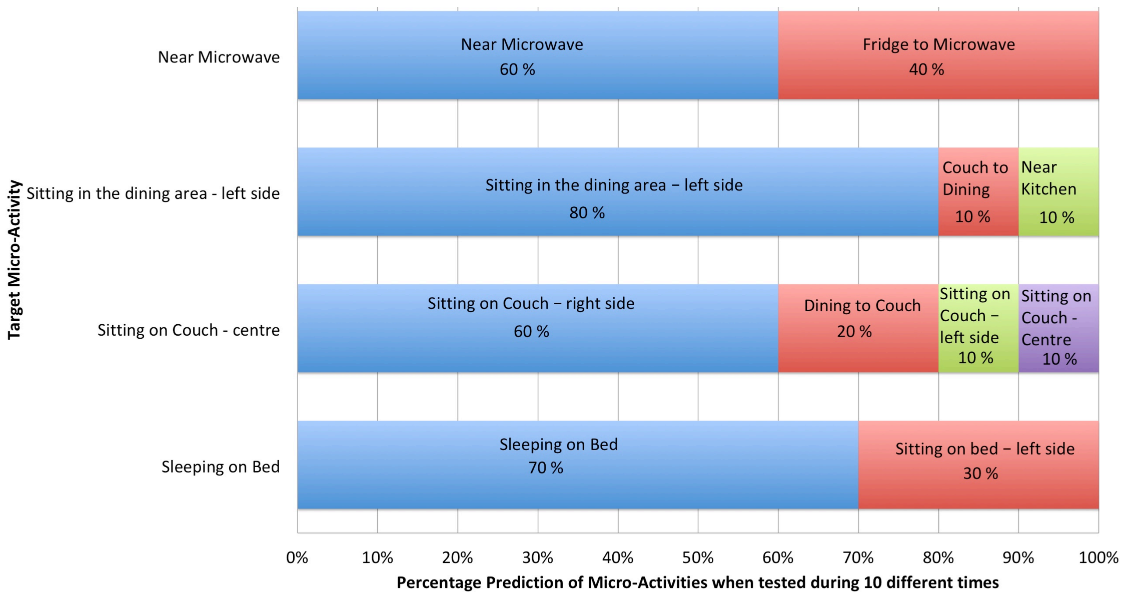


Figure 4.9: Performance assessment of individual micro-activities Using Test Dataset-2

bed, 16. Near bedroom cupboard

Figure 4.8 illustrates the performance comparison of average RMSE computed for ten test datasets for the 16 micro-activities using three approaches - BLE aided MM using DTW with step detector (BLE-MMDTW), BLE-MMDTW (without step detector) and MM using DTW (MMDTW). The proposed algorithm using the hybrid BLE-MMDTW method that includes the step counter had the least RMSE measure in each of the ten test cases with an overall average RMSE of 0.55m. The average RMSE for the BLE-MMDTW (without step detector) and the MMDTW methods were 1.09m and 1.13m, respectively. RMSE was chosen as the evaluation metric over classification accuracy in this scenario as the intention was to measure the degree of closeness of the false positive results with the ground truth. For instance, the classification results using ten different test datasets for micro-activities: *Sleeping on bed, Sitting on Couch – centre, Sitting in the dining area – left side* and *Near microwave* shown in Figure 4.9 indicate that the activities predicted as false positives are very close to the ground truth and the predicted outcome in each case was associated with the actual micro-activity taking place. In Figure 4.9, the micro-activity *Sitting on Couch – centre* was classified six times as *Sitting on Couch – right side*, twice as *Dining to Couch* and one each for *Sitting on Couch – left side* and *Sitting on Couch – centre* when tested at ten different instances. However, the predicted outcome in each case refers to *Couch* as the main landmark where the activity is carried out. Similarly for the sleeping activity, the classification labels *Sleeping on bed* and *Sitting on bed – left side* maybe different, but the locus of both these activities are almost identical (Refer Figure 4.9). The same can be said for the predicted outcome of other micro-activities. It must be noted that the false positive results occur as multiple positions and routes are considered for classification in this study (24 micro-activities and short routes). The results demonstrate the merit of the approach given the high number of different micro-activities that are to be classified (16 activities). This form of

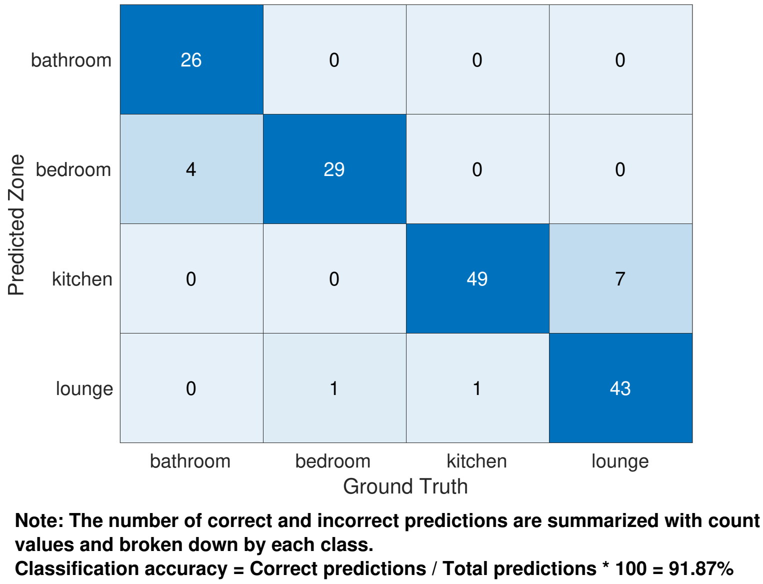


Figure 4.10: Confusion matrix for Zone-based recognition of Micro-Activities Using Test Dataset-2

location context information is crucial for supporting complex ADL recognition when the number of physical sensors deployed in the smart home is small. In other words, it is possible for us to maintain a minimal sensing environment and recognize low-level activities by using just the wearable as the lone sensor data.

4.7.1.4 Zone Based Classification Accuracy Using Test Dataset-2

Based on the earlier cross-validation results using the ten test datasets, the 16 micro-activities were classified into their respective zones in the trial home. The confusion matrix for zone-based recognition of micro-activities using the proposed BLE-MMDTW method is shown in Figure 4.10. A classification accuracy of 91.87% was achieved, indicating that the zone of occurrence of the micro-activities was recognized correctly in most cases inside a confined living space. The classification accuracy in this study was obtained by calculating the percentage ratio of correct predictions to total predictions made. However, the classification accuracy drops to 51.25% when the beacon data was eliminated and the MM approach was carried out independently.

4.7.2 Performance Assessment Of Recognition Of Walking Routes in Trial home-1

4.7.2.1 Using Test Dataset-1

Table 4-B: List of Long walking routes considered in Trial home-1

Route No.	Name
1	Kitchen Fridge to Bathroom
2	Bathroom to Kitchen Fridge
3	Kitchen fridge to bedroom door
4	Bedroom door to Kitchen fridge
5	Fridge to Couch
6	Couch to fridge
7	Bedroom door to Couch
8	Couch to bedroom door
9	Bedroom door to main door
10	Main door to Bedroom door
11	Couch to main door
12	Main door to Couch
13	Bathroom to bedroom
14	Bedroom to bathroom
15	Dining Table to Kitchen stove
16	Kitchen Stove to Dining table

A list of the long walking routes considered in Trial home-1 is presented in Table 4-B.

Apart from the detection of micro-activities and their zone of occurrence, the proposed algorithm also has the capability to track walking trajectories of the target user. This helps to monitor the movement of the user between different

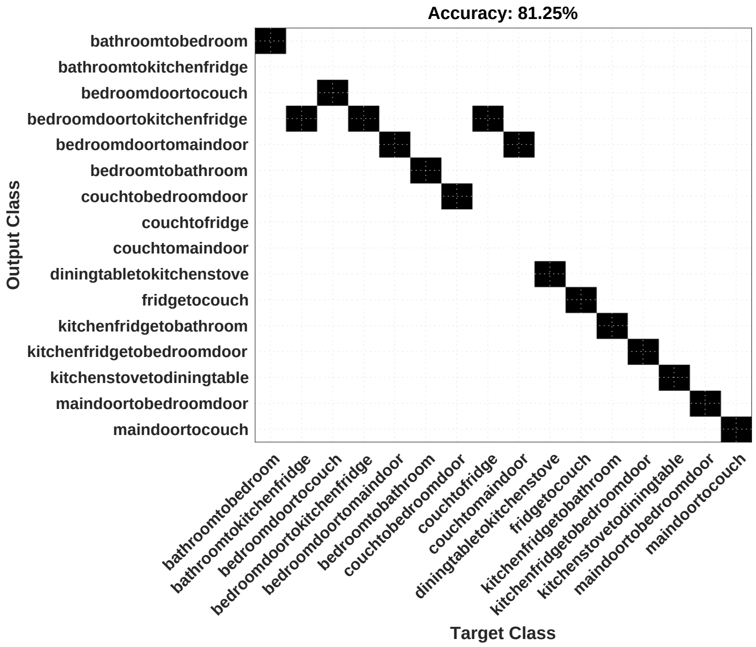


Figure 4.11: Confusion matrix for long walking routes Using Test Dataset-1 in Trial home-1 Using BLE-MMDTW Model

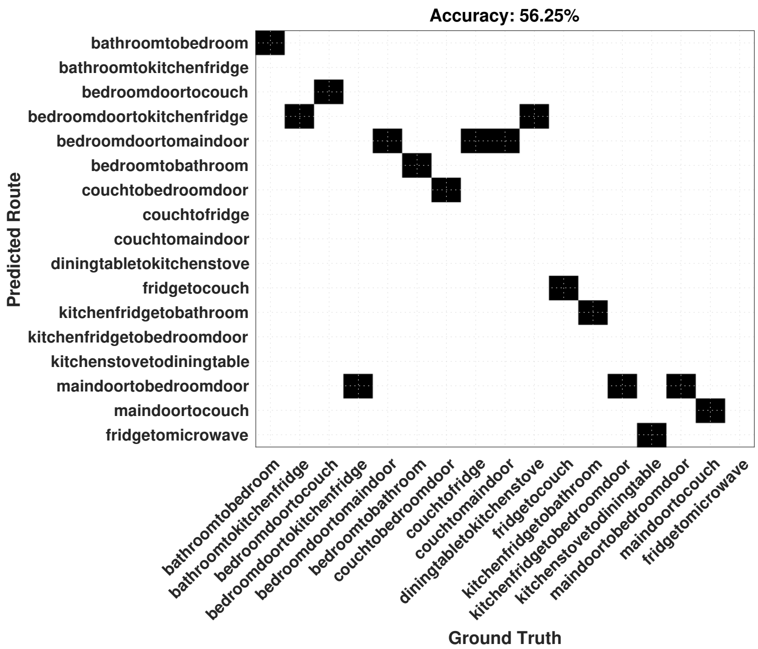


Figure 4.12: Confusion matrix for long walking routes Using Test Dataset-1 in Trial home-1 Using MMDTW Model

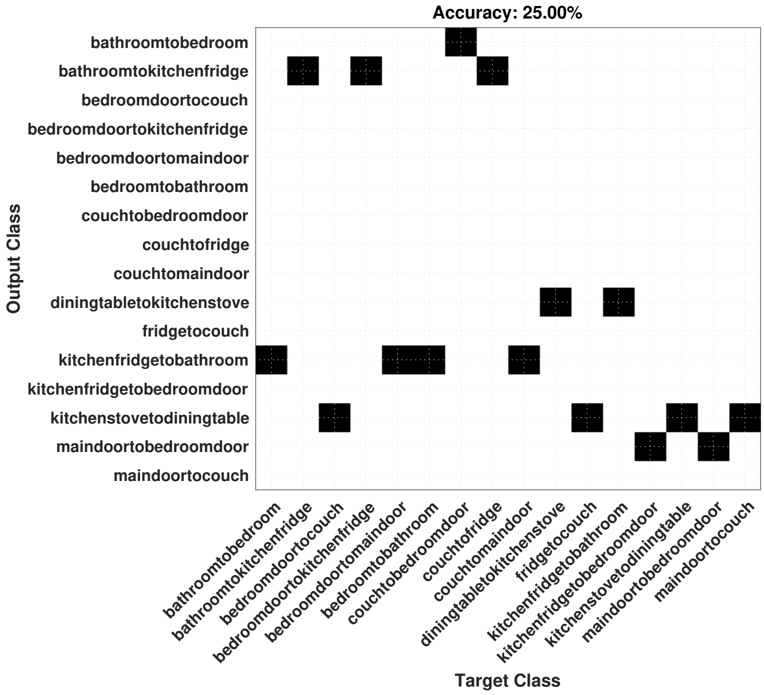


Figure 4.13: Confusion matrix for long walking routes Using Test Dataset-1 in Trial home-1 Using Bidirectional LSTM Model

rooms of the house. The confusion matrices for route classsification using the BLE-MMDTW, MMDTW and Bidirectional LSTM models are shown in Figure 4.11, 4.12 and 4.13 respectively. It can be seen that BLE-MMDTW model has the highest classification accuracy of 81.25% when compared to the other 2 models. Only three routes out of the 16 walking routes were wrongly classified. The wrong prediction is most likely due to the fact that few portions of the predicted route overlaps with the actual ground truth as they partly share the same reference points. MMDTW model has a classification accuracy of 56.25% and performs better in comparison with the state-of-the-art Bidirectional LSTM model. Unlike the good performance for micro-activities, Bidirectional LSTM performs poorly for walking routes and achieves a dismal 25% classification accuracy.

The Bidirectional LSTM model used for prediction of walking trajectories was

	BLE-MMDTW Method	MMDTW Method	BiDirectional LSTM
kitchenfridgetobathroom	0	0	2.735
bathroomtokitchenfridge	1.672	1.672	0
kitchenfridgetobedroomdoor	0	2.185	2.185
bedroomdoortokitchenfridge	0	2.335	1.672
fridgetocouch	0	0	2.537
couchtofridge	3.043	2.884	4.665
bedroomdoortocouch	0	0	2.951
couchtobedroomdoor	0	0	4.518
bedroomdoortomaindoor	0	0	2.951
maindoortobedroomdoor	0	0	0
couchtomaindoor	2.319	2.319	3.666
maindoortocouch	0	0	2.187
bathroomtobedroom	0	0	4.229
bedroomtobathroom	0	0	5.745
diningtabletokitchenstove	0	2.858	0
kitchenstovetodiningtable	0	0.8835	0

Fréchet Distance

Figure 4.14: Performance comparison of walking routes using Fréchet Distance in Trial home-1 Using Test Dataset-1

designed using the following layers and parameters: a sequence input layer with 11 features, a bidirectional LSTM layer with 100 hidden units, a fully connected layer of size 16 followed by a softmax layer and a classification layer. The maximum epochs was set to 50 in this case. Rest of the parameters were the same similar to the model developed for micro-activities and short routes explained in Section 4.7.1.1. However the Bidirectional LSTM model is not suitable for recognition of walking routes in this case due to its substandard performance.

In the case of trajectories, Fréchet distance was used as the performance metric to measure the similarity between the ground truth and the predicted outcome [133]. It takes into account the location and ordering of the distance co-ordinates along a trajectory, which makes it a suitable distance metric when comparing 2 walking routes of different lengths. The Fréchet distance measure can be mathematically represented by Eq(4.8)

$$\delta_F(P,Q) = \min_{\substack{\alpha[0,1]\rightarrow[1,N] \\ \beta[0,1]\rightarrow[1,M]}} \{\max_{t\in[0,1]} d(P(\alpha(t)), Q(\beta(t))\} \tag{4.8}$$

where P and Q are the actual and predicted trajectories of lengths N and M, respectively and d is the distance function. For simplicity, Euclidian distance is used as the distance metric. The co-ordinates α(t) in P and β(t) in Q range over continuous and increasing functions with $\alpha(0) = 0$, $\alpha(1) = N$, $\beta(0) = 0$ and $\beta(1) = M$. The Fréchet distance measures for the individual walking routes using the BLE-MMDTW, MMDTW and Bidirectional LSTM models are shown in Figure 4.15.

When mapping the predicted routes to their respective zones, BLE-MMDTW, MMDTW and Bidirectional LSTM models were found to have a classification accuracy of 75% (since 3 routes were predicted incorrectly), 37.50% and 31.25% respectively. The predicted intra-zone and inter-zone transition for these models can be seen in their respective confusion matrix plot in Figure 4.15.

4.7.2.2 Using Test Dataset-2

Ten different test datasets for 12 walking routes were collected for evaluating the classification efficiency of the proposed model. These selected routes are listed below:

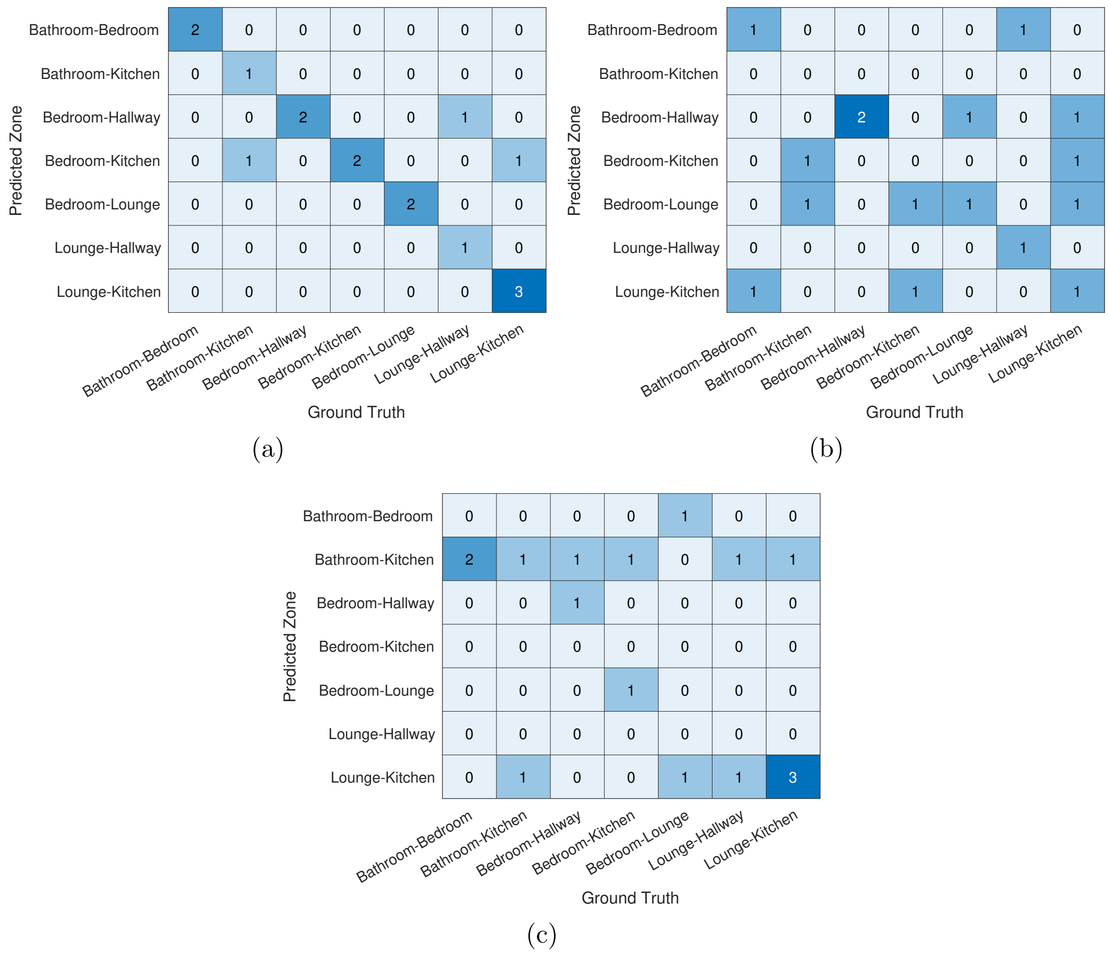
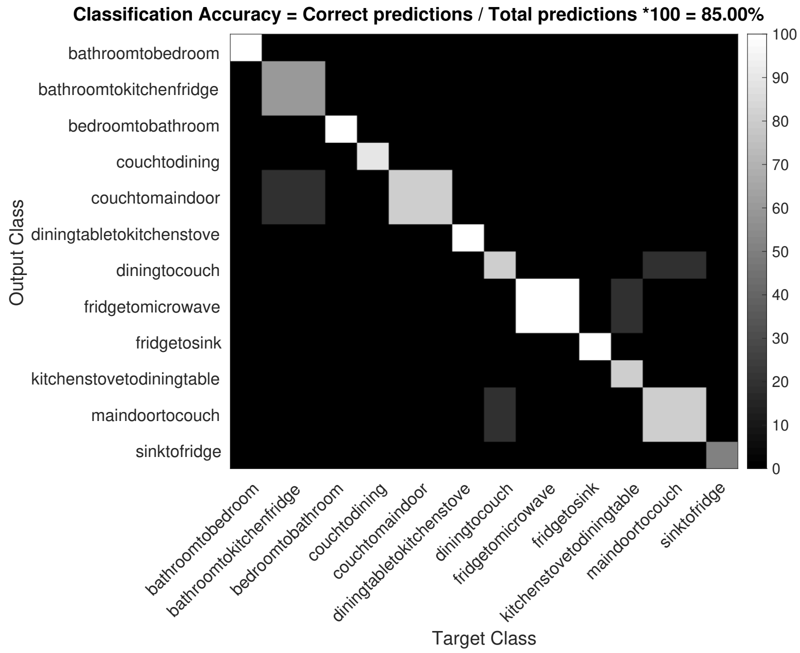


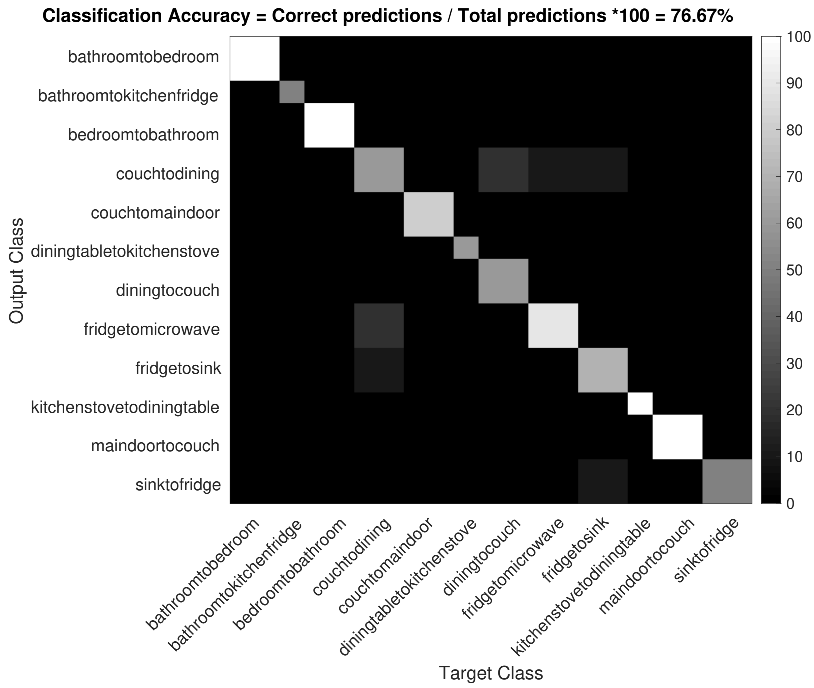
Figure 4.15: Confusion matrix for zone-based classification of walking routes Using Test Dataset-1 in Trial home-1 (a) BLE-MMDTW Model (b) MMDTW Model (c) Bidirectional LSTM Model

1. Couch to Dining, 2. Dining to Couch, 3. Dining Table to Kitchen stove, 4. Kitchen Stove to Dining table, 5. Sink to fridge, 6. Fridge to sink, 7. Bathroom to bedroom, 8. Bedroom to bathroom, 9. Main door to Couch, 10. Couch to main door, 11. Bathroom to Kitchen Fridge, 12. Fridge to Microwave

The confusion matrices for route classification using the BLE-MMDTW, MMDTW method are presented in Figure 4.21(b), respectively. The proposed BLE-MMDTW model provides a reasonable classification accuracy of 85% and outperforms the MMDTW method that provides a classification accuracy of 76.67%. However, the

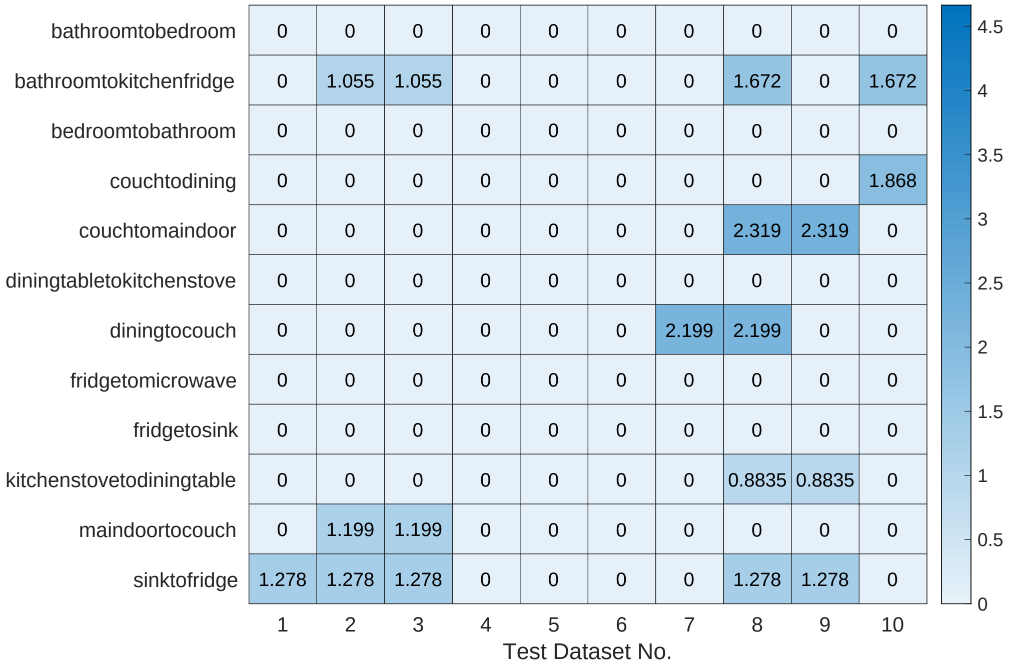


(a)

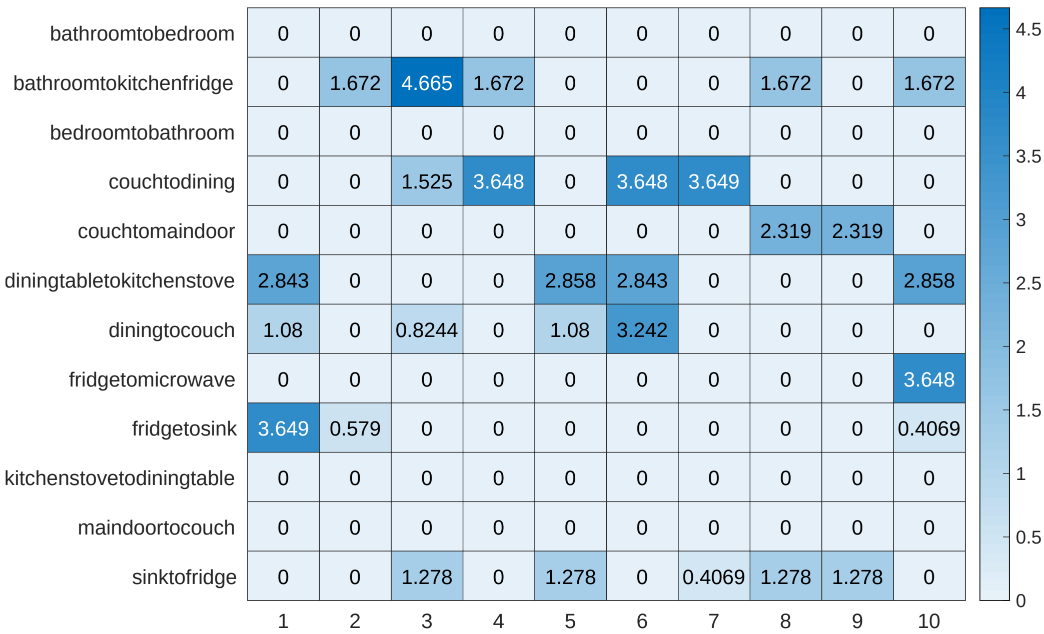


(b)

Figure 4.16: Recognition confusion matrix for walking routes Using Test Dataset-2 in Trial home-1 (a) BLE-MMDTW Model (b) MMDTW Model



(a)



(b)

Figure 4.17: Performance comparison of walking routes using Fréchet Distance in Trial home-1 Using Test Dataset-2 (a) Fréchet Distance Measure for BLE-MMDTW Model (b) Fréchet Distance Measure for MMDTW Model

MMDTW method performs well for route classification when compared to classification of micro-activities since the observed trajectories have a more unique magnetic signature for trajectories when compared to stationary points.

The Fréchet distance measure for the selected routes using the BLE-MMDTW and MMDTW models are shown in Figure 4.17.

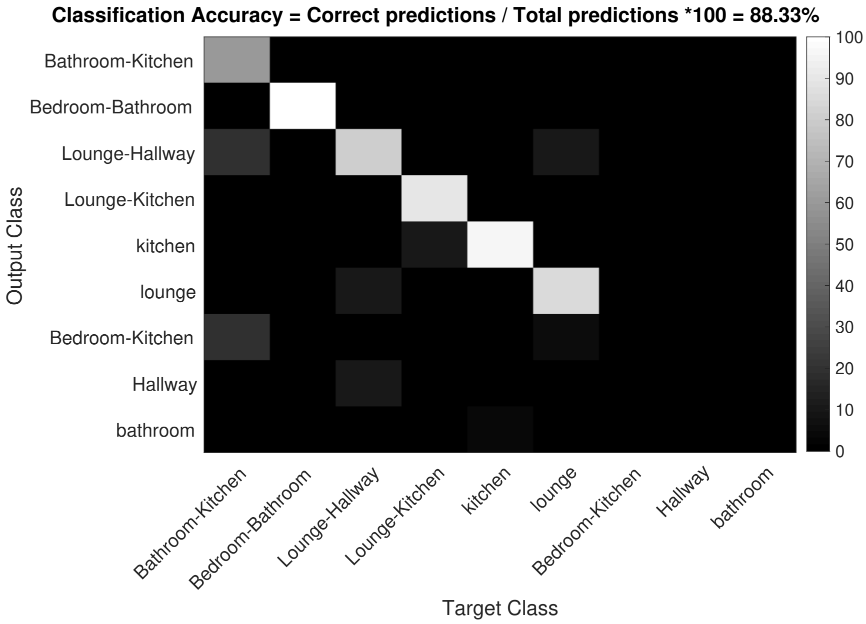
For zone-based classification, the BLE-MMDTW and MMDTW models provide a classification accuracy of 88.33% and 85%, respectively. Their respective confusion matrices for the associated intra-zone and inter-zone classification of routes are shown in Figure 4.18.

4.7.3 Performance Assessment Of Recognition Of Micro-Activities and Short Routes in Trial home-2 with Reduced Receivers

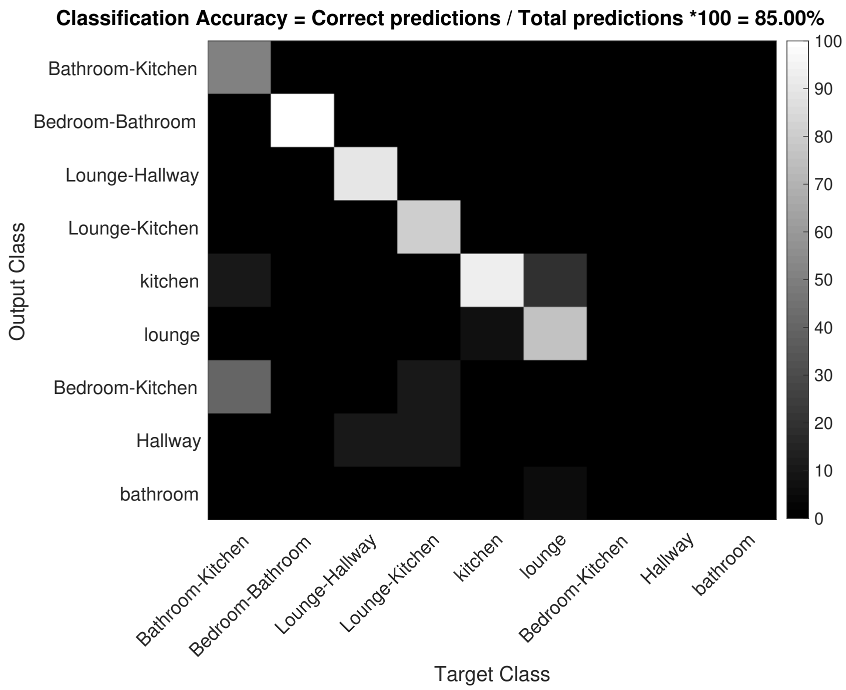
A different comparative analysis was conducted in Trial home-2 to study the impact of reducing the number of receivers and the effect of higher receiver antenna gain on the final outcome using the proposed algorithm. As described earlier, five Raspberry-Pi receivers equipped with external antennas (5dBi and 1dBi) were deployed in the slightly larger second trial home to test the robustness of the hybrid approach with lesser number of receivers.

4.7.3.1 Using Test Dataset-1

The different micro-activities and short routes in Trial home-2 is listed in Table 4-C.



(a)



(b)

Figure 4.18: Recognition confusion matrix for zone-based classification of walking routes Using Test Dataset-2 in Trial home-1 (a) BLE-MMDTW Model (b) MMDTW Model

Table 4-C: List of micro-activities and short routes considered in Trial home-2

Micro-activity/Short Route No.	Name
1	Bathroom sink
2	Near kettle and sink
3	Shower
4	Sitting at dining table left hand side
5	Sitting at dining table right hand side
6	Sitting on centre of couch
7	Sitting on left of bed
8	Sitting on left of couch
9	Sitting on right of bed
10	Sitting on right of couch
11	Bedroom door to front door
12	Couch to dining table
13	Dining table to couch
14	Fridge to sink
15	Front door to bedroom door
16	Sink to fridge
17	Couch to tv
18	Tv to couch

A total of 18 micro-activities and short routes are considered for performance analysis when the receivers are fitted with 5dBi higher gain antennas and the lower 1dBi gain antennas to check if there is any significant improvement in the performance of the proposed model (BLE-MMDTW Model) for these two cases. RMSE is used as the metric to assess the accuracy of the predicted micro-activities and short routes. The stem plot showing the RMSE for the individual micro-activities and short routes while using 5dBi and 1dBi antennas can be seen in Figure 4.19. Table 4-C can be used for referring to the class labels for the respective micro-activity/short route numbers. While using 5dBi antennas, the average RMSE was found to be a reasonable 0.39m with seven micro-activities and short routes being predicted correctly. In the case of 1dBi antennas, the average RMSE was found to be 1.03m.

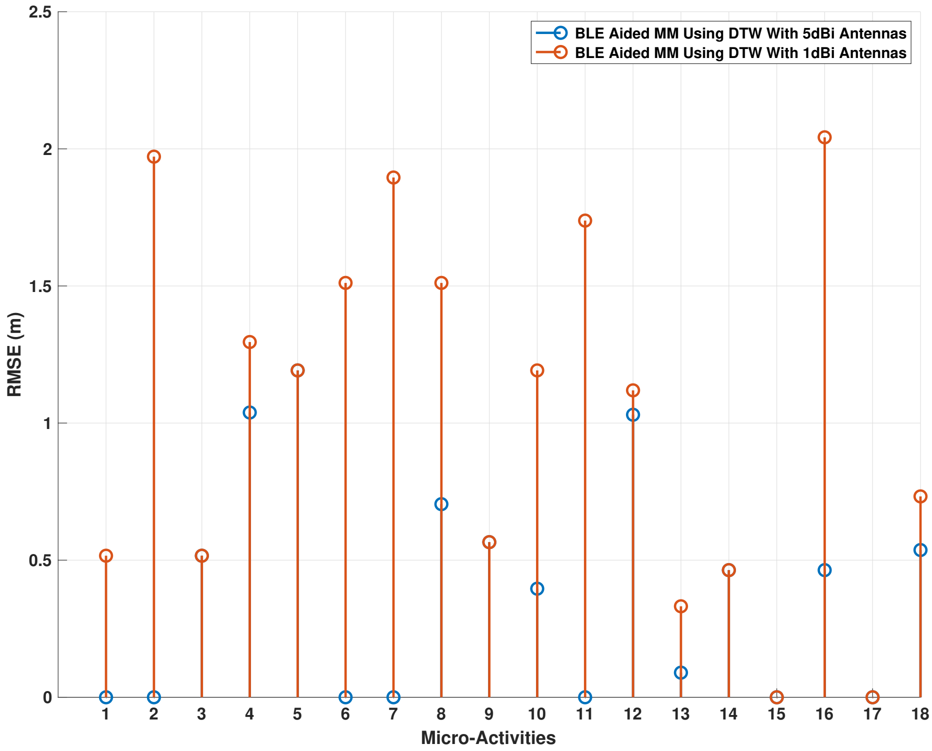
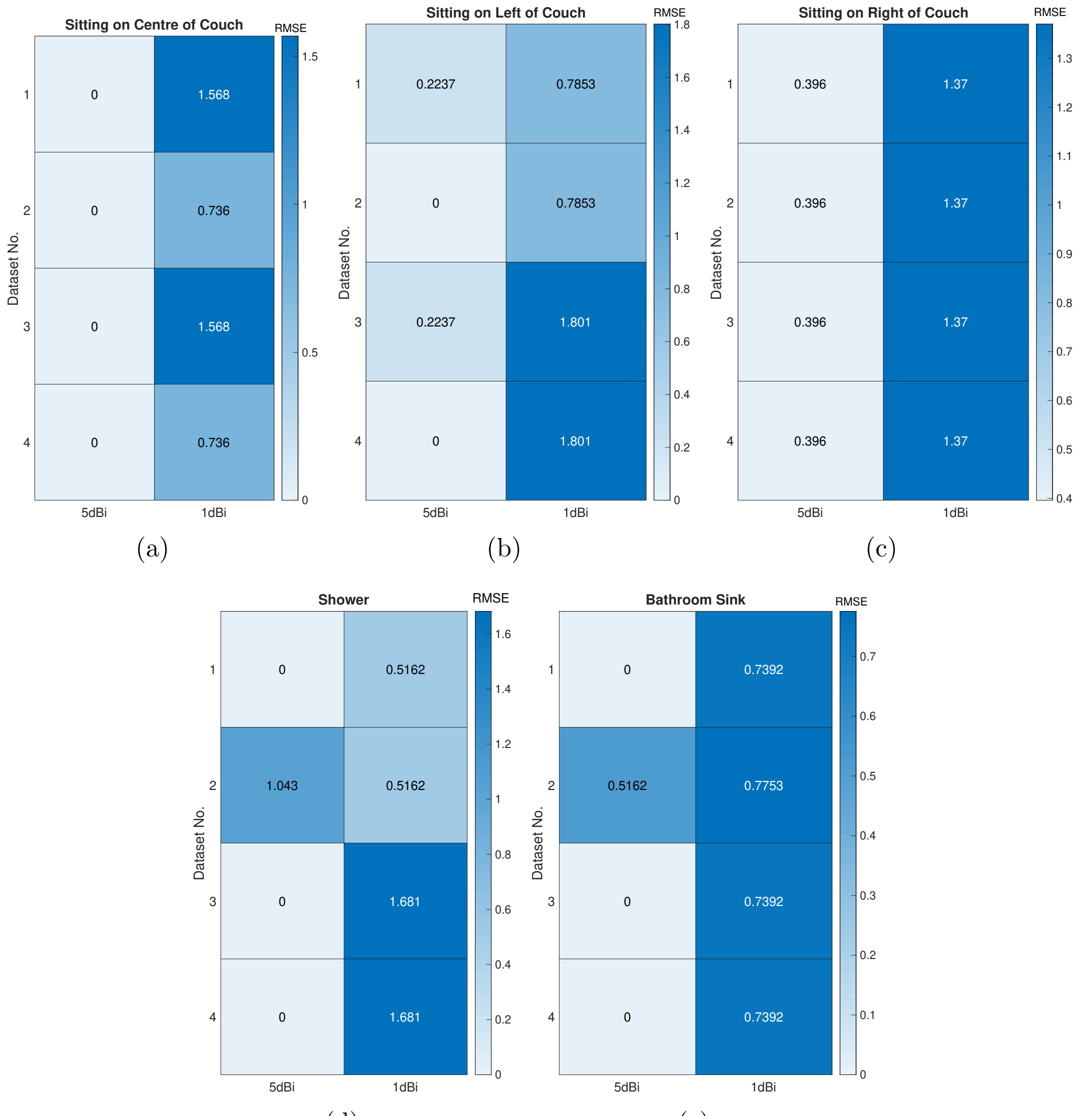


Figure 4.19: RMSE of micro-activities and short routes in Trial home-2 Using the proposed BLE-MMDTW Model for Test Dataset-1

Since the same set of micro-activities was considered for both 1 dBi and 5dBi antennas, a *paired T-Test* was performed between RMSE values to check for statistical significance. The difference is significant if the p value is less than 0.05. A p value of 0.0020 was achieved indicating a significant difference between the two groups.The use of high gain antennas showed a significant reduction in the overall error and boosted the performance of the BLE-MMDTW model using just five receivers in this case.



(a) (b) (c)

(d) (e)

Figure 4.20: RMSE for these micro-activities in Trial Home-2 Using Test Dataset-2 (a) Sitting on Centre of Couch (b) Sitting on Left of Couch (c) Sitting on Right of Couch (d) Using the Shower (e) Using the Bathroom Sink

4.7.3.2 Using Test Dataset-2

As part of the Test Dataset-2, four different datasets of five micro-activities were selected for analysis that were collected on different days spread over a week. The five micro-activities selected for analysis were: *1) Sitting on Centre of Couch, 2)*

Sitting on Left of Couch, 3) Sitting on Right of Couch, 4) Using the Shower, 5) Using the Bathroom Sink.

Figure 4.20. illustrates the RMSE for these micro-activities when the experimental study was conducted separately with receivers fitted with 5dBi and 1dBi antennas respectively. The results indicate that the RMSE of predicted activities is a lot smaller when the receivers are fitted with 5dBi antennas than with 1dBi antennas similar to the results of Test Dataset-1 . This is because an increase in antenna gain improves the range of the Raspberry-Pi receivers such that they can detect the beacon from a greater distance [134]. Hence sufficient accuracy is still maintained with reduced number of receivers when equipped with high gain antennas. However, accuracy is compromised with low-gain antennas due to reduced coverage as only five receivers are used in Trial home-2 compared to eight in Trial home-1. In cases where high gain antennas are used, the predicted outcome is precise in most cases for activities {1,2,4,5} and in other instances provides sub-meter level precision. Similar to Trial home-1, the locus of the predicted activity for different sitting positions on the couch (Activities {1-3}) using 5dBi antennas for all test samples was found to be the *Couch*. The use of a pressure sensor can therefore be avoided and rely solely on the positioning results to find out if the person has been spending some time on the couch. Opting for low gain antennas can also prove useful if the requirement is only to predict the room or zone where the activity is taking place. The average error is around a meter when low gain antennas are used.

4.7.3.3 Performance Assessment Of Recognition Of Walking Routes in Trial home-2 with Reduced Receivers

4.7.3.4 Using Test Dataset-1

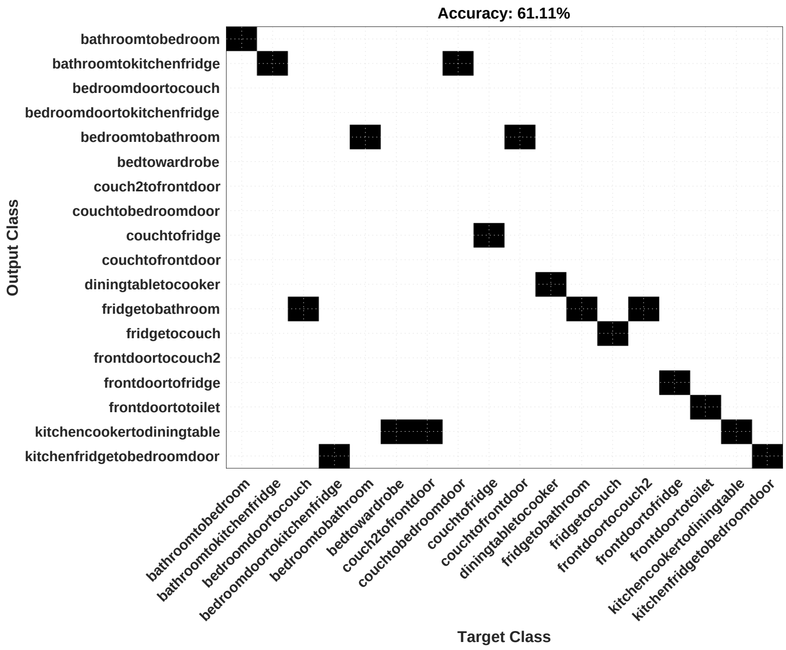
Table 4-D: List of all Long routes considered in Trial home-2

Route No.	Name
1	Bathroom to kitchen fridge
2	Bedroom door to couch
3	Bedroom door to kitchen fridge
4	Couch to bedroom door
5	Couch to fridge
6	Couch to front door
7	Dining table to cooker
8	Fridge to couch
9	Fridge to bathroom
10	Kitchen cooker to dining table
11	Kitchen fridge to bedroom door
12	Bathroom to bedroom
13	Bedroom to bathroom
14	Bed to wardrobe
15	Front door to couch2
16	Couch2 to front door
17	Front door to fridge
18	Front door to toilet

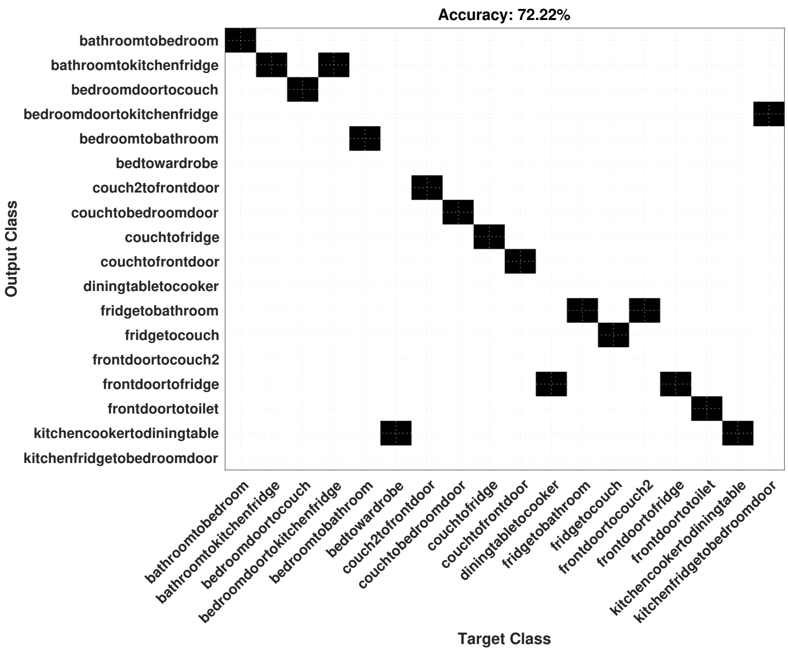
A list of all the long walking routes in Trial home-2 is shown in Table 4-D.

A comparative analysis was performed for long walking routes (> 5 steps) when the receivers were fitted with 5dBi and 1dBi antennas, respectively. 18 long routes were part of that training database of Trial home-2. When the testing was done using the Test-datset-1, the performance when using high gain antennas proved to be better even for the lengthy walking routes. A classification accuracy of 72.22% was achieved with 5 dBi antennas and 61.11% with 1 dBi antennas. The respective confusion matrices illustrating the predictions for different routes can be seen in

FIgure 4.21.



(a)



(b)

Figure 4.21: Recognition confusion matrix for walking routes Using Test Dataset-1 in Trial home-2 (a) Using 1dBi antennas (b) Using 5dBi antennas

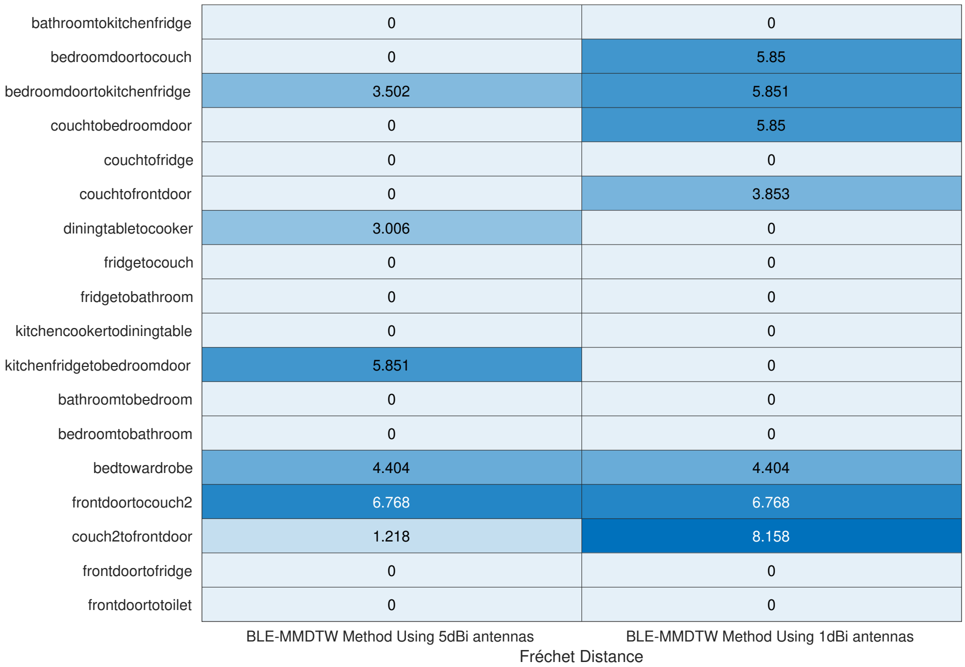


Figure 4.22: Performance comparison of walking routes using Fréchet Distance in Trial home-2 Using Test Dataset-1

Similar to Trial home-1, Fréchet distance was used as the performance metric to measure the similarity between the actual and predicted results. The Fréchet distances corresponding to their respective walking routes using 5dBi and 1dBi antennas is seen in Figure 4.22. Route No. 4, 7, 11 has a higher Fréchet distance error while using 5 dBi antennas than when using 1 dBi antennas. On closer inspection, all three routes has reference points passing through the hallway. A possible reason for the weak performance may be due to the interference of the beacon signal caused by the thick walls while crossing through the hallway. Receivers with low gain antennas tend to perform much better in such cases. This has been further explained in detail in the next Chapter which concentrates specifically on several parameters to improve BLE fingerprinting in Trial home-2.

4.7.3.5 Using Test Dataset-2

Four datasets of five different walking routes were selected for experimental analysis in Trial home-2. These were *1) Bathroom to Kitchen Fridge, 2) Kitchen Fridge to Bathroom, 3) Kitchen Fridge to Sink, 4) Couch to Front Door, 5) Couch No.2 to Front Door*. A comparative analysis was performed for walking routes when the receivers were fitted with 5dBi and 1dBi antennas, respectively.

The Fréchet distance results of the selected five routes are illustrated in Figure 4.23. The predicted outcome for routes 1 and 2 were precise when using 5dBi antennas for each of the four test datasets as seen in Figure 4.23. Overall, the Fréchet distance between the target route and the predicted route when using high gain 5dBi antennas is considerably lesser when compared to using low gain 1dBi antennas for all the five routes indicating high similarity between the predicted route and the actual route. In comparision, the Fréchet distances while using 1dBi antennas are slightly on the higher side as the overall coverage by the receivers is reduced across various rooms in the flat. Thus, it can be deduced that increasing the receiver antenna gain raises the likelihood of improvement and helps reduce the number of Raspberry-Pis deployed in the test environment while maintaining sufficient accuracy.

4.7.4 Selection of Time Window Length for Segmentation of Incoming Data in Trial home-1

So far the test sequences have been considered as a whole for performance evaluation for the experimental evaluation in Trial home-1 and Trial home-2 In this section, a sliding window approach was used for segmentation of incoming wear-

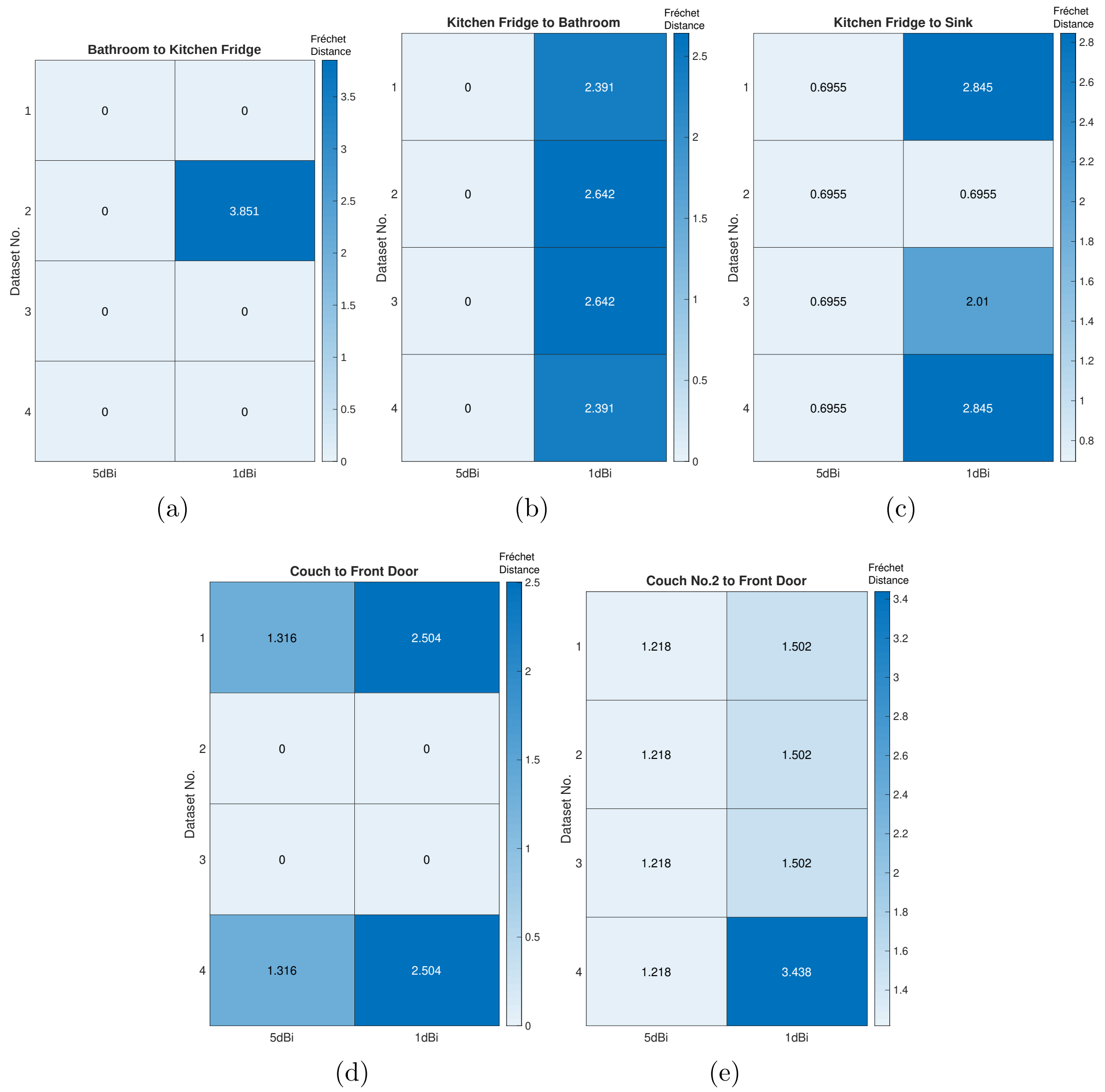


Figure 4.23: Performance comparison of walking routes using Fréchet Distance in Trial home-2 Using Test Dataset-2 (a)Bathroom to KitchenFridge (b) Kitchen-Fridge to Bathroom (c) Kitchen Fridge to Sink (d) Couch to Front Door (e) Couch No.2 to Front Door

able sensor data to check the suitability of the proposed framework in a real world scenario. Based on the sampling rate and the length of the trajectories to be measured, a suitable time window, T_w length needs to be selected such that the segmented data contains sufficient information to output a micro-activity or trajectory. In order to test the system responsivity, the classification accuracy of routes for three different time windows of length T_{w1} = 8s , T_{w2} = 12s and T_{w3} =

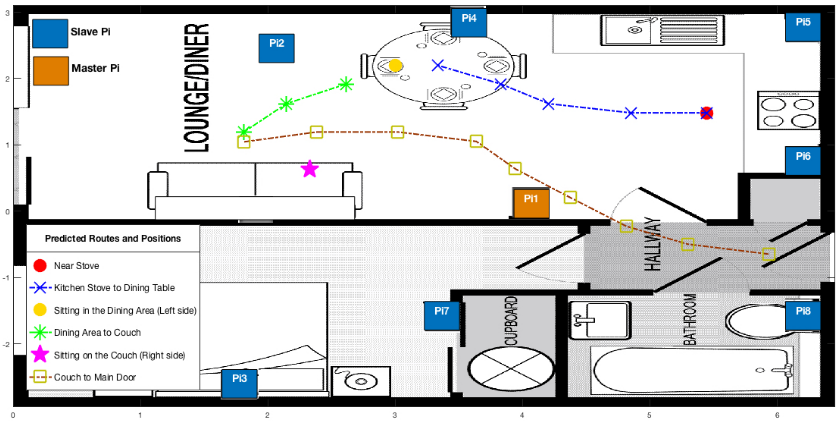
15s were computed. When T_{w1} and T_{w2} are the chosen parameters, a classification accuracy of 66.67% and 77.67% were obtained, respectively. $T_{w3} = 15$s was selected for which a maximum classification accuracy of 85% is achieved.

4.7.5 Case Study Evaluation

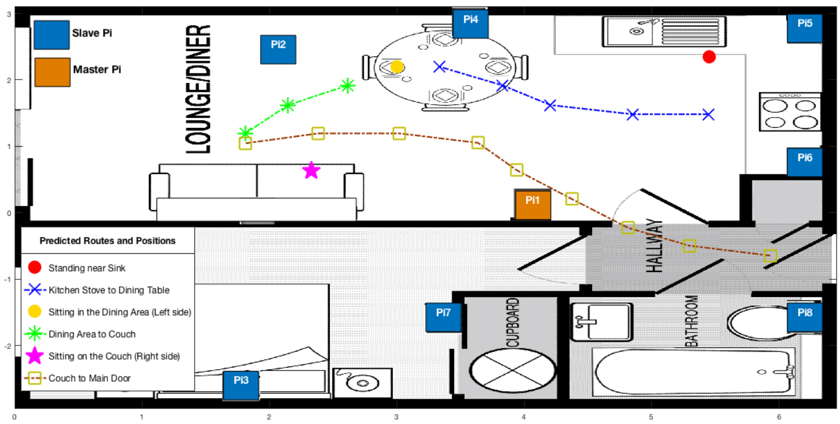
A case study evaluation was conducted in the two test apartments to evaluate the performance of the proposed method employing the BLE-MMDTW approach against the solo use of MFV fingerprinting. This was determined when the user was moving inside the apartment performing a series of random activities that reflect regular human day-to-day behavior. A sliding window of $T_w = 15$s was used in this case study for both the trial homes. The test results of Trial home-1 and Trial home-2 (using 5dBi antennas) are highlighted in Figure 4.24 and Figure 4.25, respectively. The positions or routes specified in both the figures are the results of each method, which are in the order of the activities performed by the user. The resulting output from the case studies prove that the predicted routes and positions obtained by the proposed method are much closer to the actual results as compared to using only MFV sequences for location estimation. Furthermore, the results indicate that the independent use of the MFV fingerprinting method is ineffective and therefore contributes to a high mismatch rate.

4.8 Discussion

The need to design a reliable context based location aware system for an increasingly dynamic and complex domestic environment is crucial as they form the basis for a number of remote home healthcare applications. The results from Section



(a)



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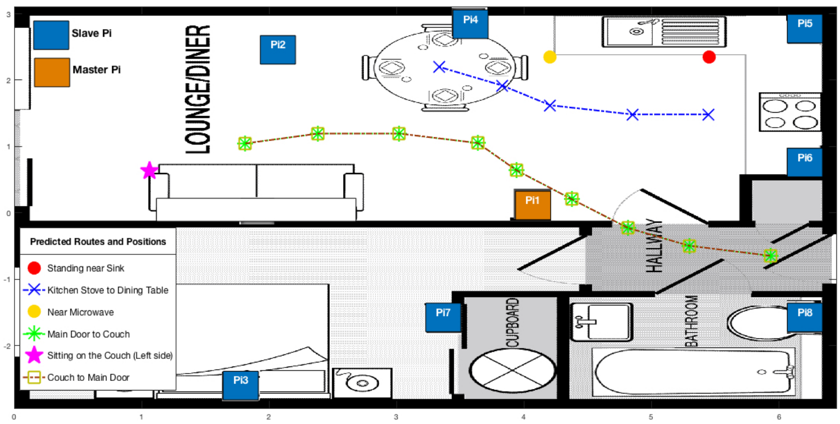
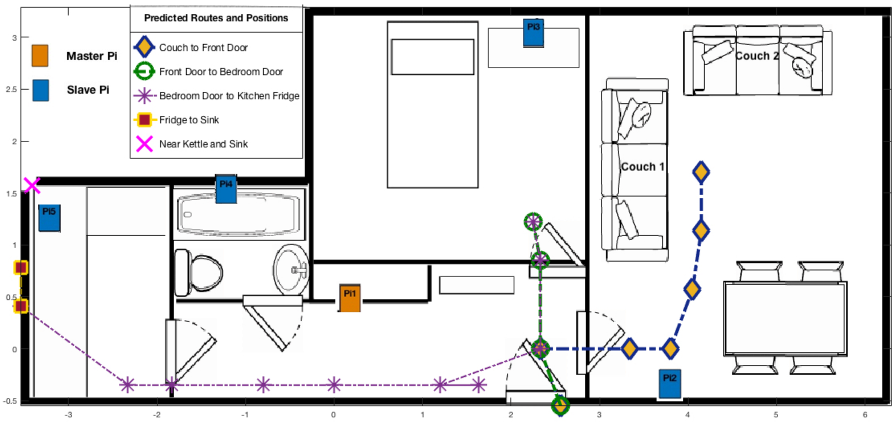
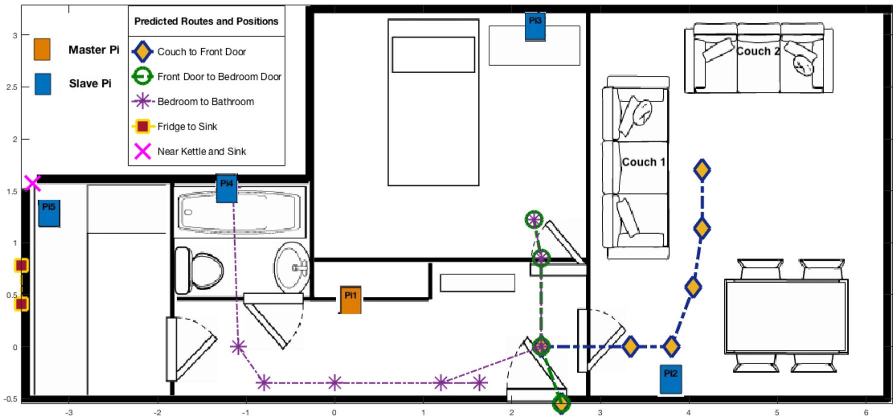


(c)

Figure 4.24: Case Study Illustration when user performs the following activities in Trial home-1 (a) Actual Walking Route (b) Predicted Walking Route (Using Beacon RSSI + MFV Fingerprinting Method) (c) Predicted Walking Route (Using only MFV Fingerprinting Method)



(a)



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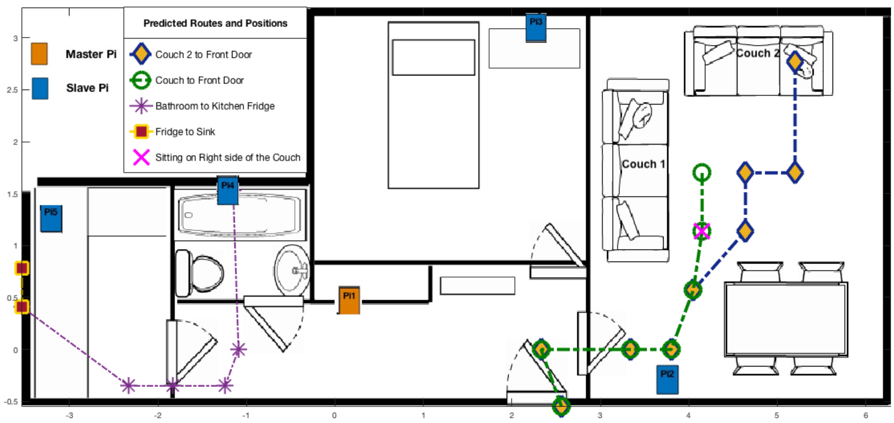

(c)

Figure 4.25: Case Study Illustration when user performs the following activities in Trial home-2 (a) Actual Walking Route (b) Predicted Walking Route (Using Beacon RSSI + MFV Fingerprinting Method) (c) Predicted Walking Route (Using only MFV Fingerprinting Method)

4.7 demonstrate that the hybrid BLE-MMDTW method with the inclusion of step detector information outperforms the individual use of MMDTW method in all the test case scenarios for micro-activities and walking routes. The findings are more conclusive since they were assessed in a home environment with strong NLOS conditions. The proposed model was also tested against state-of-the-art Bidirectional LSTM model for all routes and positions in Trial home-1. The performance of the Bidirectional LSTM model for recognition of micro-activities is comparable with the proposed model providing an error of 0.31m. The RMSE achieved by the proposed model for micro-activities is 0.18m. The low error rate proves the capability of the proposed model to achieve fine-grained positioning. In the case of walking routes, BLE-MMDTW model outperformed the performance of the Bidirectional LSTM model by achieving a high accuracy of 81.25%. The latter provided a poor classification accuracy of 25%. As per the results, it can be deduced that the Bidirectional LSTM model is not suitable for prediction of walking trajectories when reduced amount of training data is available. In this study, only single observation of sequential data for each walking route and micro-activity was available in the training database. The proposed model was able to perform decently even in such conditions.

Overall, the performance assessment and the case study results corroborate the hypothesis that the fusion of BLE and MFV fingerprinting with added information from inertial sensors complement each other to accomplish low-level recognition of multiple activities and user trajectory prediction in a smart home environment. Furthermore, the decision to evaluate 1dBi and 5dBi interchangeable external antennas in Trial home-2 was to determine the level of localization accuracy with fewer receivers using the proposed algorithm. Experimental results indicate that adequate accuracy can still be maintained with a reduced infrastructure, by deploying receivers with higher gain antennas. Besides, the data collection approach used in this study along with radio map construction for sequence-based inputs and trajectory measurements can be extended to other location estimation technologies (Eg: LiDAR, Radar, mmWave).

Table 4-E shows a comparison of the proposed system against recent works that have used location estimation techniques as a supporting or standalone system for activity monitoring. Most of these systems are designed only to achieve room-level accuracy [124][127][128]. Other works that consider a higher number of activities, suffer in accuracy due to the complexity involved in a multi-activity classification problem (10 or more classes) [126][129]. Location estimation techniques are used in combination with other sensing methods in both these works. In this study, indoor positioning techniques were used as a standalone system to provide more fine-grained positioning rather than room-level accuracy and to classify multiple activities. Furthermore, the study also considers the user trajectory, which is crucial for continuous monitoring applications. Despite the complexity involved, the developed system managed to achieve reasonable accuracy for both stationary positions and walking routes.

4.9 Chapter Summary

In this work, a novel algorithm has been developed for low-level micro-activity recognition and prediction of walking routes using wearable sensing. The implementation employs an inverse beacon fingerprinting scheme coupled with inertial sensors to narrow down the magnetic field vector matching space. The suggested approach helps in overcoming the shortcomings of beacon signal stability and mismatch issues in magnetic field fingerprinting. An overall improvement in prediction

Table 4-E: Comparison of Activity Monitoring Systems using Location Estimation Techniques

Reference	**Connection Type**	**Method Employed**	**Devices Used**	**Cost**	**Trajectory Prediction**	**Avg. Accuracy & Range**	**No. of Classes**
[124]	Wi-Fi	Fingerprinting	Smartphone	Low	No	89% ; Room-level accuracy	8 activity classes
[129]	Bluetooth; ZigBee	Random Forest classifier	Power meters; current transformers; Ultrasonic sensor	Medium	No	79.39%	10 class high-level activities
[127]	BLE	Smoothing, machine learning algorithms with fingerprinting	Wearable beacon; fixed raspberry-pis	Low	No	Precision: 84.2%; F-measure: 80.9%; Room-level accuracy	6 ADL classes
[128]	BLE	Fingerprinting	Fixed beacons; smartphone	Low	No	93% (room estimation; 83% (frailty classification); Room-level accuracy	3 class frailty classification
[126]	BLE	Recursive Bayesian approach	binary sensors, capacitive smart floor; smart watch with beacon	High	No	68%	24 high-level ADL's
Proposed Method	BLE	Sequence Matching; DTW Algorithm using WiFi & MFV Fingerprinting with stepdetection	Wearabe (beacon, accelerometer, gyroscope, magnetometer); Raspberry-Pi receivers	Low	Yes	Micro-activity: RMSE = 0.55m; 91.87% (zone) ; Routes = 85%; 88.33% (zone)	16 micro-activities; 12 routes (Total: 40 positions/routes)

accuracy is made possible by amalgamating the results of both techniques. Furthermore, a context-oriented, trajectory-based radio map model for location estimation is adopted in this study to provide a realistic scenario for testing that is better suited in setting up an activity recognition system at home. The empirical results demonstrate that the proposed method has high potential in providing centimeter-level positioning accuracy for micro-activities and a reasonable classification accuracy over 80% can be achieved for walking routes. The method proposed in this chapter provides an accurate and cost-effective solution for monitoring applications within a home environment as it delivers sufficient prediction accuracy on its own without the use of object-based sensing methods. Furthermore, complex ADL recognition is feasible when the suggested method is combined with posture recognition methods or used in ambient sensing environments, instrumented with only the essential sensors required for monitoring.

Chapter 5 uses the ranking feature of the positioning algorithm described in this Chapter and provides an evaluation of the key parameters involved in setting up the BLE fingerprinting system by using reduced receivers with interchangeable high gain and low gain antennas.

Chapter 5

Evaluation of Factors Affecting Inverse Beacon Fingerprinting Using Route Prediction Algorithm

Conventional Radio Frequency (RF) based fingerprinting still remains one of the most popular methods amongst other indoor positioning techniques due to its inherent accuracy and reliability. However, not much prominence has been shown in analyzing certain factors that may affect the outcome of the fingerprinting method while designing the localization system.

In this chapter, an analysis of the factors that possibly influence the performance of the indoor positioning method explained in Chapter 4 is discussed here. Furthermore, the chapter makes few suggestions surrounding the hardware setup which helps in boosting the overall performance of the beacon fingerprinting method implemented in Chapter 4. All the experiments conducted in this Chapter was performed in Trial home-2. Ranking accuracy with a route selection algorithm (without the steps correction phase) is used as the basis to analyze the performance of the fingerprinting method.

The rest of the chapter is organized as follows; Section 5.1 and 5.2 highlights the main motivations and main contributions of this chapter. Related work is discussed in Section 5.3. Section 5.4 describes the route prediction algorithm. The performance analysis results of various factors including antenna gain and electrical interference are discussed in Section 5.5.

5.1 Motivation for the study

Despite the recent advances in indoor positioning systems, setting up a reliable smart space for localization in compact domestic homes still remains an open challenge. One of the reasons of not being able to devise a practical localization solution for small-scale homes is mainly due to the dynamic nature of a domestic space that is constantly subjected to heavy attenuation caused by the surrounding walls and furniture. Deploying independent RF fingerprint based solutions in such compact spaces will prove ineffective, as the signal will be unstable in a strong non-line of sight (NLOS) environment. To develop a potential RF fingerprinting system for a home environment, importance has to be extended in choosing the right hardware elements and data collection method, apart from improving the location estimation algorithm.

Important parameters such as deciding the number of receivers to be deployed, deciding the average length of walking routes to maintain in training database, effect of receiver coverage density on position accuracy are discussed in Chapter 5. The reason for including these details after Chapter 4 is because it facilitates understanding of the technical concepts and the impact of these parameters on location fingerprinting presented in Chapter 5.

5.2 Main Contributions of this Chapter

The main contributions of this chapter are summarized as follows:

1. Motivated by the above, this chapter will provide an insight into the concept of ranking accuracy, which is used as the metric for performance analysis of the BLE fingerprinting method described in Chapter 3. The results from this study can help improve the BLE fingerprinting performance in Chapter 3 and bring about improved localization in small-scale homes.

2. An in-depth study on the impact of control variables such as receiver antenna gain, route length, number of detected receivers on the ranking accuracy of routes is carried out. The chapter also discusses the effect of surrounding electrical interference on the beacon signal.

3. Location estimation algorithms are not the focus of this chapter as there is sufficient research already carried out on them. The key findings from this study will help the reader consider different factors that can help improve the overall performance of the RF localization system, and will serve as a reference case study for future research when deciding on hardware characteristics during deployment of RF fingerprint based indoor positioning systems.

5.3 Related Work

Some of the important factors that determine the accuracy of this type of scene survey method is the procedure used for collecting RSSI fingerprints, the accuracy of the radio map, the location estimation algorithm and other miscellaneous factors, such as hardware setup and configuration, building layout and environment noise. Apart from the location estimation algorithm and the data collection procedure, there has been minimal research done in evaluating other factors that affect indoor location fingerprinting systems. It is essential to take note of these external elements while designing a stable location aware system.

One such quality control study by Liu et al. involves analyzing and summarizing the potential impact factors affecting Wi-Fi fingerprinting that is implemented on a simulation platform [135]. The research involves studying various factors such as AP density, AP distribution, radio signal attenuation factor, radio signal noise, and reference point (RP) density. The final results indicate that an increase in AP density, RP density and the signal attenuation factor with low signal noise level contribute to better performance. The study also claimed that the AP distribution had no particular impact on the end result. In another study conducted by Moghtadaiee et al., the design characteristics such as the effects of the number and geometry of APs, RPs and number of RSSI samples for an indoor positioning system were analyzed [136]. Results from this study revealed that merely increasing the number of APs beyond a suitable number for a given indoor space barely influences the end result.

The attenuation caused by the human body is another key factor to be considered in indoor positioning systems. At most times, accuracy is affected when a human body shields the direct line of sight path between the transmitter and the receiver. A number of studies have introduced compensation factors into the positioning algorithm to account for the path loss encountered due to the presence of a human body [137]-[138]. In [139], the fluctuations in signal strength in indoor environment caused by human movement are studied. Various attenuation models based on movement speed were built for a single-person and three-person scenario. Though the effect of the human body was not studied in detail in the research presented in this chapter, readings were collected in all directions for a given path to ensure that the interference from signals passing through the human body was

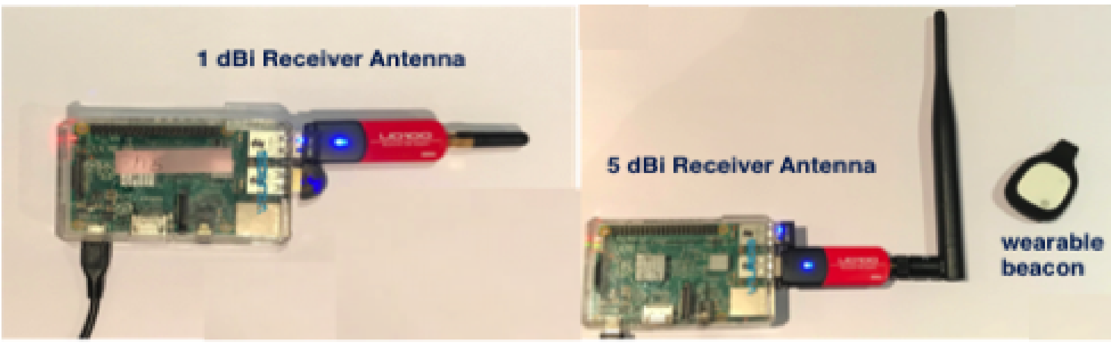

Figure 5.1: Project hardware components: Raspberry-Pi receiver with external 1dBi and 5dBi antennas along with wearable beacon

taken into account while creating the radio map.

5.3.1 Route Prediction Rank Based Algorithm

The route prediction rank based algorithm is based on Phase I of the positioning algorithm described in Chapter 5 (Refer to Section 5.6.1.1). For determining the correct path during the online phase, a section of routes were tested by physically walking along the trajectory and collecting RSSI data whilst moving. The collected RSSI data was then passed to a prediction algorithm that outputs a list of routes

Algorithm 3 Route Prediction Using RSSI Fingerprinting

Inputs: $RSS_{offline} \leftarrow$ Offline radio map with labeled routes, $RSS_{online} \leftarrow$ Online RSSI data, $n \leftarrow$ number of receivers considered, $RPi_{ID} \leftarrow$ Raspberry-Pi Identified where (1 $\leq$ ID $\leq$ n)

Output: *selectedRoutes* $\leftarrow$ Top 10 most likely routes ranked in decreasing order of likelihood that was walked by the target

```
for i = 1: sizeof(RSS_offline) do
    Compute rank matrix 'α' where each row 'i' contains the RPi_ID sorted in descending order based on the strongest RSSI
end for
for i = 1: sizeof(RSS_online) do
    I_online ← RPi_ID in descending order based on the strongest incoming RSS_online
    β[i] ← Retrieve respective walking route label of matched rows in I_online from 'α'
    occ[i] ← Compute the frequency of occurrence of matched walking routes in β[i]
end for
γ ← Results from 'β', categorized by group_occ ← number of routes grouped by occ and sum_occ ← total number of observations of each routes
δ ← Sort Routes 'γ' based on sum_occ and on group_occ incase of ties
return selectedRoutes ← Retrieve top 10 walking routes from 'δ'
```

ranked in order of descending likelihood to the actual route walked by the resident. The first step involved sorting the entire training database and the collected online beacon signal samples based on their strongest RSSI vectors. RSSI values with "-120" collected by receivers are indexed as zero referring to the fact that the respective Raspberry-Pis is out of range of the beacon. This is followed by creating a rank matrix individually for the offline and online data where each row contains the corresponding Raspberry Pi identifier based on the previous sorting. The ranked datasets are finally matched against each other to find the top ten most likely routes that was walked by the target person. The Pseudo code explaining the above steps is shown in Algorithm 3.

5.3.2 Advantages and Applications

In this chapter, a deeper analysis of the factors that help in raising the accuracy of the beacon fingerprinting method is performed, such that the probability of the actual route appearing in the top ten or top five positions using Algorithm 3 are improved. This approach is tested in a one bed apartment and would be useful in designing a reliable Activities of Daily Life (ADL) monitoring system or can be developed into a suitable user-friendly Internet of Things (IoT) application. The proposed technique can also be extended to an industrial environment where location based services play a pivotal role in supply chain management or can help managers to collect and analyze information regarding the worker's movement patterns. The experiments conducted in this study provides an insight on how the efficacy can be improved using the deployed hardware.

5.4 Results and Analysis

The experiments in this Chapter were performed on the Trial home-2 test bed. Further information regarding the layout of the test bed, hardware setup and data collection process is mentioned in Chapter 3 under Section 3.4. The layout of the trial home along with the placement of the master and slave Raspberry-Pi receivers is the same as seen in Figure 3.4.

The training database comprised a total of 36 routes including stationary points. RSSI data samples for the 24 walking routes listed in Table 5-A were selected to study the performance analysis between receivers equipped with 1dBi and 5dBi antennas individually, out of which 17 routes were measured 4 times (Route No. 1

to 20) and 7 routes were measured 10 times (Route No. 21 to 24). When a route was not found in the top ten rankings, it was assigned the value "eleven". In this section, the rank based route selection method explained in Algorithm 3 was used as the basis to assess the performance against various factors. For the remainder of the sections and figures in this Chapter, the routes will be mentioned in terms of their route numbers. Refer to table 5-A for information regarding the route names for a given route number.

5.4.1 Impact of Antenna Gain on Ranking Accuracy of Routes

Antenna gain is a measurement of how well the antenna focuses a signal in a specified direction (strength and reach of the antenna's signal), which is typically measured in dBi. An evaluation was performed to assess if increased antenna gain improves the position of the correct route in the rankings using the method described in Algorithm 3. An analysis on the collective measurements of all walking routes yielded an average median rank of 7.58 for 1dBi antenna setup that improved to 6.1 when 5dBi antennas were deployed. Figure 5.2 represents the corresponding individual average median route rankings for 1dBi and 5dBi antenna gain. The median was chosen to perform the analysis rather than the mean in order to reduce the effect of outliers. The average improvement in rank while using 5dBi antenna is a movement of 1.5 positions over 1dBi. It can be noticed in Figure 5.2 that most of the routes connecting the kitchen and living room are not improved by the high antenna gain. One possible cause could be the placement of the antenna of Pi1 next to the thick wall, as nearly half of the antenna's gain is lost when it tries to pick up signals from the surrounding walls.

Table 5-A: List of Walking Routes Used for the Analysis

Route No.	Route Name	Points on Route	Route Length (m)
1	Bathroom to kitchen fridge	6	2.7
2	Bedroom door to couch	8	5.7
3	Bedroom door to kitchen fridge	12	7
4	Bedroom door to front door	4	2
5	Couch to dining table	5	2.2
6	Couch to bedroom door	8	5.7
7	Couch to fridge	16	9.4
8	Couch to front door	8	4.4
9	Dining table to cooker	20	8.3
10	Dining table to couch	5	2.2
11	Fridge to bathroom	13	2.7
12	Kitchen fridge to bedroom door	12	7
13	Sink to fridge	2	0.6
14	Bedroom to bathroom	10	6
15	Bed to wardrobe	10	4.6
16	Front door to fridge	8	5.6
17	Front door to toilet	8	4.6
18	Fridge to couch	16	9.4
19	Fridge to sink	2	0.6
20	Kitchen cooker to dining table	16	8.3
21	Front door to bedroom door	4	2
22	Bathroom to bedroom	10	6
23	Front door to couch 2	9	5.2
24	Couch 2 to front door	10	5.2

Since the same set of routes were walked for 1dBi and 5dBi setup, a Paired-t test was used to match the individual route rankings against each other to check if there is a significant difference in the results between these two groups. The difference is considered to be statistically significant if the p-value ≤ 0.05. In this case, the p-value was found to be 0.0324, which indicates a notable difference between the 1dBi and 5dBi measures. When the improvement of each route was analyzed individually, the rank of 67% of the walking routes improved while using 5 dBi antennas as opposed to their rank using the 1dBi stub antennas. Taking into account those that did not change, 91% of routes were equal or better at 5 dBi compared to 1 dBi gain.

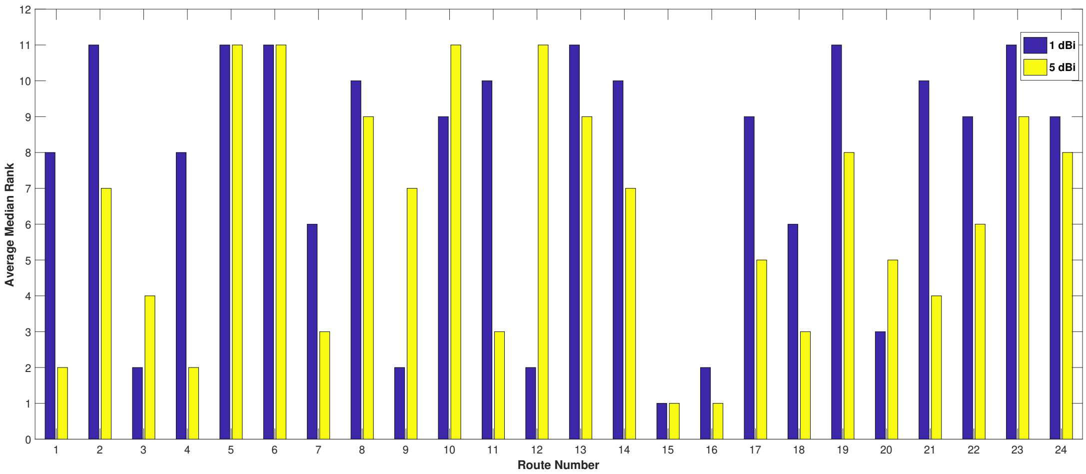

Figure 5.2: Comparative analysis median rank analysis of 24 selected routes using 1dBi and 5dBi receiver antenna

It has to be noted that the sole use of this method will not help in accurate location positioning. The very purpose of this analysis in this thesis was to check if an increased antenna gain helped in boosting the probability of a route appearing in the top 10 positions consistently, so that the outcome of the method described in Section 3.6 of Chapter 4 is improved. Furthermore, the analysis also helps in deciding an optimal setting for any indoor positioning system using BLE fingerprinting technique.

5.4.2 Correlation between Route Length and Rank Improvement

It was expected that there would be a direct correlation between the length of a specific route and an improved ranking. This was based upon the assumption that if the signature of the route was longer, it would more likely be unique and therefore, more accurately matched against the radio map built during the training stage. However, this was not the case as shown in Figure 5.3.

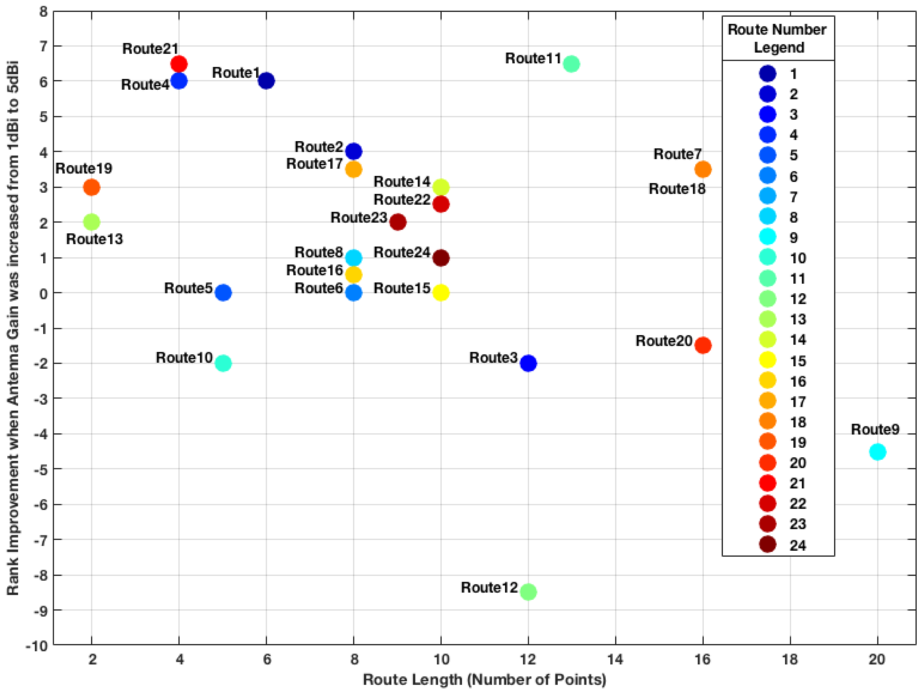

Figure 5.3: Relationship between Route Length and Rank Improvement

A large percentage of the longer routes, which consist of more than 10 points (Routes 3, 12, 20 and 9), did not show a marked improvement in ranking when 5dBi antennas were used. The reason for such performance deterioration maybe due to the existence of several walking routes of shorter length that share the same order of reference points as that of the longer routes in the training database. Furthermore, receivers with 5 dBi BLE dongles provide a greater coverage range compared to those with 1dBi dongles (More on this in Section 5.4.3). However, with increased beacon coverage area, number of receivers detecting the beacon will be higher at each reference point resulting in fingerprints of greater dimensionality. The uniqueness of the data sample at each reference point along the longer walking route is thus diluted for higher gain antennas resulting in more route matches from the training database in contrast to using lower gain antennas. The poor result is thus understandable making it harder to identify the exact walking route as longer routes cover numerous segments of existing shorter routes.

The results highlight the fact that the most consistently improved routes in ranking are those between eight and ten points; primarily routes of medium length.

5.4.3 Effect of the Number of detected Raspberry-Pis on the Ranking Accuracy

5.4.3.1 5dBi Median Route Rankings Vs Minimum Number of Raspberry-Pis detecting the beacon

Whilst there was no improvement in ranking performance due to the increased route length, it was noticed that the number of Raspberry-Pis detecting the beacon had a positive influence on the performance rankings for each route. For any given route, the number of Raspberry-Pis detecting the beacon can vary between one and five in this case study. In order to measure the performance efficiency, the minimum number of Raspberry-Pi receivers detecting the beacon was identified for each route along with their respective rank position outcome. The tests indicate that an increase in the minimum number of detected Raspberry-Pis raises the likelihood of improvement, which is reflected in the ranking position for a given route (as shown in Figure 5.4).

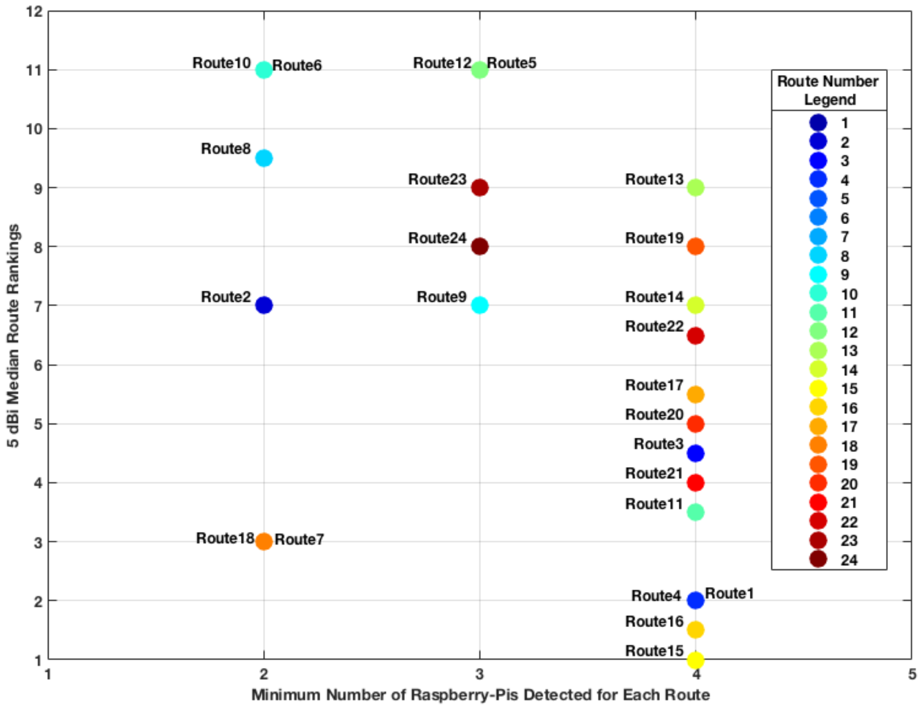

Figure 5.4: 5dBi Median Route Ranking Vs Minimum Number of Raspberry-Pis detecting the beacon

In Figure 5.4 plot, the y-axis identifies the rank, with one being the highest; all routes outside the top ten are demarcated by the value 'eleven'. It is evident from this plot that a large section of routes (Route No. 1,3,4,11,13-17,19-22) have at least four Raspberry-Pis detecting the beacon as a result of using 5 dBi antennas at any given time. Around nine of these thirteen routes are found to have an average median rank ranging from one to five, confirming that the relative rankings improve with the increase in the number of receivers detecting the beacon.

5.4.3.2 Improvement in Rank Vs Number of Raspberry-Pis detecting the beacon

It was observed that the number of Raspberry-Pis detecting the beacon using 5dBi antennas were comparatively higher than when using 1dBi antennas (Refer Table 5-B). Consequently, there was also an improvement in the average median rank by using receivers with higher antenna gain when the minimum number of Raspberry-Pis detecting the beacon increased (Refer to Figure 5.5).

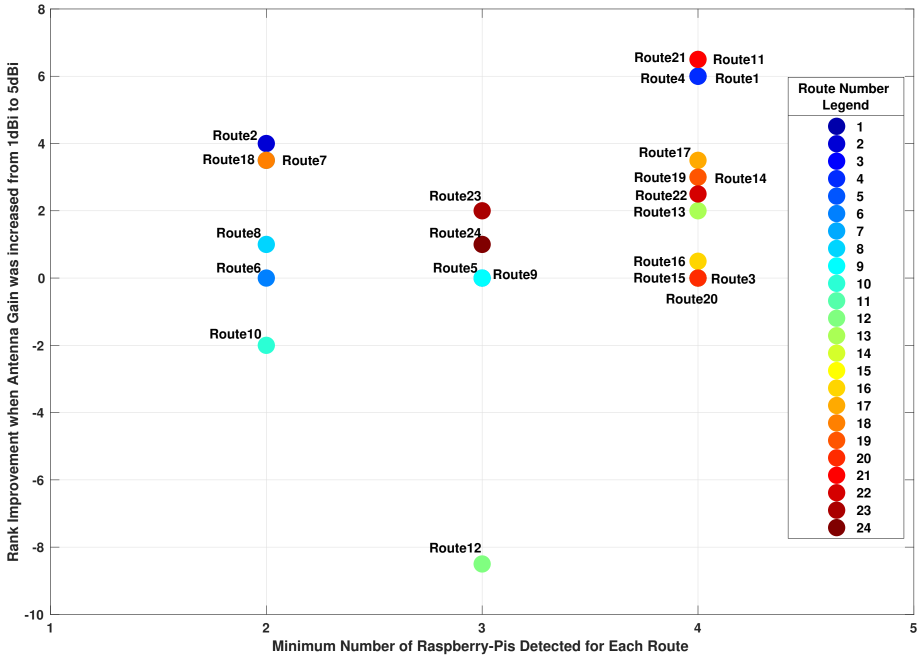

Figure 5.5: Improvement in Rank Vs Minimum Number of Raspberry-Pis detecting the beacon

For instance, it was noted that the same routes (Routes: 1,3,4,11,13-17,19-22), which had at least four Raspberry-Pis detecting the beacon, were seen to improve in rank position or remain unchanged when the antenna gain was increased by 4 dBi. None of the routes were found to deteriorate in the rankings when the minimum number of receivers detected were four, and the performance worsened for only one route (Route No: 12 - Kitchen fridge to Bedroom door) when the number of receivers detected were three.

5.4.4 Impact of Increased Antenna Gain on the Number of Raspberry-Pis Deployed

Using the hypothesis that higher antenna gain increases the density of coverage within the property, it was considered a possibility that it would help reduce the number of Raspberry-Pis deployed in the test environment while maintaining sufficient accuracy. This was tested by removing the Raspberry-Pi located in the bathroom (Pi-4), because of its proximity to the Raspberry-Pi in the kitchen (Pi-5) and the one in the hallway (Pi-1) (Refer to Figure **??**). By line of sight measurement, the distances from the bathroom Raspberry-Pi to the hallway and kitchen Raspberry-Pi were 1.8m and 2.5m respectively. The resulting rankings were recomputed after removing Pi-3 from the training and test datasets.

To determine whether reducing the number of Raspberry-Pis to four had a detrimental impact on the route rankings, the average median rank improvement was investigated when the antenna gain was increased to 5dBi from 1dBi. It was observed that the average improvement in rank in the case of deploying four Raspberry-Pis was 1, compared to 1.5 with five Raspberry-Pi receivers (Refer to Figure 5.6). In addition to the decreased average rank improvement, there was a significant reduction in the number of individual routes that improved in its ranking position while using four Raspberry-Pi receivers. It was found that only 45% of routes improved when four Raspberry-Pi receivers were used. The use of an additional Raspberry-Pi therefore presents a significant improvement in the

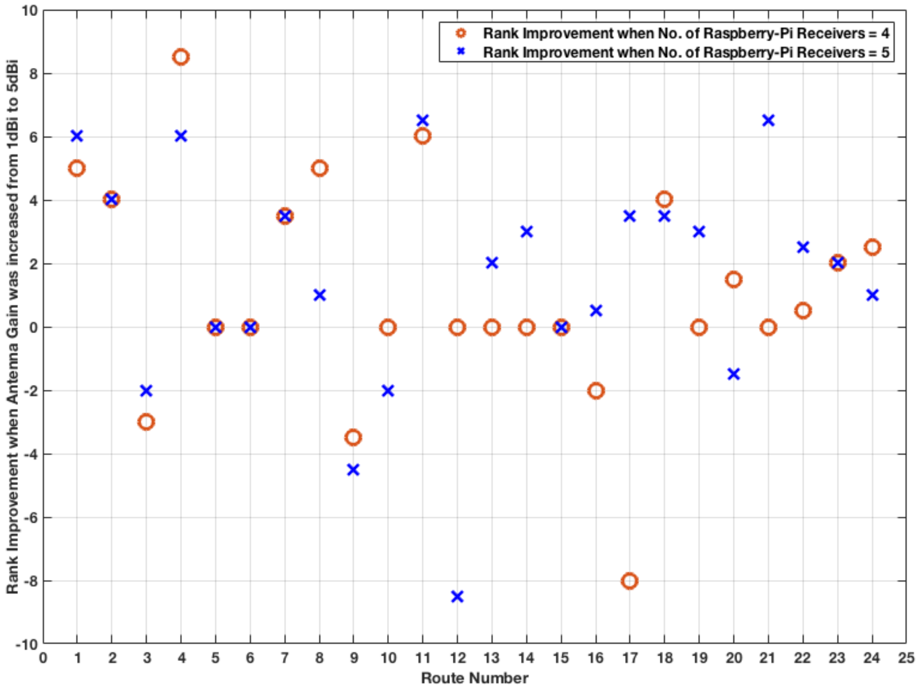

Figure 5.6: Difference in rank improvement between Differing Number of Receivers

overall performance. This would therefore suggest that there is a requirement for a receiver to be placed inside every room, when the beacon cannot be detected by all the Raspberry-Pis in the test property as matching against the fingerprint database will be less precise.

5.4.5 Effect of Electrical Interference on Beacon Signal Measurement

It was observed that the beacon RSSI readings were spurious at certain times of the day and inconsistent with the readings obtained at other times inside the apartment. It was presumed that this may be related to RF interference from another device in the testing area. To test this proposition, the MetaMotionR wearable was left at a particular location in the apartment for a long time period. A deeper inspection revealed that significant interference was observed when the washing machine started functioning. This phenomenon was verified through several tests confirming the result. Figure 5.7 shows the placement of the washing machine denoted by 'W' and the beacon denoted by 'B' in the test apartment.

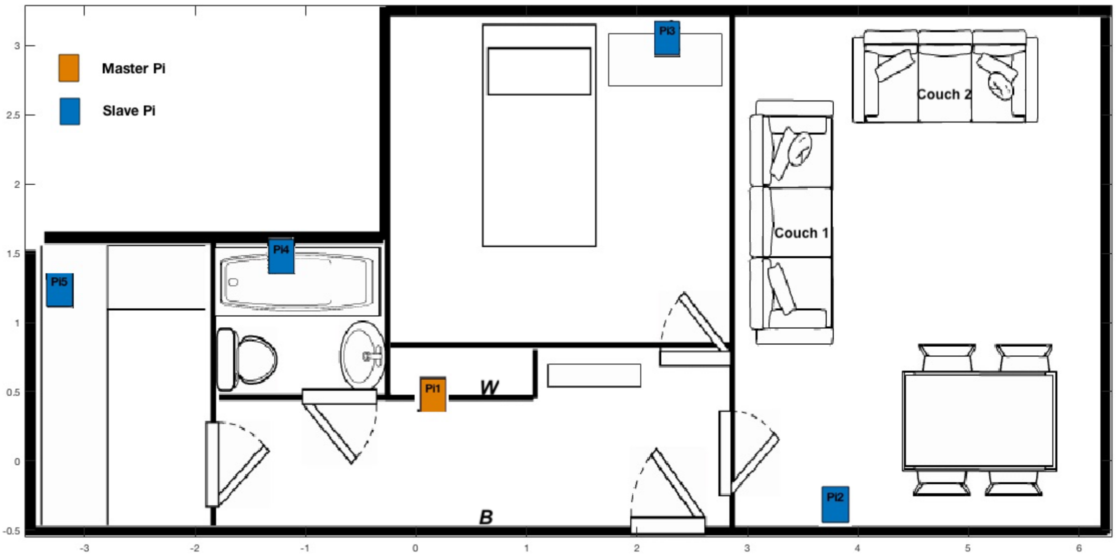

Figure 5.7: Interference with respect to beacon position (B) and washing machine (W)

The resulting RSSI signal variability due to interference was plotted against time as seen in Figure 5.8. The washing machine was left on a timer and the rapid variability of the beacon signal can be clearly seen when the machine was in the middle of its operating cycle (right hand side of the chart). The effect of electrical interference should especially be kept in mind while collecting RSSI samples during the training stage as the entire positioning system depends on the accuracy of the radio map. This is a good example of the susceptibility of indoor localization systems using only RSSI data and should therefore be combined with

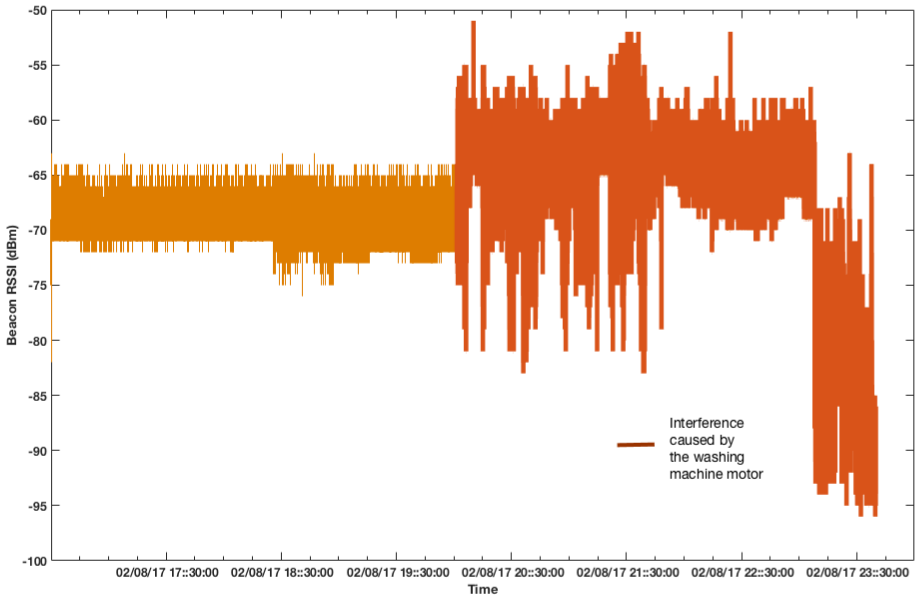

Figure 5.8: Interference from a washing machine in the test apartment

other techniques mentioned in the earlier section to reduce the impact of electrical interference.

Interference is unfortunately inevitable, but steps can be taken to reduce their impact. Electrical interference may also come from devices such as refrigerators, microwave, vacuum cleaner and other motorized devices. This may be a cause of concern when the electrical device is in close proximity to areas where the home occupant spends more time at specific spots such as the bed, couch, dining area. In such cases, it is best to position the electrical devices at a safe distance away from these spots.

As it can seen from Figure 5.7, the beacon was intentionally left in a single spot for an extended time frame in close proximity to the washing machine to highlight the inconsistencies in the beacon signal. However, the impact of the interference caused by the washing machine functioning will be less during test data collection in this scenario since the probability of the person spending more time at the beacon's position as seen in Figure 5.8 is quite rare. Sudden changes in beacon signal will not prove consequential when the person is passing through the hallway at regular walking speed. That said, identifying the root cause of the interference is more crucial in order to be able to deal with such excessive beacon signal variation.

5.4.6 Comparison of Using Onboard BLE Chip Against External BLE Antennas

The Raspberry Pi 3 Model B has a built in Bluetooth radio with a maximum gain of 1.5 dBi. A brief comparison was made between the performance of the onboard chip and the external 1dBi and 5dBi dongles on the premise that a higher antenna gain increases the number of Raspberry-Pis that can detect the beacon. This behavior was confirmed earlier. Working on the principle that a higher number of receivers detecting the beacon improves the overall rank, a similar process of finding the minimum number of Raspberry-Pis detecting the beacon for all routes was estimated using the onboard BLE module.

The number of Raspberry-Pis detecting the beacon for each walking route using 1dBi, 1.5dBi and 5dBi antennas is illustrated in Figure 5.9 and the results summary for all the routes using these antennas are shown in Table 5-B. The results indicate that an increase in antenna gain of 0.5 dBi has little or no impact on the number of Raspberry-Pis that detect the beacon, and therefore, there will be no realistic improvement in the rankings. A more substantial increase in receiver antenna gain is therefore required to increase the number of Raspberry-Pis that are able to detect the beacon, as demonstrated by the marked improvement in performance

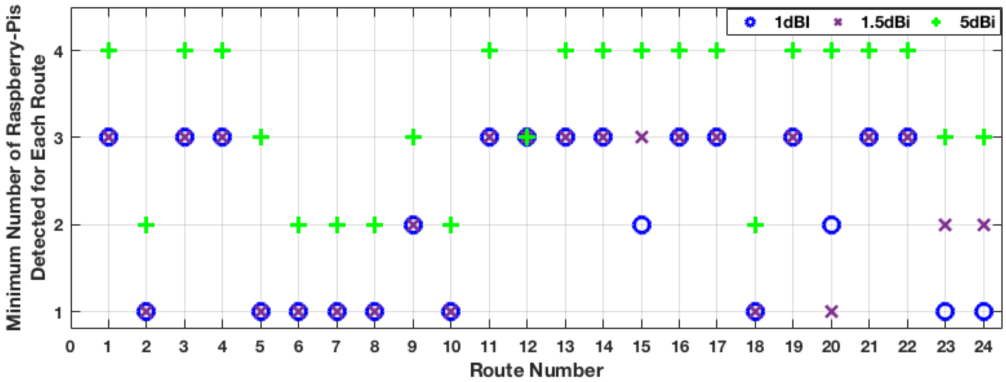

Figure 5.9: Minimum number of Raspberry-Pis detected per route using 1dBi, 1.5dBi and 5dBi antennas

Table 5-B: Summary of Beacon Range

Number of Raspberry-Pis detecting beacon	Number of Routes		
	1 dBi	*1.5 dBi*	*5 dBi*
4	0	0	13
3	12	13	5
2	3	3	6
1	9	8	0

while using the 5 dBi antennas.

5.5 Chapter Summary and Discussion

There are very few indoor positioning systems specially designed to cater to a domestic environment. In this chapter, a modified inverse procedure of RF fingerprinting was designed and implemented using a beacon that uses a trajectory-based radio map model for location estimation. The main focus was on analyzing some of the hardware and external factors that influence the positioning performance of the beacon fingerprinting method.

A direct comparison was made for a selected number of paths by using different interchangeable receiver antennas to assess the impact of antenna gain on the position of the correct route in the resulting rankings. It was found that an increase in antenna gain improves the range of the Raspberry-Pi receivers such that they can detect the beacon from a further distance. Consequently, it was proved that the performance of the fingerprinting system improved with the increase in the number of receivers detecting the beacon, and not with the increase in route length. Experimental results also suggest that the number of receivers deployed in the test environment have a strong influence on the localization performance. This was confirmed by removing a single Raspberry-Pi from the system and even with an increased antenna gain, the performance of the fingerprinting technique was found to deteriorate. Furthermore, it was observed that the electrical interference resulting from the washing machine motor had an undesirable effect on the beacon signal.

From the analysis done, it was observed that a majority of routes passing through the narrow hallway area performed poorly with higher gain antennas in comparison with lower gain antennas. In particular, Routes 3 and 12 (Bedroom door to kitchen fridge – forward and reverse routes), Routes 9 and 20 (Dining table to cooker – forward and reverse routes) showed reduced performance with 5dBi antennas throughout this study. Some of the possible reasons for such poor results are discussed here. Firstly on closer observation, it was realized that the number of receivers detected for the routes passing through the hallway were either 2 or 3 even when higher gain 5dBi antennas were used (Refer Figure). Secondly the presence of thick walls in the narrow hallway is prone to beacon signal degradation resulting in poorer signal quality. Thirdly, importance was not given to the antenna radiation patterns in this study. Typically, higher gain omnidirectional antennas will provide a doughnut shaped radiation pattern compared to a lower dBi antenna, which will provide more of a round shaped signal pattern. It is possible that majority of the receiver's antenna gain was lost when the doughnut shaped coverage pattern of the 5dBi antennas was not directed correctly making the signal reflection or interference stronger between the two walls in the hallway. In the case of the lower gain 1dBi antennas, this would not be much of an issue as the signal quality is slightly better for a shorter radius with better signal projection also in the vertical plane. The use of low-gain antennas for such spaces may help in negating the effects ensuing in the narrow hallway area.

The study was carried out to assess whether increased antenna gain improves the ranking accuracy of the BLE fingerprinting system previously developed in Chapter 3. The analysis done in this chapter will help in planning the setup and choosing the number of equipment required for a given area. Integrating localization and ambient sensor systems provide a significant boost to activity recognition results and can help bring down the deployment cost by using minimal sensor equipment. Future work will investigate if using a combination of high and low gain antennas in the flat will improve the performance across narrow hallways and look for possible solutions to combat the effect of RF interference. Another important research topic is the optimal placement and orientation of the receivers and the impact of certain building properties such as wall thickness on the localization accuracy.

Until now, Chapters 3, 4 and 5 provided details regarding the proposed indoor positioning system for recognition of micro-activities and walking routes. The next Chapter implements a knowledge engineering based system which combines ontologies and Markov Logic Networks for recognition of complex activities.

Chapter 6

Recognition of Complex Activities using Stream Reasoning and Probabilistic Inference

Knowledge-based approaches are often too brittle to handle the uncertainty and noise present in an incoming sensor stream. Statistical Artificial Intelligence (AI) uses probabilistic representations such as probabilistic graphical models to capture uncertainty. This chapter aims to investigate probabilistic stream reasoning using ontology for continuous recognition of complex activities. In the first sections of the chapter, the theoretical foundations of Stream Reasoning and Markov Logic Networks (MLN) are presented followed by a review of the related work. Sections 6.4 to 6.6 provide details regarding the design of the developed model, experimental setup and performance evaluation respectively. The chapter concludes with a short summary and critical analysis of the developed model.

6.1 Background and Definitions

6.1.1 Introduction to Stream-Reasoning

The Stream Reasoning framework provides the abstractions, foundations, methods, and tools required to integrate data streams and reasoning systems [140]. Data streams are unbounded sequences of time-varying data elements that form a continuous flow of information. Traditional activity recognition approaches have well defined boundaries for reasoning tasks indicating when it has to perform inference and when the results need to be delivered. Whereas stream reasoning adopts a continuous model where incoming incremental data is evaluated and reasoned against static knowledge base. However, little work has been done with usage of stream reasoning with probabilistic reasoning techniques. There has been ongoing research on stream reasoning and its suitability for various domains owing to the unbounded incremental time-varying nature of real time data and the requirement for continuous inference against this constant flow of information. In recent years, different frameworks for stream reasoning such as C-SPARQL, SPARQLstream, Continuous Query Evaluation over Linked Stream (CQELS) have been introduced [141], [142], [143], [144]. In this study, Continuous SPARQL (C-SPARQL) is used to run continuous queries over Resource Description Framework(RDF) graphs and RDF streams. Building a prototype for activity recognition becomes effortless by incorporating it into a stream-reasoning framework such as C-SPARQL. Furthermore, the ability of deriving sensor-activity relations and other corresponding inter-relations from static knowledge bases for inference is an added bonus. In the semantic web context, data is usually modeled according to RDF [145]. C-SPARQL engine is an extension of SPARQL 1.1 and processes incoming sensor data in the form of RDF triples comprising a subject → predicate → object relationship.

The ordered sequence of a sensor stream and their respective timestamps is of the following format:

$$(< subj_i, pred_i, obj_i >, T_i)$$
$$(< subj_{i+1}, pred_{i+1}, obj_{i+1} >, T_{i+1})$$

,where $(T_i \leq T_{i+1})$ are monotonically non-decreasing timestamps accompanying the sensor stream.

Some notable advantages of using the C-SPARQL engine architecture are presented.

6.1.1.1 Advantages of C-SPARQL Engine Architecture

1. **Simple, modular architecture**: The engine serves as a middleware for runtime management of RDF streams, C-SPARQL query and as a result listener. The queries are evaluated with high throughput and low latency.
2. **Support for Background RDF graph access**: This is made possible as C-SPARQL has the ability to query for results by merging information from data streams with static ontology knowledge bases.
3. **Reasoning on massive heterogeneous data with multiple queries**: C-SPARQL also supports parallel processing of sensor streams emerging from different heterogeneous sources [142]. Multiple queries can be registered to

reason on either the same or in a different RDF stream. In this research study, two different queries are processed simultaneously on the incoming sensor stream that may have different sets of RDF triple information for every sensor event triggered.

6.1.2 Probabilistic Reasoning with Markov Logic networks

Markov Logic Networks (MLN) are statistical relational models that combine Markov networks with first-order logic (FOL). By unifying FOL and probabilistic graphical models into a single representation, MLN is able to handle complexity and uncertainty of the real world [146]. A FOL knowledge base such as an ontology can be seen as a set of hard constraints on a set of possible worlds. The basic idea in Markov logic is to soften these constraints by associating weights with FOL formulas, which reflects the importance of the constraint. These weights imply that violating a formula makes it less probable, but not impossible. MLN can be viewed as a template for constructing ground Markov networks and are represented as log-linear models [146]. The formal definition of a Markov Logic Network L is given by a set of pairs $< F_i, w_i >$,where F_i is a formula in FOL and w_i is a real-valued weight. Together with a finite set of constants C $= c_1, c_2, \ldots, c_{|C|}$, it defines a Markov network $M_{L,C}$. The ground Markov Network $M_{L,C}$ specifies a probability distribution over a set of possible worlds (X) given by Equation 6.1 and 6.2.

$$P(world) \propto e^{\sum weights-of-formulas-it-satisfies} \tag{6.1}$$

$$P(x) = \frac{1}{Z} exp(\sum_i w_i n_i(x)) \tag{6.2}$$

,where n_i(x) is the number of true groundings of FOL formula F_i in world x and Z is a normalisation constant.

6.2 Related Work

6.2.1 Ontology based activity recognition with uncertainty

Semantic knowledge has been successfully used to support activity recognition by integrating different contextual attributes in a number of research studies. However these methods do not take into consideration the uncertainty involved in activity prediction. Probabilistic models such as MLN and Bayesian Networks can be used to handle uncertainty. PR-OWL provides a means for representing uncertainty in ontologies using Bayesian probabilities [147]. It is based on Multi Entity Bayesian Network (MEBN) and uses the UnBBayes framework to execute probabilistic inference over the domain ontology.

MLNs that combine probabilistic and logical reasoning along with ontological reasoning have been used in few AAL projects to better handle uncertainty and contradictory knowledge. For instance, Riboni et al. adopt an unsupervised method for recognition of interleaved activities using ontological and probabilistic reasoning [72]. Semantic correlations among sensor events and activities are derived through ontological reasoning to form a prior probability matrix. A statistical reasoner is then used to match the incoming sensor events with semantic correlations and provides an initial hypothesis of the occurred activity. This is further refined through probabilistic reasoning with a MLN model exploiting constraints derived from the ontology. The same framework is extended in [148] to include collaborative active learning to discover new semantic correlations and to improve the recognition rate. The work by Gayathri et al. also augments ontology based activity recognition with probabilistic reasoning through MLN [71]. The constructed domain ontology is transformed to its FOL equivalent using a transformation tool and weights for the MLN model are learned from the ABox of the developed ontology by employing weight learning algorithms.

The authors of [149] create a classification model for recognizing ADLs from acoustic information by combining logic formal representation through ontologies with probabilistic inference using MLN. Sensor outputs are statistically processed before generating evidence data for MLN. However, their design does not support temporal data reasoning and recognition of interleaved activities. Vision-based activity recognition systems have also used MLN for recognizing simple and complex activities where the weights are learnt from corresponding ontology axioms [150].

6.2.2 Other Studies Employing Probabilistic Logic Models for ADL Recognition

Another method closely related to MLN is ProbLog and the study conducted in [151] investigates the connection between them. The authors of [152] use ProbLog to define probabilistic facts and rules and infer activities. The probability values in ProbLog are manually assigned or mined from a dataset. By performing marginal inference, the authors claim that they were able to efficiently recognize ADLs in an online fashion with an F-measure of 83%.

Online inference is vital in certain scenarios where clinical decision-making systems need to be aware of current user needs. The authors of [153] use MLN for online activity recognition to provide responsive information from domotic sensors throughout the day. For this purpose, they tested the responsiveness of different MLN inference engines such as Alchemy, Tuffy and ProbCog, out of which Alchemy seemed to have the best response time, as the engine relies on a compiled code. In this thesis, the open-source Alchemy tool is also the chosen as the MLN engine for performing weight learning and inference.

6.2.3 Stream Reasoning for Activity Recognition

Stream reasoning has been used for real time monitoring and analysis for a wide range of applications [154], [155], [156], [157]. In their study, the authors of [158] carry out mobile activity recognition by applying a hybrid model using machine learning algorithms and ontology based stream reasoning techniques. Composite activities using accelerometer and GPS data from mobile devices were inferred through use of C-SPARQL queries and rich background knowledge represented in the form of ontologies. When compared to their approach, probabilistic reasoning with MLN has been used in this research study along with stream reasoning framework to deal well with ambiguity when recognizing activities.

6.3 Main Contributions of this Chapter

The main contributions of this chapter include:

1. Incorporating C-SPARQL as a stream-reasoning engine to process continuous incoming sensor data against a static ontology modeled using the available domain knowledge.

2. Overcoming the drawbacks of pure deductive reasoning by handling uncertainty using Markov Logic networks built and trained using the existing ontology.

3. Recognising complex activities carried out in an interwoven manner in real time using an unsupervised approach.

4. Integration of stream reasoning framework with probabilistic semantic-knowledge based reasoning.

6.4 Model and System Overview

Figure 6.1 represents the high-level architecture of the proposed ontology-based probabilistic stream-reasoning framework. The design constitutes three main units: Knowledge Representation Layer, C-SPARQL Stream Reasoning module and Markov Logic Networks (MLN) module. The recognised activity is forwarded to the decision-making system designed to meet the requirements of the smart-home application. Some example use-cases of the decision-making system include alerting the caregiver incase of any abnormality, sending out an alert in the form of a voice message or to initiate automation based on the inferred activity.

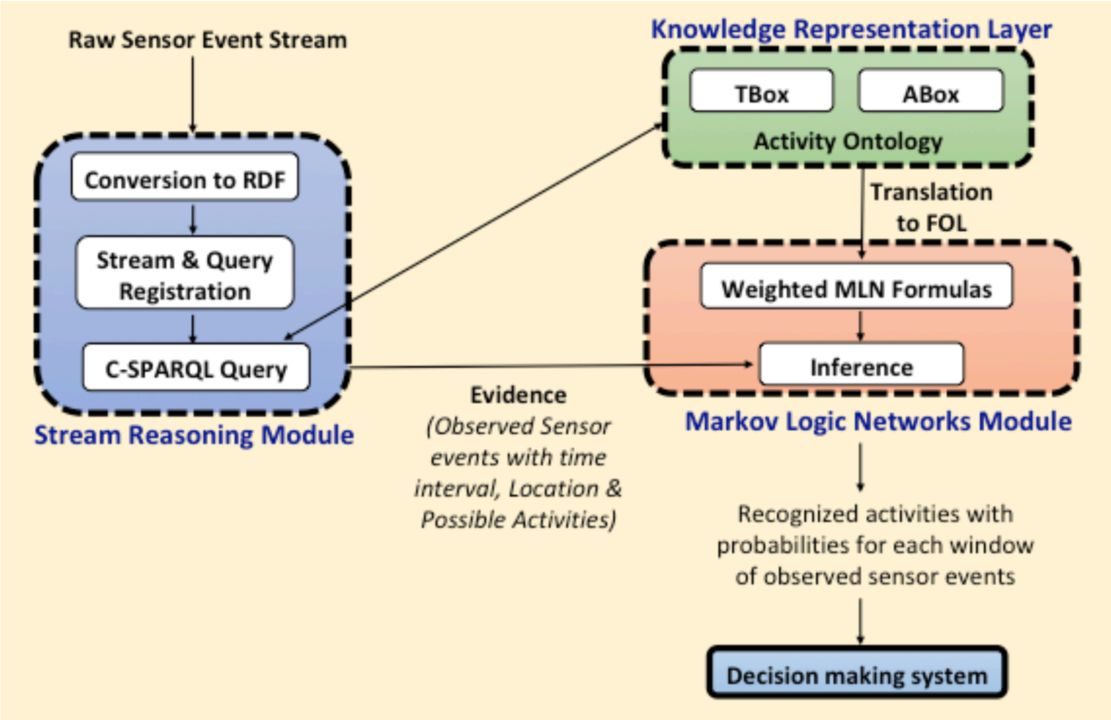

Figure 6.1: Architecture of Proposed System

6.4.1 Knowledge Representation Layer

The Semantic Web Ontology Language (OWL) is designed for use by a number of applications that requires representation of rich and complex knowledge for any domain and is the preferred language for authoring ontologies [159]. Ontologies are useful in representing the domain knowledge in the form of named individuals, its relevant classes and the relationships between them using object and data properties. Several activity recognition systems that use knowledge-driven techniques use ontologies as the basis to represent the relevant domain knowledge [65],[52].

A number of smart home domain specific ontologies are present for modelling the data [160]. They can help reduce the knowledge engineering effort by reusing the existing ontologies. The ontology used in this study is an extension of the

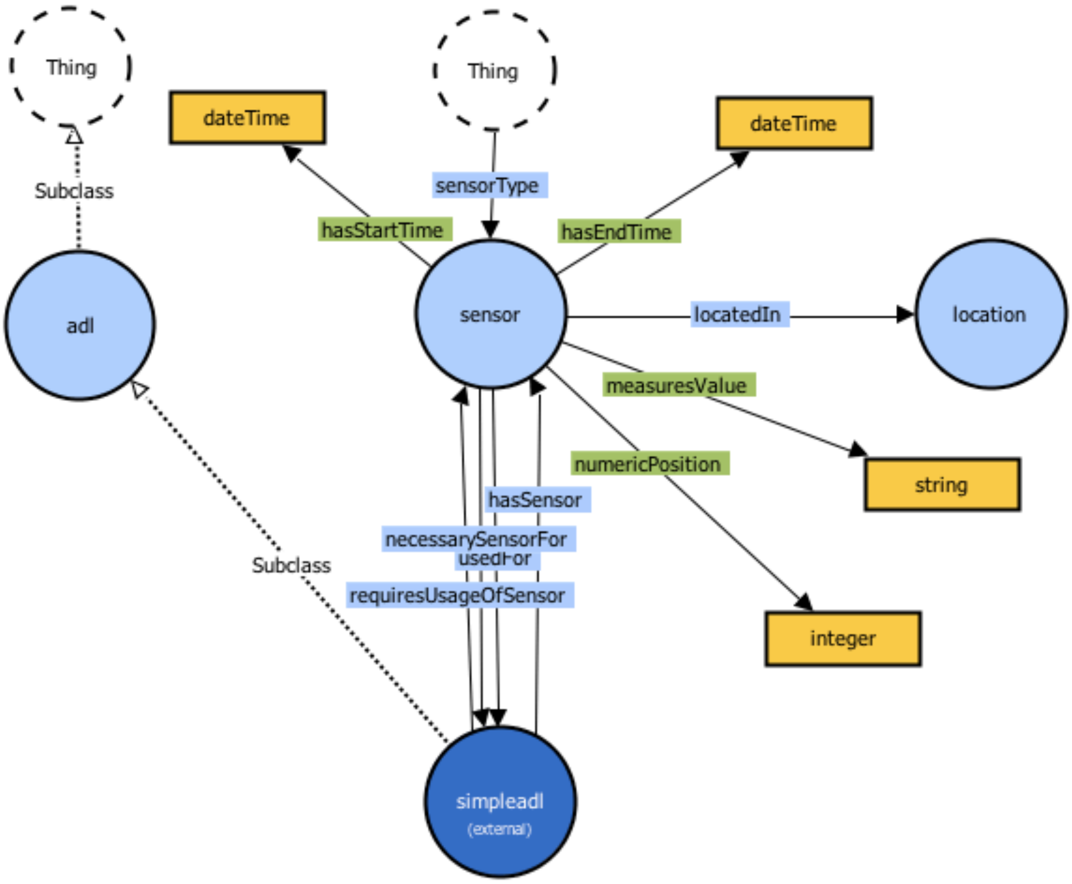

Figure 6.2: Activity Ontology Model

COSAR ontology [53] since it has all the necessary attributes required to model any smart home activity recognition system. It has been customised to suit the proposed design by extending it with few other classes, artifacts and data properties such as *hasStartTime*, *hasEndTime* and *numericPosition*. The same ontology was used for modelling both the smart home public datasets in this study.

The ontology is populated with statements that are a combination of terminologies (TBox) and assertions (ABox). The TBox statements describe definitions of concepts (classes), sub-concepts and properties that establish the structural relationships between them. The ABox contains individuals, which are instantiated from TBox concepts. Figure 6.2 shows the activity ontology model used in this study highlighting the classes, sub-classes and the relevant object and data properties (TBox). The ABox of the activity ontology is populated with instances of the defined sensors, location and activities. The mapping of sensor events with their relevant activities is done using the information gained through the interaction of item, door or water sensors attached to the participating objects for a given activity. The motion sensors were mapped to appropriate activities when there is an overlap in their location of installation with the location where the activities are primarily carried out. All object sensors (item, door and water sensors) are considered as necessary sensors as their change in status are strong indicators of the performed activity.

6.4.2 C-SPARQL Stream Reasoning module

The incoming raw sensor feed is parsed and converted to a stream of RDF triples, which will serve as the input for the stream-reasoning module. The RDF stream and the C-SPARQL queries are registered initially in the C-SPARQL engine. The queries are formulated in the C-SPARQL engine according to the requirement that is needed by the system. The engine is now ready to receive the stream of RDF quadruples and execute queries using the defined domain ontology as per the time window size mentioned in each C-SPARQL query. Two different queries are considered in this study – *Time Query and Activity Query.*

6.4.2.1 Time Query

The time query has been developed to compute the start and end time of individual sensor events observed for a given fixed time interval mentioned in the registered

```
"REGISTER QUERY CASASINTERWOVEN1 AS "
+ "PREFIX xsd: <http://www.w3.org/2001/XMLSchema#> "
+ "PREFIX casas: <http://www.casas_inferredontology.com#> "
+ "PREFIX time: <http://www.w3.org/2006/time#>"
+ "SELECT ?s ?tstart ?tend "
+ "FROM STREAM <http://casas.sensordata.com/stream> [RANGE 120s STEP 5s] "
+ "FROM <http://www.casas_inferredontology.com/COSAR_ontology.rdf> "
+ "WHERE { "
+ "{ SELECT ?s (MIN(?t1) AS ?tstart) (MAX(?t2) AS ?tend) "
+ "WHERE { "
+ "?sensor time:numericPosition ?t1 . ?sensor1 time:numericPosition ?t2 . "
+ "FILTER (?t2 > ?t1) "
+ "FILTER ((contains(str(?sensor),'ON')) && (contains(str(?sensor1),'OFF'))) "
+ "BIND (substr(str(?sensor),39,3) AS ?st1) "
+ "BIND (substr(str(?sensor1),39,3) AS ?st2) "
+ "FILTER (?st1 = ?st2) "
+ "BIND( IRI(REPLACE(str(?sensor),\"_ON\",\"\")) AS ?s) } GROUP BY ?s } "
+ "UNION "
+ "{ SELECT ?s (MIN(?t1) AS ?tstart) (\"0\"^^xsd:integer AS ?tend) "
+ "WHERE { "
+ "?sensor time:numericPosition ?t1 . "
+ "FILTER ((!contains(str(?sensor),'AD1')) && (contains(str(?sensor),'ON'))) "
+ "BIND( IRI(REPLACE(str(?sensor),\"_ON\",\"_OFF\")) AS ?soff) "
+ "BIND( IRI(REPLACE(str(?sensor),\"_ON\",\"\")) AS ?s) "
+ "FILTER NOT EXISTS {?soff time:numericPosition ?t2 } } GROUP BY ?s } "
+ "UNION "
+ "{ SELECT ?s (\"0\"^^xsd:integer AS ?tstart) (MAX(?t1) AS ?tend) "
+ "WHERE { "
+ "?sensor time:numericPosition ?t1 . "
+ "FILTER ((!contains(str(?sensor),'AD1')) && (contains(str(?sensor),'OFF'))) "
+ "BIND( IRI(REPLACE(str(?sensor),\"_OFF\",\"_ON\")) AS ?son) "
+ "BIND( IRI(REPLACE(str(?sensor),\"_OFF\",\"\")) AS ?s) "
+ "FILTER NOT EXISTS {?son time:numericPosition ?t2 } } GROUP BY ?s } "
+ "FILTER (!isBlank(?s)) } ";
```

Figure 6.3: Queries executed in the C-SPARQL engine - C-SPARQL Time Query

query. An example of the developed time query used in this study is provided in Figure 6.3. The start and end times of the observed events are extracted based on the sensor ON and OFF notifications respectively. In this query, the RANGE 120s STEP 5s refers to the length of the time window as 120s that is progressively advanced by a step size of 5s. The resulting variable bindings in the C-SPARQL query expire as soon as the query is recomputed for the next window.

6.4.2.2 Activity Query

The activity query makes use of the RDF stream data as well as the static knowledge represented in the domain ontology to detect the respective activities, location and attached objects mapped to the observed sensor event. Furthermore, it is possible to narrow down on the possible activities taking place in the current time window based on the sensor-activity correlations described in the ontology. Object properties, data properties and annotation properties are utilized in this context to retrieve the required results. Various cases are considered to filter the results and eliminate the activities that are unlikely to have taken place. The first case considers the scenario when multiple object sensors such as item, door or water sensors are mapped to the same activity in the domain ontology. The second case considers the scenario when a motion and an object sensor are observed together in the same window. In the third case when two motion sensors are triggered together, all possible activities mapped to the motion sensors are retrieved from the ontology even if the observed events are mapped to the same activity in the ontology. This is because motion sensors are triggered frequently within a smart home and are often linked to multiple activities taking place in close proximity to where they are installed. They are also unreliable when compared to the object sensors and therefore are more likely to generate false positive events. It is left to the MLN module to pick the most probable activity when motion sensor events are observed alone and when they are not accompanied with other object sensors that are part of the same activity instance. There are also several instances where C-SPARQL query is incapable to detect the plausible activity when a lone sensor event that is part of multiple activities is observed in a time window. These types of happenings are observed often in real time when a time window contains an incomplete set of sensor event information. The MLN module best handles such situations to predict the most probable activity. A snapshot of the developed C-SPARQL activity query is shown in Figure 6.4.

```
"REGISTER STREAM CASASINTERWOVEN2 AS "
+ "PREFIX xsd: <http://www.w3.org/2001/XMLSchema#> "
+ "PREFIX casas: <http://www.casas_inferredontology.com#> "
+ "PREFIX rdfs: <http://www.w3.org/2000/01/rdf-schema#>"
+ "PREFIX rdf: <http://www.w3.org/1999/02/22-rdf-syntax-ns#>"
+ "SELECT DISTINCT ?case ?s ?activity ?object ?loc ?property "
+ "FROM STREAM <http://casas.sensordata.com/stream> [RANGE 120s STEP 5s] "
+ "FROM <http://www.casas_inferredontology.com/COSAR_ontology.rdf> "
+ "WHERE { "
+ "?s rdfs:comment ?object ; casas:locatedIn ?loc . "
+ "{ SELECT DISTINCT ?case ?s ?activity ?property "
+ "WHERE { "
+ "VALUES ?property {casas:necessarySensorFor casas:usedFor} "
+ "?sensoron casas:measuresValue ?val ; casas:sensorType ?s . ?s rdf:type casas:sensor . "
+ "?s rdfs:isDefinedBy \"artifact\"^^xsd:string ; ?property ?activity . "
+ "OPTIONAL {?sensoron1 casas:measuresValue ?val1 ; casas:sensorType ?s1 . "
+ "?s1 rdf:type casas:sensor ; rdfs:isDefinedBy \"artifact\"^^xsd:string ; ?property ?activity . "
+ "?activity casas:requiresUsageOfSensor ?s ; casas:requiresUsageOfSensor ?s1 . "
+ "FILTER (?s != ?s1) "
+ "FILTER (BOUND(?s1)) } "
+ "BIND (\"Option1\"^^xsd:string AS ?case) } } "
+ "UNION "
+ "{ VALUES ?property {casas:usedFor} "
+ "VALUES ?property1 {casas:necessarySensorFor} "
+ "?sensoron casas:measuresValue ?val ; casas:sensorType ?s . "
+ "?s rdf:type casas:sensor ; rdfs:isDefinedBy \"Motion\"^^xsd:string . "
+ "?s ?property ?activity . ?activity casas:requiresUsageOfSensor ?s1 . "
+ "?sensoron1 casas:measuresValue ?val1 ; casas:sensorType ?s1 . "
+ "?s1 rdf:type casas:sensor ; rdfs:isDefinedBy \"artifact\"^^xsd:string . "
+ "?s ?property ?activity ; ?property1 ?activity . ?activity casas:hasSensor ?s . "
+ "FILTER ((?val != ?val1) || (?val = ?val1)) "
+ "FILTER (?s != ?s1) "
+ "FILTER (BOUND(?s1)) "
+ "BIND (\"Option2\"^^xsd:string AS ?case) } "
+ "UNION "
+ "{ VALUES ?property {casas:usedFor} "
+ "?sensoron casas:measuresValue ?val ; casas:sensorType ?s . ?s rdf:type casas:sensor . "
+ "?s rdfs:isDefinedBy \"Motion\"^^xsd:string ; ?property ?activity . "
+ "FILTER NOT EXISTS { ?sensoron1 casas:measuresValue ?val1 ; casas:sensorType ?s1 . "
+ "?s1 rdf:type casas:sensor ; rdfs:isDefinedBy \"artifact\"^^xsd:string ; ?property ?activity . "
+ "FILTER (?s != ?s1) } "
+ "BIND (\"Option3\"^^xsd:string AS ?case) } "
+ "} ORDER BY ?case ";
```

Figure 6.4: Queries executed in the C-SPARQL engine - Activity Query

6.4.3 Markov Logic Networks (MLN) Module

The registered C-SPARQL queries are executed continuously on the RDF sensor stream resulting in continuous flow of information to the MLN module. The process of construction of MLN template from the activity ontology, weight learning of the first-order clauses and the use of MLN inference algorithms are described below.

6.4.3.1 Construction of MLN model for ADL recognition

The classes and predicate definitions that form the TBox in the activity ontology are translated into theirs corresponding first order equivalent. Consider the following examples:

> **Example 1**:
>
> **Classes in activity ontology:** *sensor, adl, simplead*
>
> **FOL equivalent for the classes:** *simpleadl(a)* $\Rightarrow$ *adl(a)*

The FOL statement defines the subclass relationship between classes simpleadl and adl derived from the activity ontology.

> **Example 2**:
>
> Object Properties in activity ontology: *usedFor, necessarySensorFor*
>
> FOL equivalent of object-properties with their associated classes as domain and range:
>
> *necessarySensorFor(s,a)* $\Rightarrow$ *simpleadl(a)*
>
> *necessarySensorFor(s,a)* $\Rightarrow$ *sensor(s)*
>
> *usedFor(s,a)* $\Rightarrow$ *simpleadl(a)*
>
> *usedFor(s,a)* $\Rightarrow$ *sensor(s)*

The variables in the MLN template will be replaced by constants of their respective defined classes during the weight learning and inference operations. In the above example, the variables s and a will hold the instance values of classes of type sensor and activity respectively. Additional formulas may be added using the defined classes and predicates. The following rule is formulated in order to correctly map the sensor events to their respective activities if multiple activities occur in the same window.

Rule 1:

sensor(s1) $\wedge$ *sensor(s2) $\wedge$ usedFor(s1,a) $\wedge$ *usedFor(s2,a) $\wedge$ *necessary-SensorFor(s1,a) $\wedge$ *necessarySensorFor(s2,a) $\wedge$ (s1 $\neq$ s2) $\Rightarrow$ simpleadl(a)

The weights for this rule are learned from the first-order equivalent of the ontology's ABox using a weight-learning algorithm[1] that is discussed in the next section.

When the activities are carried out in an interwoven manner, it is important to find the temporal boundaries for each activity occurring in a time window. This is deduced using the below MLN formula and are considered to be hard constraints which have infinite weight value. A world that violates a hard constraint has zero probability.

Rule 2 - Start Time Calculation for each activity:

sensor(s1) $\wedge$ hasStartTime(s1,t1) $\wedge$ hasEndTime(s1,t2) $\wedge$ sensor(s2) $\wedge$ hasStartTime(s2,t3) $\wedge$ hasEndTime(s2,t4) $\wedge$ usedFor(s1,a) $\wedge$ usedFor(s2,a) $\wedge$ (t1 $\leq$ t3) $\wedge$ (s1 $\neq$ s2) $\wedge$ (t2 $\neq$ 0) $\wedge$ (t4 $\neq$ 0) $\Rightarrow$ activitystarttime(a,t1).

[1]When predicates in a formula are preceded by *, the MLN weight learning process considers all possible ways in which * can be replaced by !. For more details refer to `https://alchemy.cs.washington.edu/user-manual/4_2MLN_Syntax.html`

Rule 3 - End Time Calculation for each activity:

sensor(s1) $\wedge$ hasStartTime(s1,t1) $\wedge$ hasEndTime(s1,t2) $\wedge$ sensor(s2) $\wedge$ hasStartTime(s2,t3) $\wedge$ hasEndTime(s2,t4) $\wedge$ usedFor(s1,a) $\wedge$ usedFor(s2,a) $\wedge$ (t4 $\geq$ t2) $\wedge$ (s1 $\neq$ s2) $\wedge$ (t2 $\neq$ 0) $\wedge$ (t4 $\neq$ 0) $\Rightarrow$ activityendtime(a,t4).

In the above rules, *t1,t2* and *t3,t4* are variables used to denote start and end times of sensor variables *s1* and *s2* respectively.

6.4.3.2 Weight Learning in MLN

The MLN, which acts as a template for constructing a Markov network, is a set of weighted first-order formulas or clauses. With the use of clause weights, probability of occurrence can be defined, thus providing additional tolerance to the logic formulas. Weights can be assigned manually or learned automatically from data. There are various weight learning algorithms that can assign weights to different combinations of attributes for each formula based on the observed training data. The training data must contain the truth values of a number of ground atoms for efficient weight learning. Any ground atoms that are not part of the training database are assumed to be false. The clause weights were learned generatively using a pseudo-log likelihood algorithm where the goal is to learn a joint probability distribution over all atoms [161]. For this study, sensor-activity, sensor-object and sensor-location mappings described in the ABox of activity ontology were used to learn the weights of the first order clauses. This type of unsupervised approach eliminates the need for any additional training data to learn the weights and employing such weight learning algorithms makes the whole learning process undemanding.

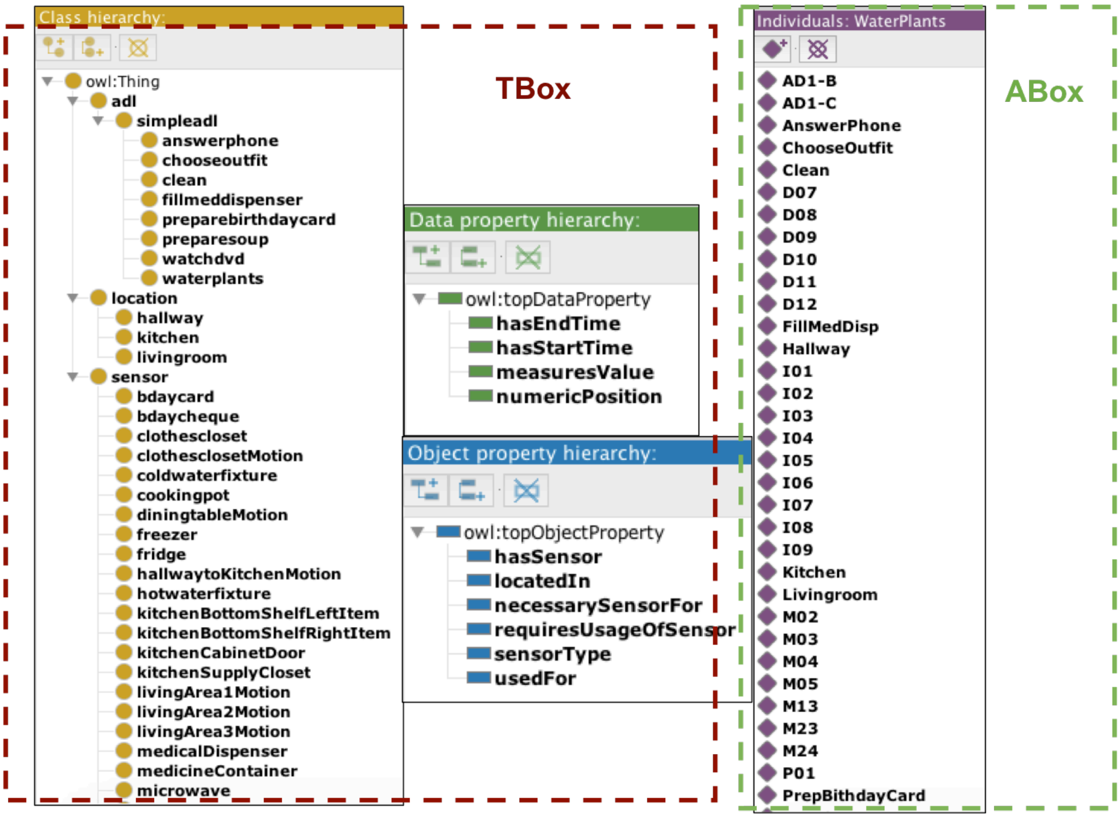

Figure 6.5: Ontology modelled using Protégé

6.4.3.3 MLN as Inference Engine

With the learned MLN model, the queries can be answered by performing inference on them. The standard Markov Network inference methods such as Markov Chain Monte Carlo (MCMC) can be used on the instantiated network. MC-SAT which is essentially a slice sampling MCMC inference algorithm is designed to deal efficiently with probabilistic and deterministic dependencies. It is used along with a satisfiability solver (MaxWalksat) to sample from the slice [162].

Algorithm 4 Implementation of Stream Reasoning with MLN

Inputs: $SE \leftarrow$ Continuous Sensor Event Sequence $< SE_i, ...SE_n >$($1 \leq$ i $\leq$ n), $Ont_{ADL} \leftarrow$ Domain Activity Ontology, $MLN_{weighted} \leftarrow$ Input MLN File of weighted FOL formulas

Output: $ADL_{predicted} \leftarrow$ Activities predicted by the MLN module with their respective probabilities

for each TimeWindow **do**
  $SE_{i_{start}}, SE_{i_{end}} \leftarrow$ Execute TimeQuery //*Calculate Start and End time of observed SE*
  $MLN_{time_{SE_i}} \leftarrow SE_{i_{start}}, SE_{i_{end}}$ //*Translation to MLN Predicate format*
  $MLN_{evidence} \leftarrow MLN_{time_{SE_i}}$
  $SE_{i_{obj}}, SE_{i_{loc}}, SE_{i_{activity}} \leftarrow$ Execute ActivityQuery //*Infer Attached Object, Location and Relevant activities for observed SE from* Ont_{ADL}
  $MLN_{activity_{SE_i}} \leftarrow SE_{i_{obj}}, SE_{i_{loc}}, SE_{i_{activity}}$ //*Translation to MLN Predicate format*
  $MLN_{evidence} \leftarrow MLN_{activity_{SE_i}}$
  $ADL_{predicted} \leftarrow MLN_{weighted}, MLN_{evidence}$ //*Perform MLN Inference*
  return $ADL_{predicted}$
end for

6.4.3.4 Hardware and Software Requirements

The C-SPARQL engine with MLN framework was hosted in a system with 1.6 GHz Intel Core i5 processor and 4GB RAM. The activity ontology was implemented using the open source Protégé tool [163] and the conversion of OWL concepts and object properties into their respective unary and binary FOL predicates were performed using an existing transformation tool called Incerto [164]. Figure 6.5 illustrates the TBox and ABox of the developed ontology using Protégé. The transformed model was then used as input to the Alchemy system, which is also an open-source tool [165]. The formulae are automatically translated into clausal form before grounding. The Alchemy package provides the necessary algorithms for statistical relational learning and probabilistic logic inference based on the Markov logic representation.

6.5 Implementation of Stream Reasoning with MLN

Algorithm 4 shows the steps involved in the implementation of the Stream reasoning with the MLN framework. A running example illustrating the resulting output at various stages of the proposed system is also presented. Figure 6.6(a) shows a fragment of the incoming continuous sensor feed from the smart home. The sensor feed is embedded with information regarding the status of the sensor events along with its associated timestamp. The stream reasoner executes the C-SPARQL Time Query and Activity Query simultaneously for the defined time window and extracts the results using the activity ontology. The output of C-SPARQL queries are translated into their corresponding predicate formats with embedded constant values that are recognized by the MLN processor as shown in Figure 6.6(b). These constant values are the observed sensor events and their associated locations, activities and time intervals derived from the initial hypothesis of executing the ontology-based C-SPARQL queries. The C-SPARQL results form the evidence database, which will be used by the MLN inference engine. The generated evidence for each time window along with the already defined weighted MLN template are used to perform online inference to determine the most probable activity. Figure 6.6(c) displays the MLN inference results for the observed sensor events in Figure 6.6(a) using the evidence file as test data (Figure 6.6(b)). From the figure, it can be seen that WatchDVD and ChooseOutfit are the inferred activities with their respective marginal probabilities for that particular time window. Their respective start and end times are also inferred using the defined hard constraint MLN formulas described in Section 6.3.3.1.

```
rdf http://www.casas_inferredontology.com#D12_ON http://www.casas_inferredontology.com#measuresValue http://www.casas_inferredontology.com#1 . (1223567108000)
rdf http://www.casas_inferredontology.com#D12_ON http://www.casas_inferredontology.com#sensorType http://www.casas_inferredontology.com#D12 . (1223567108000)
rdf http://www.casas_inferredontology.com#D12_ON http://www.w3.org/2006/time#numericPosition "1223567108"^^xsd:integer . (1223567108000)

rdf http://www.casas_inferredontology.com#M23_ON http://www.casas_inferredontology.com#measuresValue http://www.casas_inferredontology.com#1 . (1223567108000)
rdf http://www.casas_inferredontology.com#M23_ON http://www.casas_inferredontology.com#sensorType http://www.casas_inferredontology.com#M23 . (1223567108000)
rdf http://www.casas_inferredontology.com#M23_ON http://www.w3.org/2006/time#numericPosition "1223567108"^^xsd:integer . (1223567108000)

rdf http://www.casas_inferredontology.com#D12_OFF http://www.casas_inferredontology.com#measuresValue http://www.casas_inferredontology.com#0 . (1223567118000)
rdf http://www.casas_inferredontology.com#D12_OFF http://www.casas_inferredontology.com#sensorType http://www.casas_inferredontology.com#D12 . (1223567118000)
rdf http://www.casas_inferredontology.com#D12_OFF http://www.w3.org/2006/time#numericPosition "1223567118"^^xsd:integer . (1223567118000)

rdf http://www.casas_inferredontology.com#M23_OFF http://www.casas_inferredontology.com#measuresValue http://www.casas_inferredontology.com#0 . (1223567122000)
rdf http://www.casas_inferredontology.com#M23_OFF http://www.casas_inferredontology.com#sensorType http://www.casas_inferredontology.com#M23 . (1223567122000)
rdf http://www.casas_inferredontology.com#M23_OFF http://www.w3.org/2006/time#numericPosition "1223567122"^^xsd:integer . (1223567122000)

rdf http://www.casas_inferredontology.com#M02_ON http://www.casas_inferredontology.com#measuresValue http://www.casas_inferredontology.com#1 . (1223567124000)
rdf http://www.casas_inferredontology.com#M02_ON http://www.casas_inferredontology.com#sensorType http://www.casas_inferredontology.com#M02 . (1223567124000)
rdf http://www.casas_inferredontology.com#M02_ON http://www.w3.org/2006/time#numericPosition "1223567124"^^xsd:integer . (1223567124000)

rdf http://www.casas_inferredontology.com#I05_ON http://www.casas_inferredontology.com#measuresValue http://www.casas_inferredontology.com#1 . (1223567127000)
rdf http://www.casas_inferredontology.com#I05_ON http://www.casas_inferredontology.com#sensorType http://www.casas_inferredontology.com#I05 . (1223567127000)
rdf http://www.casas_inferredontology.com#I05_ON http://www.w3.org/2006/time#numericPosition "1223567127"^^xsd:integer . (1223567127000)

rdf http://www.casas_inferredontology.com#M02_OFF http://www.casas_inferredontology.com#measuresValue http://www.casas_inferredontology.com#0 . (1223567130000)
rdf http://www.casas_inferredontology.com#M02_OFF http://www.casas_inferredontology.com#sensorType http://www.casas_inferredontology.com#M02 . (1223567130000)
rdf http://www.casas_inferredontology.com#M02_OFF http://www.w3.org/2006/time#numericPosition "1223567130"^^xsd:integer . (1223567130000)

rdf http://www.casas_inferredontology.com#I05_OFF http://www.casas_inferredontology.com#measuresValue http://www.casas_inferredontology.com#0 . (1223567135000)
rdf http://www.casas_inferredontology.com#I05_OFF http://www.casas_inferredontology.com#sensorType http://www.casas_inferredontology.com#I05 . (1223567135000)
rdf http://www.casas_inferredontology.com#I05_OFF http://www.w3.org/2006/time#numericPosition "1223567135"^^xsd:integer . (1223567135000)
```

(a)

```
hasStartTime(I05,1223567127)
hasStartTime(M02,1223567124)
hasEndTime(M23,1223567122)
hasStartTime(D12,1223567108)
hasEndTime(M02,1223567130)
hasEndTime(D12,1223567118)
hasStartTime(M23,1223567108)
hasEndTime(I05,1223567135)
locatedIn(D12,Hallway)
necessarySensorFor(I05,WatchDVD)
clothesclosetMotion(M23)
necessarySensorFor(D12,ChooseOutfit)
usedFor(M23,ChooseOutfit)
locatedIn(I05,Livingroom)
locatedIn(M23,Hallway)
usedFor(D12,ChooseOutfit)
tvshelfMotion(M02)
clothescloset(D12)
usedFor(M02,WatchDVD)
locatedIn(M02,Livingroom)
tvshelfLeftDVD(I05)
usedFor(I05,WatchDVD)
```

(b)

```
simpleadl(WatchDVD) 0.926957
simpleadl(ChooseOutfit) 0.933957
activitystarttime(WatchDVD,0) 4.9995e-05
activitystarttime(WatchDVD,1223567127) 4.9995e-05
activitystarttime(WatchDVD,1223567124) 0.99995
activitystarttime(WatchDVD,1223567122) 4.9995e-05
activitystarttime(WatchDVD,1223567108) 4.9995e-05
activitystarttime(WatchDVD,1223567130) 4.9995e-05
activitystarttime(WatchDVD,1223567118) 4.9995e-05
activitystarttime(WatchDVD,1223567135) 4.9995e-05
activitystarttime(ChooseOutfit,0) 4.9995e-05
activitystarttime(ChooseOutfit,1223567127) 4.9995e-05
activitystarttime(ChooseOutfit,1223567124) 4.9995e-05
activitystarttime(ChooseOutfit,1223567122) 4.9995e-05
activitystarttime(ChooseOutfit,1223567108) 0.99995
activitystarttime(ChooseOutfit,1223567130) 4.9995e-05
activitystarttime(ChooseOutfit,1223567118) 4.9995e-05
activitystarttime(ChooseOutfit,1223567135) 4.9995e-05
activityendtime(WatchDVD,0) 4.9995e-05
activityendtime(WatchDVD,1223567127) 4.9995e-05
activityendtime(WatchDVD,1223567124) 4.9995e-05
activityendtime(WatchDVD,1223567122) 4.9995e-05
activityendtime(WatchDVD,1223567108) 4.9995e-05
activityendtime(WatchDVD,1223567130) 4.9995e-05
activityendtime(WatchDVD,1223567118) 4.9995e-05
activityendtime(WatchDVD,1223567135) 0.99995
activityendtime(ChooseOutfit,0) 4.9995e-05
activityendtime(ChooseOutfit,1223567127) 4.9995e-05
activityendtime(ChooseOutfit,1223567124) 4.9995e-05
activityendtime(ChooseOutfit,1223567122) 0.99995
activityendtime(ChooseOutfit,1223567108) 4.9995e-05
activityendtime(ChooseOutfit,1223567130) 4.9995e-05
activityendtime(ChooseOutfit,1223567118) 4.9995e-05
activityendtime(ChooseOutfit,1223567135) 4.9995e-05
```

(c)

Figure 6.6: Running Example of Proposed Stream Reasoning with MLN Framework (a) Excerpt of Incoming Continuous Sensor Feed (b) Output of C-SPARQL Time Query and Activity Query (c) MLN Inference Results

6.6 Experimental Analysis

Experimental results of the described probabilistic stream reasoning architecture with two public datasets and a comparative analysis against other state-of-the-art approaches are presented in this section.

6.6.1 Dataset Description

The WSU CASAS smart home dataset [166] and Kasteren House-B dataset [1] is used for experimental analysis in this study.

6.6.1.1 WSU CASAS smart home dataset

The layout of the WSU CASAS smart home along with the placement of the respective sensors is illustrated in Figure 6.7. The dataset represents 21 participants performing eight different ADLs in an apartment namely: Fill Medication Dispenser (ADL1), Watch DVD (ADL2), Water Plants (ADL3), Answer the Phone (ADL4), Prepare Birthday Card (ADL5), Prepare Soup (ADL6), Clean (ADL7) and Choose Outfit (ADL8). During data collection, only one person was present in the smart home. The participants were asked to perform the activities separately and they were recorded in individual files. Later, data were recorded when they were asked to perform the entire set of eight activities again in any order, interweaving or in parallel, if desired. The latter set of data files were chosen to perform the evaluation as it closely reflects the real-world setting in a home environment where the occupant performs activities in an interwoven fashion and in no particular time or order.

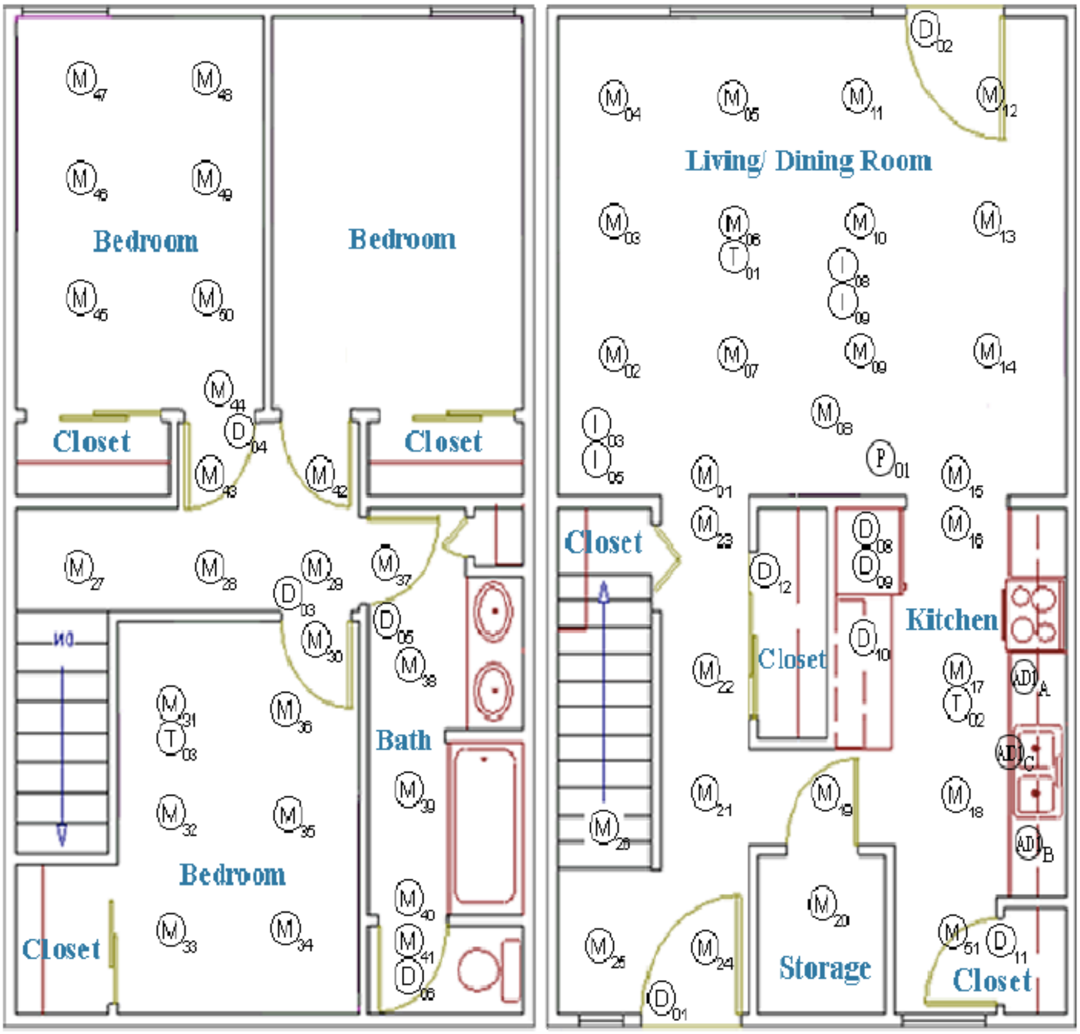

Figure 6.7: Sensor Layout of WSU CASAS smart home dataset (indicated by motion (M), temperature (T), door (D), water (AD) and item used(I). Adopted from [166]

A total of 70 sensors were used to record the sensor events in the CASAS ADL dataset. But only 25 sensors[2] were considered in this study that gathered data about movement, use of water, interaction with items, doors, cabinets and phone. The sensors used to collect observations were chosen because they were highly correlated with a specific activity taking place.

[2]Selected sensors from the dataset are AD1-B, AD1-C, D07, D08, D09, D10, D11, D12, I01, I02, I03, I04, I05, I06, I07, I08, I09, M02, M03, M04, M05, M13, M23, M24, P01.

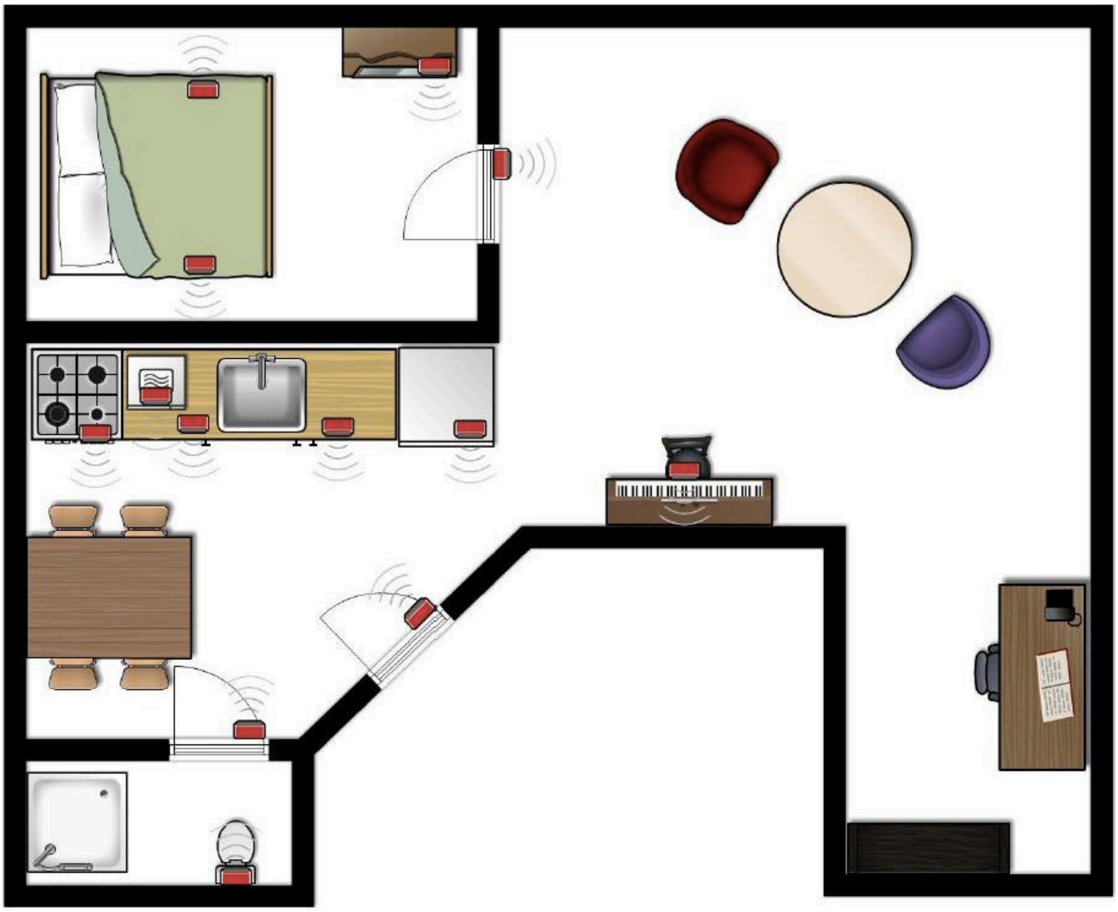

Figure 6.8: Floor Plan of Kasteren smart home B dataset with sensor locations. Adopted from [1]

6.6.1.2 Kasteren House-B dataset

The floor plan with the sensor layout of Kasteren house-B is shown in Figure 6.8. Thirteen different ADL's were carried out by a single person aged 28 for fourteen days in a two-bedroom apartment. The ADL's performed were: *Brush Teeth (ADL1), Eat Brunch(ADL2), Eat Dinner (ADL3), Get Dressed (ADL4), Get Drink (ADL5), Go To Bed (ADL6), Leave House (ADL7), Others (ADL8), Prepare Brunch (ADL9), Prepare Dinner (ADL10), Take Shower (ADL11), Use Toilet (ADL12), Wash Dishes (ADL13). Others* class consists of all other activities that are not part of the listed ADL's. The annotation of this public dataset was done manually by the resident by recording the readings in a personal diary.

Twenty three heterogeneous binary sensors such as pressure mats, mercury contacts, passive infrared-PIR, float sensors and reed switches were used to collect sensor data in the house. For this study, PIR sensor readings were not considered as the sensor firings were common to many activities and was not particularly useful in ADL prediction.

6.6.2 MLN Rules based on Domain Knowledge

Additional MLN rules were formulated based on common-sense knowledge for a given smart home domain. Temporal knowledge was used as the basis to distinguish between various activities when they share the same set of sensors between them. Following are some example MLN rules that provide additional information regarding the occurrence of a specific ADL for a given set of observed contextual attributes.

Example 3: In the CASAS smart home dataset, cabinet sensor D11 and a set of motion sensors installed in the living room are highly correlated to *ADL7 Clean* and *ADL3 Water Plants*. Therefore *Rule 4* and *Rule 5* help in distinguishing between the two activities during the MLN inference process even when an incomplete set of sensor events are observed. *Rule 4* states that the motion sensors for *Clean* ADL in the living room are activated only after removal of cleaning supplies from kitchen supply closet and *Rule 5* states that watering can is retrieved after opening of the supply closet followed by filling it with water.

Rule 4:

hasStartTime(D11,d11st) ∧ hasStartTime(s,sst) ∧ greaterThan(sst,d11st) ∧ usedFor(D11,a) ∧ usedFor(s,a) ∧ locatedIn(s,l) ∧ livingroom(l) ∧ clean(a) ⇒ simpleadl(a)

Rule 5:

hasStartTime(D11,d11st) ∧ hasStartTime(AD1-B,ad1bst) ∧ hasStartTime(AD1-C,ad1cst) ∧ hasStartTime(s,sst) ∧ greaterThan(ad1bst,d11st) ∧ greaterThan(ad1cst,d11st) ∧ greaterThan(sst,d11st) ∧ usedFor(D11,a) ∧ usedFor(AD1-B,a) ∧ usedFor(AD1-C,a) ∧ usedFor(s,a) ∧ locatedIn(s,l) ∧ livingroom(l) ∧ necessarySensorFor(D11,a) ∧ necessarySensorFor(AD1-B,a) ∧ necessarySensorFor(AD1-C,a) ∧ !preparesoup(a) ∧ waterplants(a) ⇒ simpleadl(a)

Similarly *Rule 6* states that the necessary cooking supplies for preparing soup are retrieved from the kitchen cupboard followed by filling the bowl with water. This rule helps in distinguishing between *WaterPlants* and *Prepare Soup* ADLs.

Rule 6:

hasStartTime(D07,d07st) ∧ hasStartTime(AD1-B,ad1bst) ∧ hasStartTime(AD1-C,ad1cst) ∧ greaterThan(ad1bst,d07st) ∧ greaterThan(ad1cst,d07st) ∧ usedFor(D07,a) ∧ usedFor(AD1-B,a) ∧ usedFor(AD1-C,a) ∧ necessarySensorFor(D07,a) ∧ necessarySensorFor(AD1-B,a) ∧ necessarySensorFor(AD1-C,a) ∧ preparesoup(a) ∧ !waterplants(a) ⇒ simpleadl(a)

Example 4: In Kasteren house-B dataset, *Prepare Brunch (ADL9)* and *Prepare Dinner (ADL10)* share a majority of the same set of sensors in the kitchen area. In order to differentiate between these activities, *Rule 7* is added to check if the start time of the associated kitchen sensors is observed in the daytime or in the evening time. The daytime and evening time are preset constant values (in unix epoch time format), which is updated automatically every 24 hours. They are denoted by the constants *dt* and *nt* respectively in Rule 7.

Rule 7:

cupboardplates(cp) ∧ usedFor(cp,a) ∧ hasStartTime(cp,cpst) ∧ fridge(fr) ∧ usedFor(fr,a) ∧ hasStartTime(fr,frst) ∧ microwave(mw) ∧ usedFor(mw,a) ∧ hasStartTime(mw,mwst) ∧ stovelid(sl) ∧ usedFor(sl,a) ∧ hasStartTime(sl,slst) ∧ toaster(to) ∧ necessarySensorFor(to,a) ∧ hasStartTime(to,tost) ∧ greaterThan(cpst,nt) ∧ lessThan(cpst,dt) ∧ greaterThan(frst,nt) ∧ lessThan(frst,dt) ∧ greaterThan(mwst,nt) ∧ lessThan(mwst,dt) ∧ greaterThan(slst,nt) ∧ lessThan(slst,dt) ∧ greaterThan(tost,nt) ∧ lessThan(tost,dt) ∧ preparebrunch(a) ∧ !preparedinner(a) ⇒ simpleadl(a)

Example 5: Another example rule from the Kasteren house-B dataset is listed below. This is for the *Brush Teeth (ADL1)*. Since *Brush Teeth (ADL1)* was associated only with the bathroom door sensor in the dataset, a special rule was formulated to distinguish from the *Take Shower (ADL11)* activity, which also shares the same door sensor. It was observed that the home resident followed a daily routine of getting dressed followed by brushing teeth activity. The brushing teeth activity was also carried out after the resident returned back home (front door sensor was activated). This pattern has been expressed in Rules 8 and 9 respectively and comes into play when *Brush Teeth (ADL1)* and *Get Dressed (ADL4)* or *Brush Teeth (ADL1)* and *Leave House (ADL7)* activities occur together in the same time window.

Rule 8:
toiletdoor(td) ∧ necessarySensorFor(td,a) ∧ hasStartTime(td,tdst) ∧ dresser(dr) ∧ necessarySensorFor(dr,a1) ∧ hasEndTime(dr,drst) ∧ greaterThan(tdst,drst) ∧ !takeshower(a) ∧ brushteeth(a) ⇒ simpleadl(a)

Rule 9:
toiletdoor(td) ∧ necessarySensorFor(td,a) ∧ hasStartTime(td,tdst) ∧ frontdoor(fd) ∧ necessarySensorFor(fd,a1) ∧ hasEndTime(fd,fdst) ∧ greaterThan(tdst,fdst) ∧ !takeshower(a) ∧ brushteeth(a) ⇒ simpleadl(a)

In this way, rules for other ADLs can be modeled to distinguish between ADLs that share few or same set of sensors and to deal with situations when only partial information of the participating sensors are observed in a given time window.

6.6.3 Selection of Time Window Size for C-SPARQL Query

Selecting an appropriate time window size for the incoming sensor streams in a C-SPARQL query is one of the most important factors as it reflects on the performance of the activity recognition system. Suitable time interval needs to be selected such that it is not too small as it may hold incomplete set of sensor sequences or not too large as the window may contain multiple activities with overlapping sensor events.

Figures 6.9, 6.10, 6.11 illustrates the confusion matrices for all the eight activi-

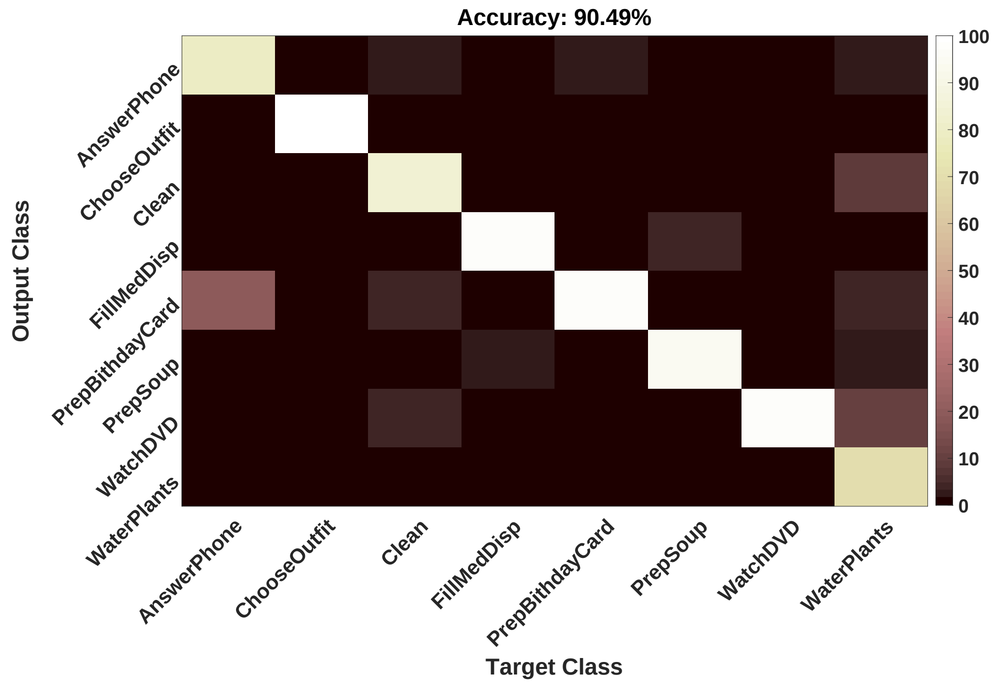

Figure 6.9: Confusion Matrix when sliding window = 60s for CASAS dataset

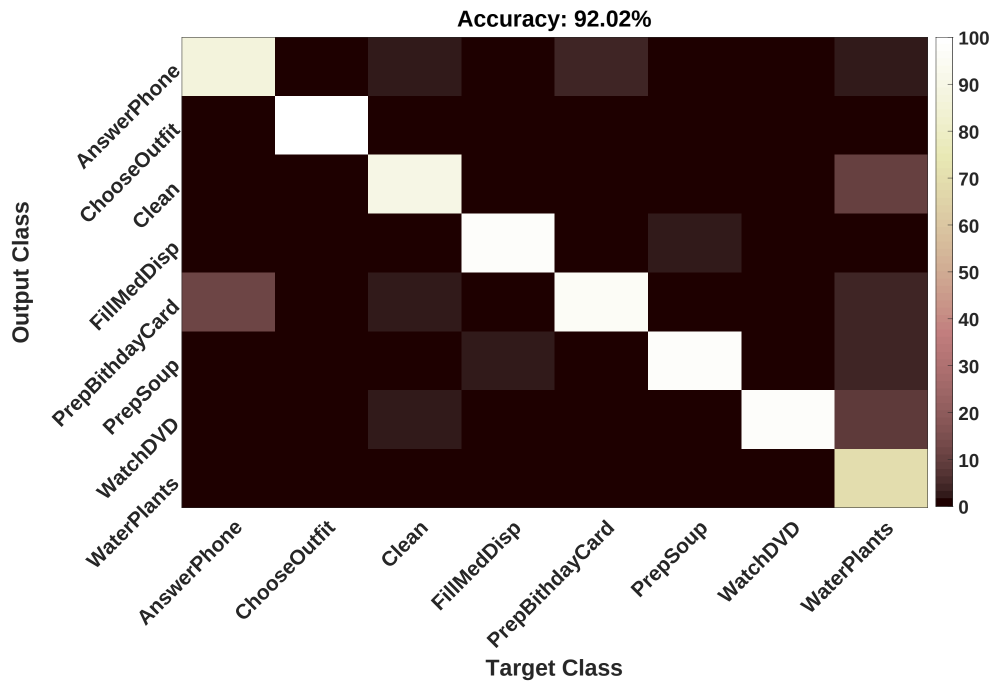

Figure 6.10: Confusion Matrix when sliding window = 90s for CASAS dataset

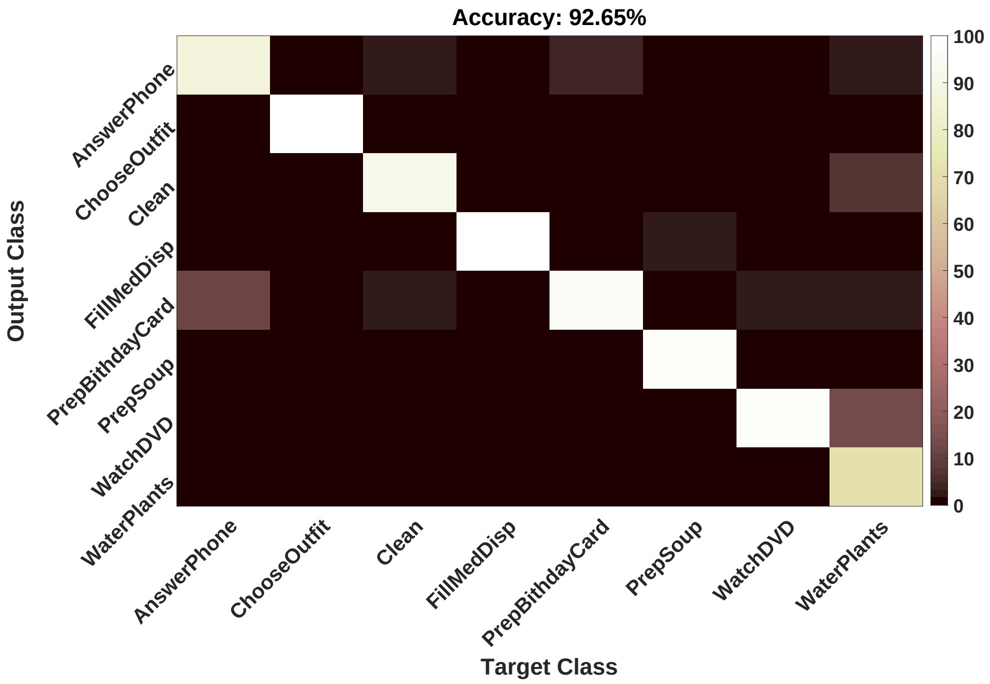

Figure 6.11: Confusion Matrix when sliding window = 120s for CASAS dataset

ties in the CASAS smart home dataset when the time window range was set to 60s, 90s and 120s respectively and Table 6-A shows the average F-measure comparison for all the eight activities for these three time window ranges. The three ranges for comparison were roughly chosen based on the least average duration taken by the participants to complete an activity which was 90s [166]. The statistical significance of the F-measure performance results for the three time windows under consideration was tested using a Friedman's test. This test helps in checking the significance between the variables when comparing three or more matched groups. Carrying out the test resulted in a small p-value of 0.0208 and Chi-square value of 7.75 indicating that the change in time window affects the output of the ADL recognition system.

A step size of 5s was considered in all the cases. It can be seen that the developed system performs well when the time interval was selected as 120s as

Table 6-A: Performance Comparison with Different Time Window Ranges for CASAS Smart home dataset

Time window Range	Avg. F-Measure of all activity labels (%)
60s	90.39
90s	91.80
120s	92.35

more context information is accumulated to determine the current activity. Hence the window size for the CASAS dataset for the remainder of the sections is 120s with a step size of 5s.

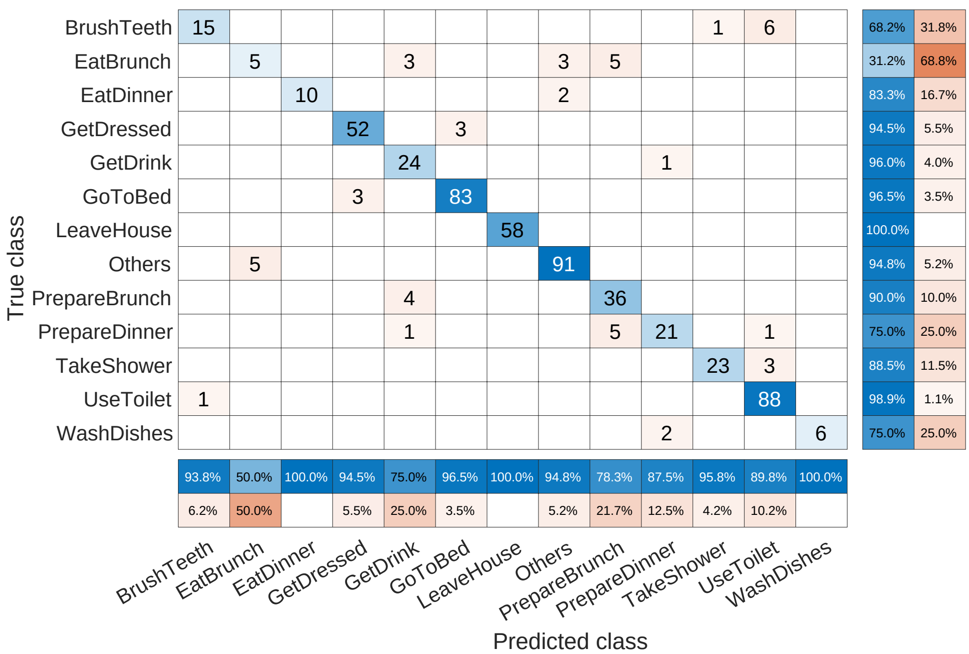

Figure 6.12: Confusion Matrix when sliding window = 60s for Kasteren House-B dataset

The confusion plots for the Kasteren House-B dataset is shown in Figures 6.12, 6.13 and 6.14 when the time window range was set to 60s, 75s and 90s respectively. Table 6-B shows the average F-measure comparison for all the thirteen

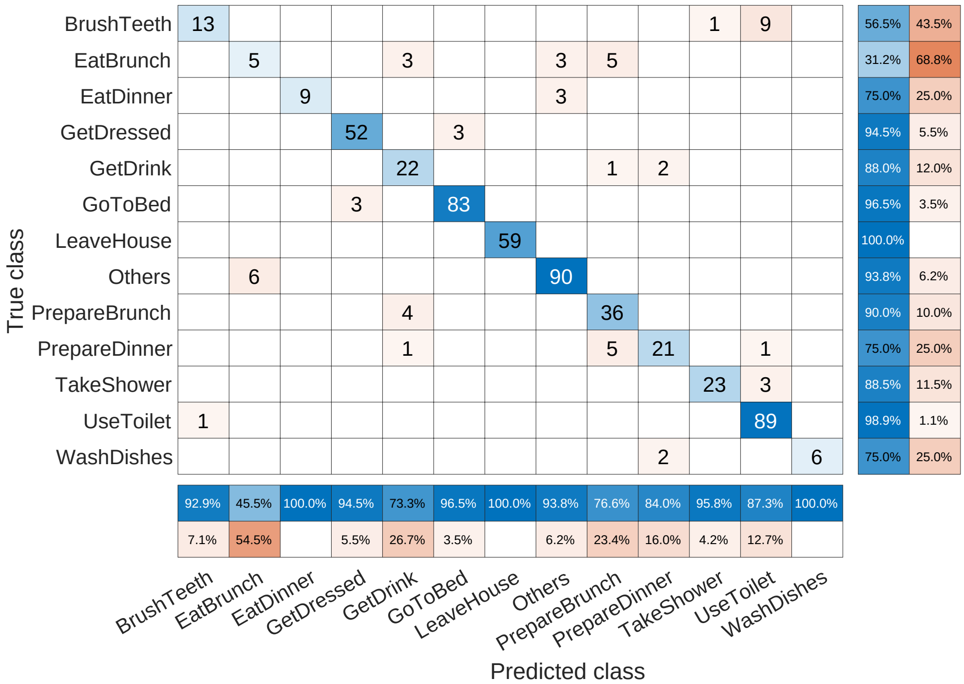

Figure 6.13: Confusion Matrix when sliding window = 75s for Kasteren House-B dataset

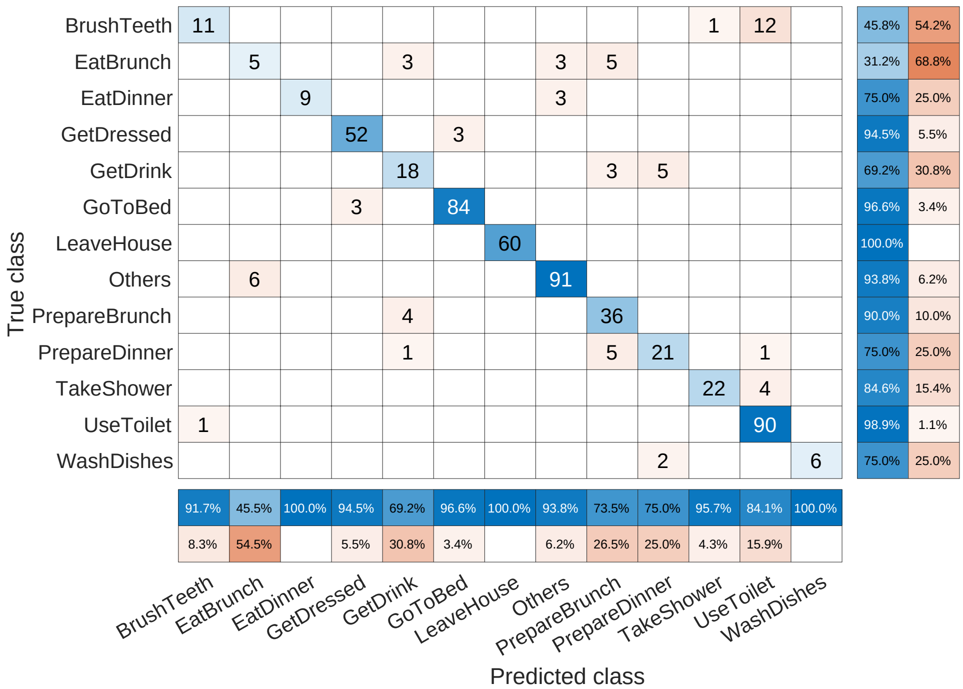

Figure 6.14: Confusion Matrix when sliding window = 90s for Kasteren House-B dataset

Table 6-B: Performance Comparison with Different Time Window Ranges for Kasteren House-B dataset

Time window Range	Avg. F-Measure of all activity labels (%)
60s	85.75
75s	83.87
90s	81.56

activities for the mentioned time window ranges. Similar to the CASAS dataset, the decision to use these ranges for comparison was based on the minimum average time duration to complete an activity which was 60s for this dataset [1]. Using a step size of 20s with 60s sliding window gave the best results. Increasing the window size to 75s and 90s leads to wrong predictions for certain activities which share the same set of sensors.

In order to check the statistical significance of the results, a Friedman's test was carried out on the individual F-scores for the 3 time windows. The test results had a chi-square value of 11.56 and a p-value of 0.0031 indicating the significance of the change in time window parameter on the overall performance of the ADL recognition system. The best performing window size of 60s is selected for rest of the sections for Kasteren House-B dataset.

6.6.4 Performance Analysis of Proposed Method

Performance metrics such as precision, recall and F-measure were used in analysing the performance of the proposed method. They are calculated using the formulas below for each class label:

Table 6-C: Precision, Recall and F-measure of Individual Activities of CASAS Smart Home dataset

CASAS Activity Label	**Precision**	**Recall**	**F-Measure**
ADL1 - Fill Medical Dispenser	0.99	0.95	0.97
ADL2 - Watch DVD	0.97	0.88	0.93
ADL3 - Water Plants	0.71	0.98	0.83
ADL4 - Answer Phone	0.87	0.88	0.88
ADL5 - Prepare Birthday Card	0.96	0.87	0.91
ADL6 - Prepare Soup	0.97	0.98	0.97
ADL7 - Clean	0.92	0.93	0.92
ADL8 - Choose Outfit	1	0.96	0.98
Avg.	**0.94**	**0.94**	**0.92**

$$precision = \frac{truepositives}{truepositives + falsepositives} \tag{6.3}$$

$$recall = \frac{truepositives}{truepositives + falsenegatives} \tag{6.4}$$

$$F_1 = 2 * \frac{precision * recall}{precision + recall} \tag{6.5}$$

6.6.4.1 CASAS Smart Home Dataset

Table 6-C shows the respective precision, recall and F-measures computed for each ADL class of the CASAS smart home dataset. The experimental results indicate that all the activities were well recognised. The activities *Water Plants*

(*ADL3*) and *Answer Phone* (*ADL4*) had the lowest recognition rate amongst all the considered ADLs. Low precision and high recall rate for *Water Plants* (*ADL3*) reflect that a sizeable portion of the predicted labels for ADLs - *Clean (ADL7)* and *Watch DVD (ADL2)* were incorrectly classified as *Water Plants (ADL3)* as seen in the confusion matrix of Figure 6.11. This can be attributed to the fact that *Water Plants (ADL3)* are not characterised by a single sensor type. *ADL2*, *ADL3* and *ADL7* share the same set of motion sensors and primarily occur in the Living room area. Similarly, *Answer Phone (ADL4)* is mainly confused with *Prepare Birthday Card (ADL5)* (Refer to Figure 6.11). Both these activities share the same movement sensor *M13* and occur in the same location. Furthermore, there were few instances where the main object sensor (phone sensor (*P01*)) was not recorded in the dataset when the participant was answering a call. These cases are particularly hard to differentiate, as the triggering of phone sensor is a strong indication of the performed activity. Classification errors for rest of the activities were minor and acceptable for real-time activity recognition. Overall, the results prove that the combination of C-SPARQL with MLN is suitable for any decision-making system. MLN particularly handles uncertainty when dealing with cases when sensor event patterns are incomplete or not clearly recognisable in a given time window through use of weighted formulas.

6.6.4.2 Kasteren Smart Home-B Dataset

Table 6-D shows the respective precision, recall and F-measures computed for each ADL class of the Kasteren smart home-B dataset. As per the results, *Leave House (ADL7)* was classified correctly at all times and the activities *Eat Brunch (ADL2)*, *Get Drink (ADL5)* and *Prepare Brunch (ADL9)* had the lowest recognition rates. Low precision and high recall rate for *Prepare Brunch* indicates that some of the

Table 6-D: Precision, Recall and F-measure of Individual Activities of Kasteren Home-B dataset

Activity Label	**Precision**	**Recall**	**F-Measure**
ADL1 – Brush Teeth	0.94	0.69	0.79
ADL2 – Eat Brunch	0.50	0.31	0.38
ADL3 – Eat Dinner	1	0.83	0.91
ADL4 – Get Dressed	0.95	0.95	0.95
ADL5– Get Drink	0.75	0.96	0.84
ADL6– Go To Bed	0.97	0.97	0.97
ADL7– Leave House	1	1	1
ADL8– Others	0.95	0.95	0.95
ADL9– Prepare Brunch	0.78	0.90	0.84
ADL10- Prepare Dinner	0.88	0.75	0.81
ADL11- Take Shower	0.96	0.89	0.92
ADL12- Use Toilet	0.90	0.99	0.94
ADL13- Wash Dishes	1	0.75	0.86
Avg.	**0.89**	**0.84**	**0.86**

predictions for ADLs - *Prepare Dinner (ADL10)* and *Eat brunch (ADL2)* were incorrectly classified as *Prepare Brunch (ADL9)* as seen in Figure 6.12. This was mainly due to incorrect labeling of the ground truth for some parts of the dataset. The dataset was wrongly annotated as *Prepare Dinner* in the morning session, which led to the system recognising it as *Prepare Brunch* activity. Of all the ADL's, *Eat Brunch* activity had the worst precision and recall rate of 50% and 31.2% respectively. One of the main reasons for such poor recognition rate is due to the fact that it had no specific associated sensors to monitor the actual activity taking place. However it was seen to have a link with the *Piano* sensor and occurred after the *Prepare Brunch* ADL whenever the resident executed the eating activity. An MLN rule was therefore formulated to capture this pattern. Due to its dependence on the preceding *Prepare Brunch (ADL9)*, the recognition rate of *Eat Brunch* activity took a toll whenever the system failed to detect *ADL9* and was incorrectly classified in the *Others* class. From the Figure 6.12, it can be seen that *GetDrink* activity was wrongly predicted few times instead of the *Prepare Brunch* ADL leading to a low precision rate. The main reason for this type of confusion is because both the activities share common sensors, common location and tend to occur simultaneously with one another. Rest of the activities were recognised with reasonable precision and recall rates proving the efficiency of the proposed classifier model. The average F-measure score was found to be 86%.

6.6.5 Comparison of Proposed Method Using Supervised and Unsupervised Methods of MLN Weight Learning

As explained in Section 6.4.3.2, weights for MLN clauses can be assigned manually or learned from data by employing weight-learning algorithms. A performance comparison was made when the weights for the MLN formulas were learned automatically from the ABox of the ontology using an unsupervised approach against a supervised approach where weights were assigned manually based on the frequency of sensor event firings for each of the eight activities from the dataset. Uncertainty of the sensor events was captured numerically from the dataset as a number between 0 and 1. The CASAS dataset representing twenty-one participants where each ADL was performed separately was considered for the evaluation of the supervised weight learning. For instance *I03* and *I05* sensors were used 14 out of 21 times and 17 out of 21 times while performing *ADL2 Watch DVD* respectively. Similarly, *M02* sensor was fired for all the 21 times the activity *Watch DVD* was

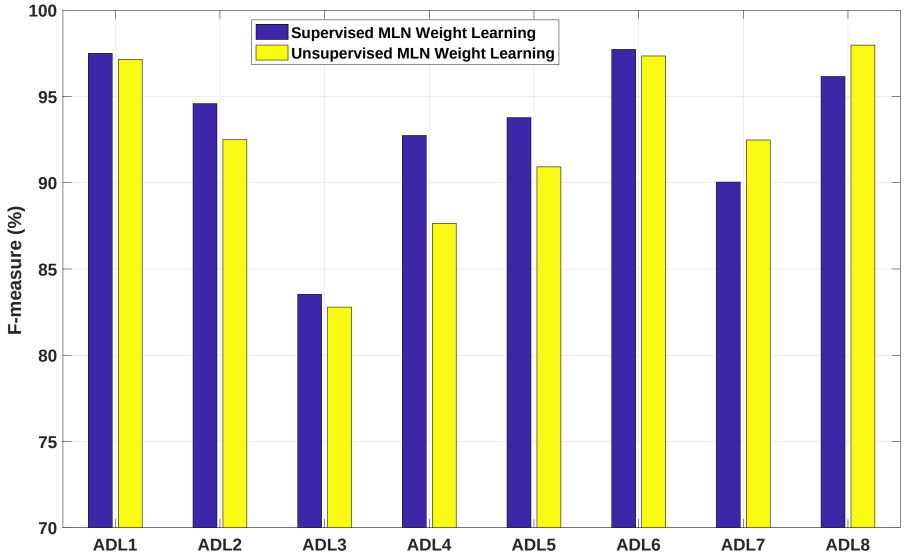

Figure 6.15: CASAS Smart Home Dataset: F-Measure Results for weights learned from dataset and for weights learned from ontology

performed by different participants. Based on this information, weight values of 0.666, 0.809 and 1 were assigned to the corresponding participating sensors (*I03, I05, M02*) for *Watch DVD* activity.

Example 4: Weight Assignment for *ADL2 WatchDVD*:

Rule 7:

0.666 tvshelfRightDVD(i03) ∧ locatedIn(i03,l) ∧ livingroom(l) ∧ necessarySensorFor(i03,a) ∧ usedFor(i03,a) ∧ watchdvd(a) ⇒ simpleadl(a)

Rule 8:

0.809 tvshelfRightDVD(i05) ∧ locatedIn(i05,l) ∧ livingroom(l) ∧ necessarySensorFor(i05,a) ∧ usedFor(i05,a) ∧ watchdvd(a) ⇒ simpleadl(a)

Table 6-E: CASAS Smart Home Dataset: F-measure comparison of Proposed Method Using Supervised and Unsupervised MLN Weight Learning Methods

CASAS Activity Label	**Supervised MLN Weight Learning**	**Unsupervised MLN Weight Learning**
ADL1	97.50	97.15
ADL2	94.59	92.50
ADL3	83.53	82.79
ADL4	92.74	87.64
ADL5	93.78	90.92
ADL6	97.73	97.35
ADL7	90.04	92.48
ADL8	96.16	97.98
Avg. F -Measure	**93.26**	**92.35**

Rule 9:

1.0 tvshelfMotion(m02) $\wedge$ locatedIn(m02,l) $\wedge$ livingroom(l) $\wedge$ usedFor(m02,a) $\wedge$ watchdvd(a) $\Rightarrow$ simpleadl(a)

Besides the manual assignment of weights to rules, the additional MLN rules formulated based on the domain knowledge (described in Section 6.6.2) were also used for the supervised method. Using this approach, the F-measure results are illustrated in Figure 6.15 and tabulated in Table 6-E. It can be deduced that the supervised approach of MLN weight learning exhibits only marginally better performance than the unsupervised approach. This confirms the effectiveness of employing weight learning algorithms to learn the weights directly from the domain ontology's ABox.

6.6.6 Performance Comparison with Other Approaches Using CASAS Smart Home dataset

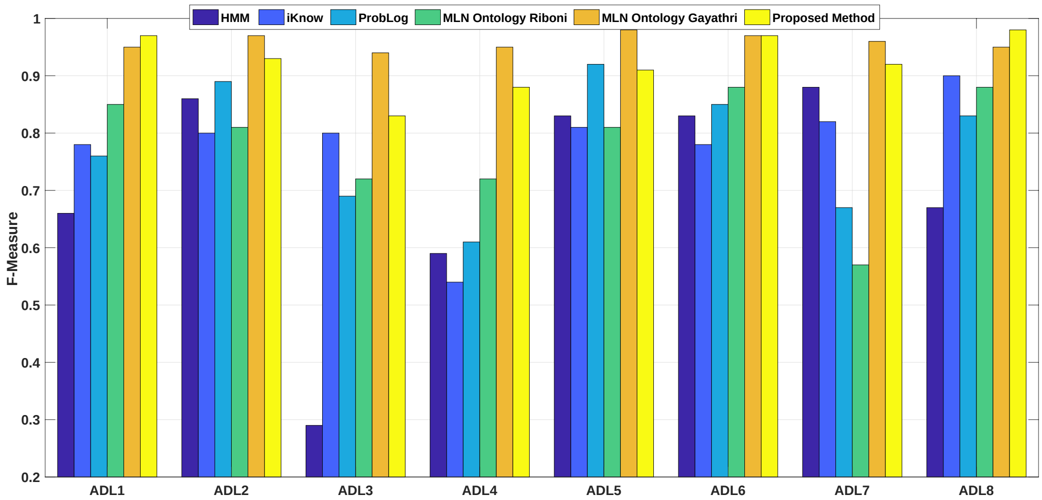

Figure 6.16: Performance Comparison of the Proposed System to Other Related Works for CASAS Smart Home dataset

The comparison of the proposed approach with other research works using the same CASAS interwoven dataset is presented in Table 6-F and illustrated in Figure 6.16. The techniques used in the selected research works for comparison help in laying out a sound comparative analysis of the developed model as they cover different approaches such as data-driven, knowledge-driven and hybrid models. The supervised HMM (time-shifted) statistical approach in [166] has the least F-measure (70%). The knowledge-driven framework, iKnow uses OWL ontologies and a context-driven situation interpretation algorithm as the main building blocks for ADL recognition [67]. The interpretation layer is implemented using the SPARQL Inferencing Notation (SPIN). An average F-measure of 78% was achieved using this approach. The study conducted in [152] employs ProbLog to recognise complex ADLs in an online fashion achieving a F-measure of 83%. Table

Table 6-F: F-Measure Performance Comparison with Other Approaches for CASAS dataset

CASAS Activity Label	HMM (time shifted)	iKnow	ProbLog	Existing Probabilistic Ontology Using MLN		Proposed Stream Reasoning with MLN Method
				Riboni et al.	Gayathri et al.	
ADL1	0.66	0.78	0.76	0.85	0.95	0.97
ADL2	0.86	0.80	0.89	0.81	0.97	0.93
ADL3	0.29	0.80	0.69	0.72	0.94	0.83
ADL4	0.59	0.54	0.61	0.72	0.95	0.88
ADL5	0.83	0.81	0.92	0.81	0.98	0.91
ADL6	0.83	0.78	0.85	0.88	0.97	0.97
ADL7	0.88	0.82	0.67	0.57	0.96	0.92
ADL8	0.67	0.90	0.83	0.88	0.95	0.98
Average F - Measure	**0.70**	**0.78**	**0.83**	**0.78**	**0.96**	**0.92**

6-F and Figure 6.16 also shows the comparison of the proposed approach with other existing studies integrating MLN with the represented domain ontology [72], [71]. Similar to the two step approach described in this chapter, Riboni et al. formulated an initial hypotheses of the ADLs using semantic correlations from the ontology using a statistical reasoner which was later refined through probabilistic reasoning by MLN [72]. Their method achieved a F-measure score of 78%. The study by Gayathri et al. had the highest recognition performance for the CASAS interwoven dataset with an average F-measure of 96%. Their study employs a hybrid fixed interval and location based segmentation approach to segment continuous sensor events, which is then used by the MLN inference system. The structure of their MLN model is learned from the defined concepts, properties and SWRL rules of the developed ontology. The authors employ a *Leave-one-day-out* approach for evaluation of their model and make use of the training data modeled in the ontology's ABox to learn the corresponding weights for the MLN formulas. Whereas the proposed model in this Chapter uses an unsupervised approach to learn weights of the MLN formulas using just the information gathered from the sensor-activity, sensor-object and sensor-locations mappings outlined in the ontology's ABox. Overall, the proposed probabilistic stream reasoning framework in this chapter performs well when compared to other approaches highlighted in Table 6-F and is comparable to the performance of the study done in [71], thus highlighting the ability of the developed system to effectively recognize activities from complex sensor event patterns.

6.6.7 Performance Comparison with Other Approaches Using Kasteren Smart Home-B dataset

The F-measure comparison of the proposed approach with other research works using the same Kasteren Home-B dataset is presented in Table 6-G and illustrated in Figure 6.17. The results from the works done in [59] and [167] that employ data-driven approachs is compared against the proposed MLN model using the same dataset. The authors of [59] use a hybrid model where Bi-directional long short term memory (BiLSTM) is used for recognising concurrent activities and Skip-chain conditional random field (SCCRF) model for recognition of interleaved activities. The average F-measure was found to be 92% for interleaved activity recognition and performs well for a majority of the individual activities than the proposed MLN model, which has an average F-measure of 86%. *ADL7, ADL8,*

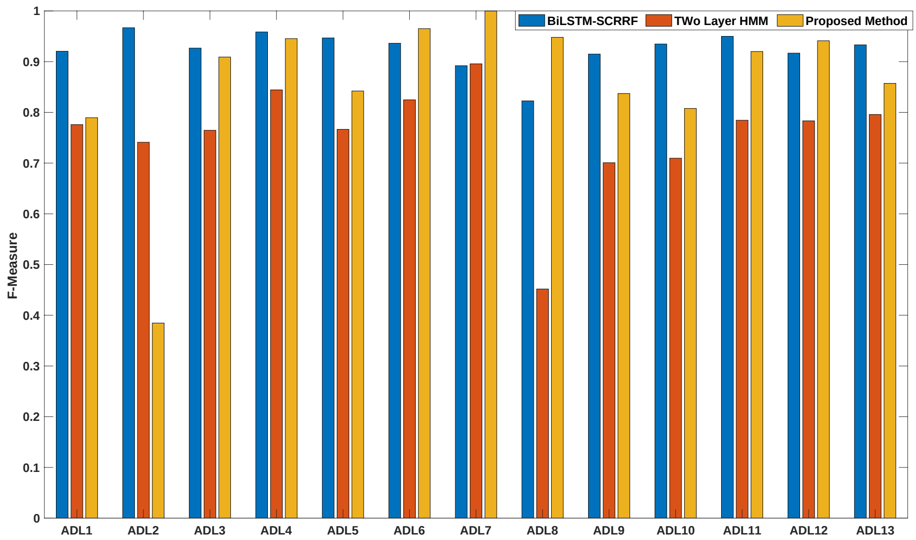

Figure 6.17: Performance Comparison of the Proposed System to Other Related Works for Kasteren Smart Home-B dataset

ADL12 and ADL13 had a better F-measure rate using the proposed method in comparison with the BiLSTM-SCCRF approach. The other study [167] used a two-layer HMM ADL prediction model to map the low-level sensor data with their corresponding high-level activity. The first layer was used to retrieve the location details of the observed sensor events and the second layer made use of the object use information to make a prediction. An average F-measure score of 76% was achieved through the two-layer HMM model. Both these studies require a sizeable training database to train their respective models before engaging the model for prediction on new data. The developed C-SPARQL-MLN model acts on unseen new data without the requirement of a large training database.

Table 6-G: F-Measure Performance Comparison with Other Approaches for Kasteren-B dataset

Activity Label	**BiLSTM-SCRRF Approach**	**Two-layer HMM Approach**	**Proposed Method**
ADL1	0.92	0.78	0.79
ADL2	0.97	0.74	0.38
ADL3	0.93	0.76	0.91
ADL4	0.96	0.84	0.95
ADL5	0.95	0.77	0.84
ADL6	0.94	0.82	0.97
ADL7	0.89	0.90	1.00
ADL8	0.82	0.45	0.95
ADL9	0.91	0.70	0.84
ADL10	0.93	0.71	0.81
ADL11	0.95	0.78	0.92
ADL12	0.92	0.78	0.94
ADL13	0.93	0.80	0.86
Average F -Measure	**0.92**	**0.76**	**0.86**

6.6.8 Execution Time of Proposed Method on Streaming Data

The computational time consumed by the proposed method for each time window over the streaming sensor data is illustrated in Figure 6.18. For this experiment, one of the participant's data from the CASAS interwoven dataset was selected. The C-SPARQL Activity and Time queries were set to RANGE = 120s with STEP size

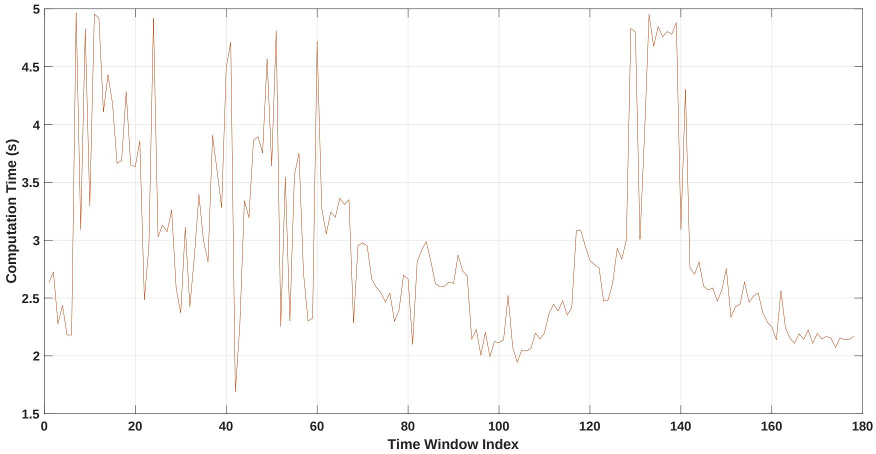

Figure 6.18: Plot of Computation Time for Each Sliding Window of the Proposed System

5s. In this scenario, the average execution time for each time window required by the proposed method to run over 892s of streaming sensor data was 2.95s. The average execution time required by the Alchemy engine alone was 2.23s as much of the computation is done in the MLN module. All experiments were performed using a two-core CPU processor. From the figure, it can be deduced that there are few cases where the model requires more computational effort to derive the most likely activity. However, for the most part, the proposed method achieves an acceptable response time and can be put to good use in real time decision-making applications.

6.7 Chapter Summary and Discussion

Considering the need for real time systems in smart homes to process continuous raw sensor data with high throughput and low latency, this study shows how to leverage on Stream Reasoning using rich background information for ADL recognition. Furthermore, due to the constraint of semantic knowledge bases in handling uncertainty, the study combines probabilistic inference with stream reasoning for complex activity recognition. The chapter demonstrates a hybrid model, which takes advantage of a C-SPARQL engine as the stream reasoner and a competent Markov Logic Network to distinguish between interwoven activities. The ability of C-SPARQL to query from static ontologies is put to good use by mapping observed sensor events to possible activities; their zone of occurrence and corresponding attached objects. C-SPARQL query is also used in deducing the start and end time for a sensor event in every time window. These collective results are used as input to the MLN engine to infer the most likely ADLs to have taken place along with their respective start and end times. The ability to formulate weighted rules based on the domain knowledge in MLN is an added bonus as it aids in predicting the correct activity even in the presence of few participating sensor events for that particular ADL in a time window.

The experimental results from Section 6.6 demonstrate that the proposed hybrid model shows great potential for deployment in smart home applications, as the model does not require use of extensive data for training the model. The developed model follows an unsupervised approach as the sensor-activity relations are modeled mainly based on common sense knowledge of the participating objects in the surrounding environment. Weight learning for the MLN model is also based on these inter-relations defined in the ontology. An average F-measure of 92.35% was obtained using the CASAS real-world dataset where twenty-one participants perform activities in no specific order or time. For the Kasteren smart home-B dataset, an average F-measure of 86% was obtained. The results are comparable or better in most cases to other state-of-the-art data-driven, knowledge-driven and hybrid techniques. Learning of MLN weights from ontology's ABox also obtains essentially the same performance when compared to the supervised approach of extracting weights from the CASAS dataset, thus validating the effectiveness of employing weight-learning algorithms.

On the negative side, the proposed model terminates with identifying the start and end times of inferred activities, and do not report the findings on which ADLs are sequential, interleaved or concurrent in nature in real time. Allen's temporal relations can be applied as a post-processing step to work out the interaction between the inferred activities with their respective start and end times as in [71]. It is also questionable on how the developed framework would fare in a multi-user scenario as the real-world dataset used in this chapter is for a single-person household. Besides, certain amount of knowledge engineering effort is also required to design the ontology ABox and formulate additional MLN rules based on the surrounding home environment. However this counts as minimal effort compared to the work involved in gathering training data and annotating large sets of data for validation as in the case of Chapters 4 and 5. Care has been taken to design the system such that it follows an unsupervised approach and efficiently handles streaming data without compromising on the prediction accuracy.

The next chapter concludes the research and discusses possible avenues for future research.

Chapter 7

Conclusions and Future Work

In this chapter, the results obtained individually from the previous chapters are summarized and assessed in relation to the research objectives set out earlier. The chapter concludes by discussing the possible avenues for future research in the field of activity recognition.

7.1 Summary of the Main Contributions

Smart home assistive systems are a great way to improve quality of living and can be truly transformative for anyone with physical challenges. A great deal of effort has been invested in many research studies to infer high-level activities from low-level sensor data and obtain satisfactory recognition performance in ambient assisted living systems. However, there are still few gaps and questions that need to be addressed as highlighted in Chapter 1. The thesis aims to tackle these challenges and suggest different methods that can be applied to solve an activity recognition problem. The techniques described in this thesis are flexible and can be adapted to existing ADL monitoring systems for healthcare.

With respect to the research questions posed in Chapter 1, the thesis identifies the following contributions:

1. In Chapter 4 of this thesis, a novel context-based location aware algorithm for identification of low-level micro-activities is proposed that can be used to derive complex ADLs performed by home-care patients. This is made possible by using a wearable beacon embedded with magnetometer and inertial sensors. The shortcomings of beacon signal stability and mismatch issues in magnetic field sequences are overcome by adopting a hybrid three-phase approach for deducing the locus of micro-activities and their associated zones in a smart home environment. The suggested approach is assessed in two different test environments. In addition to recognition of low-level activities, the methods described in Chapter 4 also identifies the person's walking trajectory within the same zone or between different zones of the house. Experimental results prove that it is feasible to obtain centimeter-level accuracy for recognition of micro-activities. A classification accuracy of 85% was achieved for trajectory prediction. These results are encouraging and imply that collection of accurate low-level information for ADL recognition is possible through integration of inertial sensors, Magnetic Field and BLE technologies from the wearable without relying on other infrastructural sensors.

2. In Chapter 5 of this thesis, a study was conducted to infer if a reduced number of receivers equipped with higher gain antennas could provide improved

BLE fingerprinting performance for the method described in Chapter 2. The evaluation was performed in a standard domestic apartment with an activity centric approach using a single wearable beacon and multiple receivers. A rank based route selection algorithm was used as the basis to identify the candidate positions or routes that indicates the most likely path of the subject. Furthermore, the chapter highlights the benefits of implementing the inverse fingerprinting method with a trajectory based prediction model. The chapter also discussed the effect of surrounding electrical interference on the beacon signal. Experimental results indicate that an increased antenna gain in addition to deploying an adequate number of receivers have a positive effect on the overall ranking accuracy, thus contributing to better positioning performance.

3. Chapter 6 of this thesis concentrates on a different activity recognition problem when compared to Chapters 4 and 5. Chapter 6 tackles the issue of handling uncertainty in knowledge-based semantic representation of activities by incorporating Markov Logic Networks (MLN), which is a statistical relational learning approach. In the thesis, MLN makes use of the domain knowledge from the ontology to form the first order rules and also learn weights automatically using an unsupervised approach. The ability to formulate weighted rules based on the domain knowledge helps in dealing with the uncertainty involved in dynamic activity recognition to a great extent. Necessary examples are provided as added proof and experimental analysis is conducted to support the argument.

Besides tackling the problem of uncertainty in knowledge-based systems, Chapter 6 also presents an innovative approach for complex activity recognition by combining stream reasoning with probabilistic inference using MLN. Both these methods use the underlying domain ontology for inference. C-SPARQL provides the initial hypothesis from continuous sensor stream by mapping the sensor events to their respective location, object and potential activity instances using the defined ontology in addition to finding the start and end times for each observed sensor event. The results of the C-SPARQL engine are then used as input by the MLN module to infer the activities and their corresponding time intervals for each temporal sliding window. Extensive experiments with two real-world datasets prove that the performance of the proposed model is comparable and in most cases better than other state-of-the-art techniques. An average F-measure score of 92.35% and 86% was achieved for recognition of interwoven activities using this method.

7.2 Future Work

This section outlines the potential future research directions that could be conducted for the methods described in previous chapters of this thesis.

7.2.1 Depression Monitoring

The different ADL models developed in this thesis were carried out as part of a larger project for monitoring depression patients at home. The predicted output of the ADL system will be integrated with a suitable decision making system that will be designed as per relevant clinical guidelines. This part of research will be carried out by amassing relevant information from a psychiatrist regarding depression treatment, patterns of behaviour and setting of pertinent goals. Though the models developed in Chapters 3 and 5 differ from each other, a combination or certain aspects of both the models may be used in recognition of goals set by the clinician.

7.2.2 Cognitive System for Delivering Prompts

The work done in this thesis could be extended for designing a cognitive system that can help deliver relevant prompts to motivate and remind the person to carry on with their daily activities.

7.2.3 Testing in Different Style Homes

The future research direction will concentrate on extending the proposed methodology in Chapter 3 for implementation in different types of home and testing with individuals who belong to different age groups making use of the same training database.

7.2.4 Active Learning

Devices such as amazon echo could be employed for active learning to handle situations when the system is unable to take a decision as a result of contradictory knowledge. The device interacts with the user, collects necessary information and feeds the response back to the AR system. The feedback can be reflected through change in assignment of weights in the MLN template. The weight learning process can then be carried out at timely intervals to keep the system updated with the surrounding changes in the environment and for better performance of the decision-making system.

7.2.5 Use of Human Posture Data

Combining human posture data from wearables with ambient and object-tagged sensing for carrying out fine-grained ADL recognition. For instance, it is possible to detect the bed occupancy through use of a pressure mat sensor. But it is not possible to infer if the person is sleeping or just sitting on the bed through the lone usage of the pressure mat sensor. The combined usage of the binary switch sensor with the accelerometer data from the wearable aids in accurate prediction and handling such situations. Furthermore, C-SPARQL has the capability to handle streams from heterogeneous sensing sources without suffering performance degradation.

7.2.6 Testing for a Multi-User Scenario

Both the models described in Chapters 3 and 5 were carried out for a single person household. Evaluation when more than one person share the smart home was not considered in this thesis. Additional fine-tuning and experiments could be carried out to determine the suitability of the developed methods for a multi-user home environment. A potential idea would be differentiate between individuals through use of wearables.

Appendix A

Author's publications

Journal papers

1. **M. Sridharan**, J. Bigham, P.M. Campbell, C. Phillips and E. Bodanese, 2019. Inferring Micro-Activities through Wearable Sensing for ADL recognition of Home-Care Patients. *IEEE journal of biomedical and health informatics.*

Conference papers

1. **M. Sridharan**, J. Bigham, C. Phillips, and E. Bodanese, "Collaborative location estimation for confined spaces using magnetic field and inverse beacon positioning", in 2017 *IEEE SENSORS. IEEE, 2017*, pp. 1–3.

2. **M. Sridharan**, J. Bigham, P. M. Campbell, and E. Bodanese, Evaluation of factors afiecting inverse beacon fingerprinting using route prediction algorithm, in 2019. *IEEE Wireless Communications and Networking Conference.*

References

[1] T. L. van Kasteren, G. Englebienne, and B. J. Kröse, "Human activity recognition from wireless sensor network data: Benchmark and software," in *Activity recognition in pervasive intelligent environments.* Springer, 2011, pp. 165–186.

[2] M. E. Mlinac and M. C. Feng, "Assessment of activities of daily living, self-care, and independence," *Archives of Clinical Neuropsychology*, vol. 31, no. 6, pp. 506–516, 2016.

[3] R. Belling, M. Whittock, S. McLaren, T. Burns, J. Catty, I. R. Jones, D. Rose, and T. Wykes, "Achieving continuity of care: facilitators and barriers in community mental health teams," *Implementation Science*, vol. 6, no. 1, p. 23, 2011.

[4] B.-R. Chen, S. Patel, T. Buckley, R. Rednic, D. J. McClure, L. Shih, D. Tarsy, M. Welsh, and P. Bonato, "A web-based system for home monitoring of patients with parkinson's disease using wearable sensors," *IEEE Transactions on Biomedical Engineering*, vol. 58, no. 3, pp. 831–836, 2010.

[5] D. De, P. Bharti, S. K. Das, and S. Chellappan, "Multimodal wearable sensing for fine-grained activity recognition in healthcare," *IEEE Internet Computing*, vol. 19, no. 5, pp. 26–35, 2015.

[6] J. Ramos-Castro, H. Mahdavi, D. P.-D. de Cerio, M. A. García-González, S. Estevez, and J. Rosell-Ferrer, "Unobtrusive activity measurement in patients with depression: the h4m approach," *Information and Communication Technologies applied to Mental Health*, p. 18.

[7] G. Hussain, M. S. Jabbar, J.-D. Cho, and S. Bae, "Indoor positioning system: A new approach based on lstm and two stage activity classification," *Electronics*, vol. 8, no. 4, p. 375, 2019.

[8] D. Moreira, M. Barandas, T. Rocha, P. Alves, R. Santos, R. Leonardo, P. Vieira, and H. Gamboa, "Human activity recognition for indoor localization using smartphone inertial sensors," *Sensors*, vol. 21, no. 18, p. 6316, 2021.

[9] B. Kayalibay, G. Jensen, and P. van der Smagt, "Cnn-based segmentation of medical imaging data," *arXiv preprint arXiv:1701.03056*, 2017.

[10] Z. Cao, G. Hidalgo, T. Simon, S.-E. Wei, and Y. Sheikh, "Openpose: realtime multi-person 2d pose estimation using part affinity fields," *IEEE transactions on pattern analysis and machine intelligence*, vol. 43, no. 1, pp. 172–186, 2019.

[11] A. Ali and J. K. Aggarwal, "Segmentation and recognition of continuous human activity," in *Proceedings IEEE Workshop on Detection and Recognition of Events in Video*. IEEE, 2001, pp. 28–35.

[12] B. Fu, N. Damer, F. Kirchbuchner, and A. Kuijper, "Sensing technology for human activity recognition: A comprehensive survey," *IEEE Access*, vol. 8, pp. 83 791–83 820, 2020.

[13] D. Tran, L. Bourdev, R. Fergus, L. Torresani, and M. Paluri, "Learning spatiotemporal features with 3d convolutional networks," in *Proceedings of the IEEE international conference on computer vision*, 2015, pp. 4489–4497.

[14] K. Arning and M. Ziefle, "“get that camera out of my house!” conjoint measurement of preferences for video-based healthcare monitoring systems in private and public places," in *International Conference on Smart Homes and Health Telematics*. Springer, 2015, pp. 152–164.

[15] M. R. Mettel, M. Alekseew, C. Stocklöw, and A. Braun, "Designing and evaluating safety services using depth cameras," *Journal of Ambient Intelligence and Humanized Computing*, vol. 10, no. 2, pp. 747–759, 2019.

[16] T. Kamizono, H. Abe, K. Baba, S. Takano, and K. Murakami, "Towards

activity recognition of learners by kinect," in *2014 IIAI 3rd International Conference on Advanced Applied Informatics*. IEEE, 2014, pp. 177–180.

[17] T. Banerjee, J. M. Keller, M. Skubic, and E. Stone, "Day or night activity recognition from video using fuzzy clustering techniques," *IEEE Transactions on Fuzzy Systems*, vol. 22, no. 3, pp. 483–493, 2013.

[18] J. Sung, C. Ponce, B. Selman, and A. Saxena, "Human activity detection from rgbd images," in *Workshops at the twenty-fifth AAAI conference on artificial intelligence*, 2011.

[19] B. Ni, G. Wang, and P. Moulin, "Rgbd-hudaact: A color-depth video database for human daily activity recognition," in *2011 IEEE international conference on computer vision workshops (ICCV workshops)*. IEEE, 2011, pp. 1147–1153.

[20] J. Han and B. Bhanu, "Human activity recognition in thermal infrared imagery," in *2005 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR'05)-Workshops*. IEEE, 2005, pp. 17–17.

[21] P. Hevesi, S. Wille, G. Pirkl, N. Wehn, and P. Lukowicz, "Monitoring household activities and user location with a cheap, unobtrusive thermal sensor array," in *Proceedings of the 2014 ACM international joint conference on pervasive and ubiquitous computing*, 2014, pp. 141–145.

[22] T. Kawashima, Y. Kawanishi, I. Ide, H. Murase, D. Deguchi, T. Aizawa, and M. Kawade, "Action recognition from extremely low-resolution thermal image sequence," in *2017 14th IEEE International Conference on Advanced Video and Signal Based Surveillance (AVSS)*. IEEE, 2017, pp. 1–6.

[23] D. Bouchabou, S. M. Nguyen, C. Lohr, B. LeDuc, I. Kanellos *et al.*, "A survey of human activity recognition in smart homes based on iot sensors algorithms: Taxonomies, challenges, and opportunities with deep learning," *Sensors*, vol. 21, no. 18, p. 6037, 2021.

[24] B. Mariani, M. C. Jiménez, F. J. Vingerhoets, and K. Aminian, "On-shoe wearable sensors for gait and turning assessment of patients with parkinson's disease," *IEEE transactions on biomedical engineering*, vol. 60, no. 1, pp. 155–158, 2012.

[25] P. Vepakomma, D. De, S. K. Das, and S. Bhansali, "A-wristocracy: Deep learning on wrist-worn sensing for recognition of user complex activities," in *2015 IEEE 12th International Conference on Wearable and Implantable Body Sensor Networks (BSN).* IEEE, 2015, pp. 1–6.

[26] J. Hayward and G. Chansin, "Wearable sensors 2015-2025: Market forecasts, technologies, players," 2015.

[27] P. T.S. (2017) The biostamp can replace today's clunky biomedical sensors. [Online]. Available: http://spectrum.ieee.org/biomedical/devices/a-temporary-tattoo-that-sensesthrough-your-skin

[28] A. Feinberg. (2017) Electronic sensor tattoos can now be printed directly onto human skin. [Online]. Available: http://gizmodo.com/5989948/electronic-sensor-tattoos-can-now-be-printeddirectly-onto-human-skin

[29] J. Bennett, O. Rokas, and L. Chen, "Healthcare in the smart home: A study of past, present and future," *Sustainability*, vol. 9, no. 5, p. 840, 2017.

[30] C. Nugent, M. Mulvenna, X. Hong, and S. Devlin, "Experiences in the development of a smart lab," *International Journal of Biomedical Engineering and Technology*, vol. 2, no. 4, pp. 319–331, 2009.

[31] M. Chan, D. Estève, C. Escriba, and E. Campo, "A review of smart homes—present state and future challenges," *Computer methods and programs in biomedicine*, vol. 91, no. 1, pp. 55–81, 2008.

[32] S. Helal, W. Mann, H. El-Zabadani, J. King, Y. Kaddoura, and E. Jansen, "The gator tech smart house: A programmable pervasive space," *Computer*, no. 3, pp. 50–60, 2005.

[33] C. Hekimian-Williams, B. Grant, X. Liu, Z. Zhang, and P. Kumar, "Accurate localization of rfid tags using phase difference," in *2010 IEEE International Conference on RFID (IEEE RFID 2010)*. IEEE, 2010, pp. 89–96.

[34] B. Kellogg, V. Talla, and S. Gollakota, "Bringing gesture recognition to all devices," in *11th {USENIX} Symposium on Networked Systems Design and Implementation ({NSDI} 14)*, 2014, pp. 303–316.

[35] W. Wang, A. X. Liu, M. Shahzad, K. Ling, and S. Lu, "Understanding and modeling of wifi signal based human activity recognition," in *Proceedings of the 21st annual international conference on mobile computing and networking*. ACM, 2015, pp. 65–76.

[36] H. Abdelnasser, M. Youssef, and K. A. Harras, "Wigest: A ubiquitous wifi-based gesture recognition system," in *2015 IEEE Conference on Computer Communications (INFOCOM)*. IEEE, 2015, pp. 1472–1480.

[37] S. Shukri, L. Kamarudin, G. C. Cheik, R. Gunasagaran, A. Zakaria, K. Kamarudin, S. S. Zakaria, A. Harun, and S. Azemi, "Analysis of rssi-based dfl for human detection in indoor environment using iris mote," in *2016 3rd International Conference on Electronic Design (ICED)*. IEEE, 2016, pp. 216–221.

[38] X. Qi, G. Zhou, Y. Li, and G. Peng, "Radiosense: Exploiting wireless communication patterns for body sensor network activity recognition," in *2012 IEEE 33rd Real-Time Systems Symposium*. IEEE, 2012, pp. 95–104.

[39] S. Shi, S. Sigg, and Y. Ji, "Passive detection of situations from ambient fm-radio signals," in *Proceedings of the 2012 ACM Conference on Ubiquitous Computing*. ACM, 2012, pp. 1049–1053.

[40] ——, "Joint localization and activity recognition from ambient fm broadcast signals," in *Proceedings of the 2013 ACM conference on Pervasive and ubiquitous computing adjunct publication*, 2013, pp. 521–530.

[41] M. Sekine and K. Maeno, "Activity recognition using radio doppler effect

for human monitoring service," *Journal of Information Processing*, vol. 20, no. 2, pp. 396–405, 2012.

[42] Z. Ma, J. Bigham, S. Poslad, B. Wu, X. Zhang, and E. Bodanese, "Device-free, activity during daily life, recognition using a low-cost lidar," in *2018 IEEE Global Communications Conference (GLOBECOM)*. IEEE, 2018, pp. 1–6.

[43] E. BODANESE, F. LUO, S. POSLAD *et al.*, "Kitchen activity detection for healthcare using a low-power radar-enabled sensor network." Institute of Electrical and Electronics Engineers, 2019.

[44] M. Tasmin, T. Ishtiak, S. U. Ruman, A. U. R. C. Suhan, N. S. Islam, S. Jahan, S. Ahmed, M. S. Zulminan, A. R. Saleheen, and R. M. Rahman, "Comparative study of classifiers on human activity recognition by different feature engineering techniques," in *2020 IEEE 10th International Conference on Intelligent Systems (IS)*. IEEE, 2020, pp. 93–101.

[45] S. Pirttikangas, K. Fujinami, and T. Nakajima, "Feature selection and activity recognition from wearable sensors," in *International symposium on ubiquitious computing systems*. Springer, 2006, pp. 516–527.

[46] E. Zdravevski, P. Lameski, V. Trajkovik, A. Kulakov, I. Chorbev, R. Goleva, N. Pombo, and N. Garcia, "Improving activity recognition accuracy in ambient-assisted living systems by automated feature engineering," *Ieee Access*, vol. 5, pp. 5262–5280, 2017.

[47] U. Naeem, A.-R. H. Tawil, I. Semelis, G. Judah, and R. Aunger, "Inference of hygiene behaviours while recognising activities of daily living," in *Proceedings of the 3rd International Conference on Context-Aware Systems and Applications*. ICST (Institute for Computer Sciences, Social-Informatics and . . . , 2014, pp. 154–161.

[48] J. Wan, M. J. O'grady, and G. M. O'Hare, "Dynamic sensor event segmen-

tation for real-time activity recognition in a smart home context," *Personal and Ubiquitous Computing*, vol. 19, no. 2, pp. 287–301, 2015.

[49] C. Pham, T. Plötz, and P. Olivier, "A dynamic time warping approach to real-time activity recognition for food preparation," in *International Joint Conference on Ambient Intelligence*. Springer, 2010, pp. 21–30.

[50] L. Chen, J. Hoey, C. D. Nugent, D. J. Cook, and Z. Yu, "Sensor-based activity recognition," *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews)*, vol. 42, no. 6, pp. 790–808, 2012.

[51] A. Artikis, M. Sergot, and G. Paliouras, "A logic-based approach to activity recognition," *Human Behavior Recognition Technologies*, p. 1–13. [Online]. Available: http://dx.doi.org/10.4018/978-1-4666-3682-8.ch001

[52] D. Riboni, L. Pareschi, L. Radaelli, and C. Bettini, "Is ontology-based activity recognition really effective?" in *2011 IEEE International Conference on Pervasive Computing and Communications Workshops (PERCOM Workshops)*. IEEE, 2011, pp. 427–431.

[53] D. Riboni and C. Bettini, "Cosar: hybrid reasoning for context-aware activity recognition," *Personal and Ubiquitous Computing*, vol. 15, no. 3, pp. 271–289, 2011.

[54] T. Gu, L. Wang, Z. Wu, X. Tao, and J. Lu, "A pattern mining approach to sensor-based human activity recognition," *IEEE Transactions on Knowledge and Data Engineering*, vol. 23, no. 9, pp. 1359–1372, 2010.

[55] F. Ordóñez, P. de Toledo, A. Sanchis *et al.*, "Activity recognition using hybrid generative/discriminative models on home environments using binary sensors," *Sensors*, vol. 13, no. 5, pp. 5460–5477, 2013.

[56] R. Nabiei, M. Parekh, E. Jean-Baptiste, P. Jancovic, and M. Russell, "Object-centred recognition of human activity," in *2015 International Conference on Healthcare Informatics*. IEEE, 2015, pp. 63–68.

[57] L. Fiorini, P. Caleb-Solly, A. Tsanaka, F. Cavallo, P. Dario, and C. Melhuish, "The efficacy of "busyness" as a measure for behaviour pattern analysis using unlabelled sensor data: a case study," 2015.

[58] M. A. Khan, T. Akram, M. Sharif, M. Y. Javed, N. Muhammad, and M. Yasmin, "An implementation of optimized framework for action classification using multilayers neural network on selected fused features," *Pattern Analysis and Applications*, vol. 22, no. 4, pp. 1377–1397, 2019.

[59] K. Thapa, A. Al, Z. Md, B. Lamichhane, and S.-H. Yang, "A deep machine learning method for concurrent and interleaved human activity recognition," *Sensors*, vol. 20, no. 20, p. 5770, 2020.

[60] N. Hnoohom, A. Jitpattanakul, I. You, and S. Mekruksavanich, "Deep learning approach for complex activity recognition using heterogeneous sensors from wearable device," in *2021 Research, Invention, and Innovation Congress: Innovation Electricals and Electronics (RI2C)*. IEEE, 2021, pp. 60–65.

[61] U. Naeem and J. Bigham, "Activity recognition using a hierarchical framework," in *2008 Second International Conference on Pervasive Computing Technologies for Healthcare*. IEEE, 2008, pp. 24–27.

[62] M. Azam, J. Loo, U. Naeem, S. Khan, A. Lasebae, and O. Gemikonakli, "A framework to recognise daily life activities with wireless proximity and object usage data," in *23rd IEEE International Symposium on Personal, Indoor and Mobile Radio Communication 2012*. IEEE, 2012, pp. 590–595.

[63] S. Nasreen, M. A. Azam, U. Naeem, and M. A. Ghazanfar, "Inference of activities with unexpected actions using pattern mining," in *Adjunct Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing and Proceedings of the 2015 ACM International Symposium on Wearable Computers*. ACM, 2015, pp. 1479–1488.

[64] L. Chen, C. D. Nugent, J. Biswas, and J. Hoey, *Activity recognition in per-*

vasive intelligent environments. Springer Science & Business Media, 2011, vol. 4.

[65] G. Okeyo, L. Chen, H. Wang, and R. Sterritt, "A hybrid ontological and temporal approach for composite activity modelling," in *2012 IEEE 11th International Conference on Trust, Security and Privacy in Computing and Communications*. IEEE, 2012, pp. 1763–1770.

[66] K. Wongpatikaseree, M. Ikeda, M. Buranarach, T. Supnithi, A. O. Lim, and Y. Tan, "Activity recognition using context-aware infrastructure ontology in smart home domain," in *2012 Seventh International Conference on Knowledge, Information and Creativity Support Systems*. IEEE, 2012, pp. 50–57.

[67] G. Meditskos and I. Kompatsiaris, "iknow: Ontology-driven situational awareness for the recognition of activities of daily living," *Pervasive and Mobile Computing*, vol. 40, pp. 17–41, 2017.

[68] G. Baryannis, P. Woznowski, and G. Antoniou, "Rule-based real-time adl recognition in a smart home environment," in *International Symposium on Rules and Rule Markup Languages for the Semantic Web*. Springer, 2016, pp. 325–340.

[69] H. Sfar, A. Bouzeghoub, N. Ramoly, and J. Boudy, "Agacy monitoring: a model for activity recognition and uncertainty handling," in *European Semantic Web Conference*. Springer, 2017, pp. 254–269.

[70] L. Zhao and G. Li, "Abnomal activity identification method based on ontology and dempster-shafer theory," in *2018 10th International Conference on Intelligent Human-Machine Systems and Cybernetics (IHMSC)*, vol. 1. IEEE, 2018, pp. 289–292.

[71] K. Gayathri, K. Easwarakumar, and S. Elias, "Probabilistic ontology based activity recognition in smart homes using markov logic network," *Knowledge-Based Systems*, vol. 121, pp. 173–184, 2017.

[72] D. Riboni, T. Sztyler, G. Civitarese, and H. Stuckenschmidt, "Unsupervised recognition of interleaved activities of daily living through ontological and probabilistic reasoning," in *Proceedings of the 2016 ACM International Joint Conference on Pervasive and Ubiquitous Computing.* ACM, 2016, pp. 1–12.

[73] Z. Ding, Y. Peng, and R. Pan, "Bayesowl: Uncertainty modeling in semantic web ontologies," in *Soft computing in ontologies and semantic web.* Springer, 2006, pp. 3–29.

[74] M. Gomathisankaran, X. Yuan, and P. Kamongi, "Ensure privacy and security in the process of medical image analysis," in *2013 IEEE International Conference on Granular Computing (GrC).* IEEE, 2013, pp. 120–125.

[75] F. D. Garcia and B. Jacobs, "Privacy-friendly energy-metering via homomorphic encryption," in *International Workshop on Security and Trust Management.* Springer, 2010, pp. 226–238.

[76] A. Chattopadhyay and T. E. Boult, "Privacycam: a privacy preserving camera using uclinux on the blackfin dsp," in *2007 IEEE Conference on Computer Vision and Pattern Recognition.* IEEE, 2007, pp. 1–8.

[77] Z. Ren, Y. J. Lee, and M. S. Ryoo, "Learning to anonymize faces for privacy preserving action detection," in *Proceedings of the european conference on computer vision (ECCV)*, 2018, pp. 620–636.

[78] P. Garcia Lopez, A. Montresor, D. Epema, A. Datta, T. Higashino, A. Iamnitchi, M. Barcellos, P. Felber, and E. Riviere, "Edge-centric computing: Vision and challenges," 2015.

[79] H. Ajakan, P. Germain, H. Larochelle, F. Laviolette, and M. Marchand, "Domain-adversarial neural networks," *arXiv preprint arXiv:1412.4446*, 2014.

[80] H. Edwards and A. Storkey, "Censoring representations with an adversary," *arXiv preprint arXiv:1511.05897*, 2015.

[81] N. Phan, Y. Wang, X. Wu, and D. Dou, "Differential privacy preservation

for deep auto-encoders: an application of human behavior prediction," in *Thirtieth AAAI Conference on Artificial Intelligence*, 2016.

[82] N. Papernot, M. Abadi, U. Erlingsson, I. Goodfellow, and K. Talwar, "Semi-supervised knowledge transfer for deep learning from private training data," *arXiv preprint arXiv:1610.05755*, 2016.

[83] P. Rashidi and D. J. Cook, "Keeping the resident in the loop: Adapting the smart home to the user." *IEEE Trans. Systems, Man, and Cybernetics, Part A*, vol. 39, no. 5, pp. 949–959, 2009.

[84] N. Zhu, T. Diethe, M. Camplani, L. Tao, A. Burrows, N. Twomey, D. Kaleshi, M. Mirmehdi, P. Flach, and I. Craddock, "Bridging e-health and the internet of things: The sphere project," *IEEE Intelligent Systems*, vol. 30, no. 4, pp. 39–46, 2015.

[85] B. Alsinglawi, Q. V. Nguyen, U. Gunawardana, A. Maeder, and S. J. Simoff, "Rfid systems in healthcare settings and activity of daily living in smart homes: A review," *E-Health Telecommunication Systems and Networks*, vol. 6, pp. 1–17, 2017.

[86] D. P.-D. de Cerio, S. R. Boque, J. Rosell-Ferrer, J. Ramoscastro, J. L. Valenzuela, and J. M. Colome, "The help4mood wearable sensor network for inconspicuous activity measurement," *IEEE Wireless Communications*, vol. 20, no. 4, pp. 50–56, 2013.

[87] A. Rocha, M. R. Henriques, J. C. Lopes, R. Camacho, M. Klein, G. Modena, P. Van de Ven, E. McGovern, E. Tousset, T. Gauthier *et al.*, "Ict4depression: Service oriented architecture applied to the treatment of depression," in *2012 25th IEEE International Symposium on Computer-Based Medical Systems (CBMS)*. IEEE, 2012, pp. 1–6.

[88] L. Chen and C. Nugent, "Ontology-based activity recognition in intelligent pervasive environments," *International Journal of Web Information Systems*,

2009.

[89] A. G. Salguero and M. Espinilla, "Ontology-based feature generation to improve accuracy of activity recognition in smart environments," *Computers & Electrical Engineering*, vol. 68, pp. 1–13, 2018.

[90] R. Kolkar and V. Geetha, "Issues and challenges in various sensor-based modalities in human activity recognition system," in *Applications of Advanced Computing in Systems*. Springer, 2021, pp. 171–179.

[91] G. Okeyo, L. Chen, H. Wang, and R. Sterritt, "Dynamic sensor data segmentation for real-time knowledge-driven activity recognition," *Pervasive and Mobile Computing*, vol. 10, pp. 155–172, 2014.

[92] D. Triboan, L. Chen, F. Chen, and Z. Wang, "Semantic segmentation of real-time sensor data stream for complex activity recognition," *Personal and Ubiquitous Computing*, vol. 21, no. 3, pp. 411–425, 2017.

[93] F. Attal, S. Mohammed, M. Dedabrishvili, F. Chamroukhi, L. Oukhellou, and Y. Amirat, "Physical human activity recognition using wearable sensors," *Sensors*, vol. 15, no. 12, pp. 31 314–31 338, 2015.

[94] A. D. Antar, M. Ahmed, and M. A. R. Ahad, "Challenges in sensor-based human activity recognition and a comparative analysis of benchmark datasets: a review," in *2019 Joint 8th International Conference on Informatics, Electronics & Vision (ICIEV) and 2019 3rd International Conference on Imaging, Vision & Pattern Recognition (icIVPR)*. IEEE, 2019, pp. 134–139.

[95] Q. Li, R. Gravina, Y. Li, S. H. Alsamhi, F. Sun, and G. Fortino, "Multi-user activity recognition: Challenges and opportunities," *Information Fusion*, vol. 63, pp. 121–135, 2020.

[96] H. Liu, H. Darabi, P. Banerjee, and J. Liu, "Survey of wireless indoor positioning techniques and systems," *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews)*, vol. 37, no. 6, pp. 1067–

1080, 2007.

[97] L. Batistíc and M. Tomic, "Overview of indoor positioning system technologies. 2018 41st international convention on information and communication technology, electronics and microelectronics (mipro), 473-478," 2018.

[98] R. Mautz, "Indoor positioning technologies," 2012.

[99] I. T. Haque and C. Assi, "Profiling-based indoor localization schemes," *IEEE Systems Journal*, vol. 9, no. 1, pp. 76–85, 2013.

[100] P. Bahl and V. N. Padmanabhan, "Radar: An in-building rf-based user location and tracking system," in *Proceedings IEEE INFOCOM 2000. Conference on computer communications. Nineteenth annual joint conference of the IEEE computer and communications societies (Cat. No. 00CH37064)*, vol. 2. Ieee, 2000, pp. 775–784.

[101] A. A. W. Ab Razak and F. Samsuri, "Active rfid-based indoor positioning system (ips) for industrial environment," in *2015 IEEE International RF and Microwave Conference (RFM)*. IEEE, 2015, pp. 89–91.

[102] Y. Á. López, M. E. de Cos Gómez, and F. L.-H. Andrés, "A received signal strength rfid-based indoor location system," *Sensors and Actuators A: Physical*, vol. 255, pp. 118–133, 2017.

[103] V. Pasku, A. De Angelis, G. De Angelis, D. D. Arumugam, M. Dionigi, P. Carbone, A. Moschitta, and D. S. Ricketts, "Magnetic field-based positioning systems," *IEEE Communications Surveys & Tutorials*, vol. 19, no. 3, pp. 2003–2017, 2017.

[104] K. A. Nguyen and Z. Luo, "Dynamic route prediction with the magnetic field strength for indoor positioning," *International Journal of Wireless and Mobile Computing*, vol. 12, no. 1, pp. 16–35, 2017.

[105] B. Gozick, K. P. Subbu, R. Dantu, and T. Maeshiro, "Magnetic maps for indoor navigation," *IEEE Transactions on Instrumentation and Measure-*

ment, vol. 60, no. 12, pp. 3883–3891, 2011.

[106] A. Alarifi, A. Al-Salman, M. Alsaleh, A. Alnafessah, S. Al-Hadhrami, M. Al-Ammar, and H. Al-Khalifa, "Ultra wideband indoor positioning technologies: Analysis and recent advances," *Sensors*, vol. 16, no. 5, p. 707, 2016.

[107] J. Torres-Sospedra, R. Montoliu, G. M. Mendoza-Silva, O. Belmonte, D. Rambla, and J. Huerta, "Providing databases for different indoor positioning technologies: Pros and cons of magnetic field and wi-fi based positioning," *Mobile Information Systems*, vol. 2016, 2016.

[108] X. Zhao, Z. Xiao, A. Markham, N. Trigoni, and Y. Ren, "Does btle measure up against wifi? a comparison of indoor location performance," in *European Wireless 2014; 20th European Wireless Conference*. VDE, 2014, pp. 1–6.

[109] P. Kriz, F. Maly, and T. Kozel, "Improving indoor localization using bluetooth low energy beacons," *Mobile Information Systems*, vol. 2016, 2016.

[110] J. Torres-Solis, T. H. Falk, and T. Chau, "A review of indoor localization technologies: towards navigational assistance for topographical disorientation," in *Ambient Intelligence*. IntechOpen, 2010.

[111] P. Zhang, Q. Zhao, Y. Li, X. Niu, Y. Zhuang, and J. Liu, "Collaborative wifi fingerprinting using sensor-based navigation on smartphones," *Sensors*, vol. 15, no. 7, pp. 17 534–17 557, 2015.

[112] S. Chaudhry, "Indoor location estimation using an nfc-based crowdsourcing approach for bootstrapping," Ph.D. dissertation, Master's Thesis). University of Oulu, Department of Computer Science and . . . , 2013.

[113] B. Zhou, Q. Li, Q. Mao, and W. Tu, "A robust crowdsourcing-based indoor localization system," *Sensors*, vol. 17, no. 4, p. 864, 2017.

[114] J. Haverinen and A. Kemppainen, "Global indoor self-localization based on the ambient magnetic field," *Robotics and Autonomous Systems*, vol. 57, no. 10, pp. 1028–1035, 2009.

[115] K. A. Nguyen, "Robot-based evaluation of bluetooth fingerprinting," *Unpublished master's thesis). Computer Lab, University of Cambridge*, 2011.

[116] R. Faragher and R. Harle, "Location fingerprinting with bluetooth low energy beacons," *IEEE journal on Selected Areas in Communications*, vol. 33, no. 11, pp. 2418–2428, 2015.

[117] L. Fernandes, S. Santos, M. Barandas, D. Folgado, R. Leonardo, R. Santos, A. Carreiro, and H. Gamboa, "An infrastructure-free magnetic-based indoor positioning system with deep learning," *Sensors*, vol. 20, no. 22, p. 6664, 2020.

[118] J. H. An and L. Choi, "Inverse fingerprinting: Server side indoor localization with bluetooth low energy," in *2016 IEEE 27th Annual International Symposium on Personal, Indoor, and Mobile Radio Communications (PIMRC)*. IEEE, 2016, pp. 1–6.

[119] Mbientlab. (2018) Product specification v0.5. [Online]. Available: https://mbientlab.com/documents/MetaMotionR-PS3.pdf

[120] P. Davidson and R. Piché, "A survey of selected indoor positioning methods for smartphones," *IEEE Communications Surveys & Tutorials*, vol. 19, no. 2, pp. 1347–1370, 2016.

[121] Y. Li, Y. Zhuang, H. Lan, P. Zhang, X. Niu, and N. El-Sheimy, "Wifi-aided magnetic matching for indoor navigation with consumer portable devices," *Micromachines*, vol. 6, no. 6, pp. 747–764, 2015.

[122] E. Wang, M. Wang, Z. Meng, and X. Xu, "A study of wifi-aided magnetic matching indoor positioning algorithm," *J. Comput. Sci. Commun*, vol. 5, pp. 91–101, 2017.

[123] S. Dernbach, B. Das, N. C. Krishnan, B. L. Thomas, and D. J. Cook, "Simple and complex activity recognition through smart phones," in *2012 Eighth International Conference on Intelligent Environments*. IEEE, 2012, pp.

214–221.

[124] J. Torres, Ó. Belmonte, R. Montoliu, S. Trilles, and A. Calia, "How feasible is wifi fingerprint-based indoor positioning for in-home monitoring?" in *2016 12th International Conference on Intelligent Environments (IE).* IEEE, 2016, pp. 68–75.

[125] M. Philipose, K. P. Fishkin, M. Perkowitz, D. J. Patterson, D. Fox, H. Kautz, and D. Hahnel, "Inferring activities from interactions with objects," *IEEE pervasive computing*, no. 4, pp. 50–57, 2004.

[126] A. Jiménez and F. Seco, "Event-driven real-time location-aware activity recognition in aal scenarios," in *Multidisciplinary Digital Publishing Institute Proceedings*, vol. 2, no. 19, 2018, p. 1240.

[127] T. Morita, K. Taki, M. Fujimoto, H. Suwa, Y. Arakawa, and K. Yasumoto, "Beacon-based time-spatial recognition toward automatic daily care reporting for nursing homes," *Journal of Sensors*, vol. 2018, 2018.

[128] T. Tegou, I. Kalamaras, M. Tsipouras, N. Giannakeas, K. Votis, and D. Tzovaras, "A low-cost indoor activity monitoring system for detecting frailty in older adults," *Sensors*, vol. 19, no. 3, p. 452, 2019.

[129] E. Nakagawa, K. Moriya, H. Suwa, M. Fujimoto, Y. Arakawa, and K. Yasumoto, "Toward real-time in-home activity recognition using indoor positioning sensor and power meters," in *2017 IEEE International Conference on Pervasive Computing and Communications Workshops (PerCom Workshops).* IEEE, 2017, pp. 539–544.

[130] X. Ye, Y. Wang, W. Hu, L. Song, Z. Gu, and D. Li, "Warpmap: Accurate and efficient indoor location by dynamic warping in sequence-type radio-map," in *2016 13th Annual IEEE International Conference on Sensing, Communication, and Networking (SECON).* IEEE, 2016, pp. 1–9.

[131] M. Sridharan, J. Bigham, C. Phillips, and E. Bodanese, "Collaborative loca-

tion estimation for confined spaces using magnetic field and inverse beacon positioning," in *2017 IEEE SENSORS*. IEEE, 2017, pp. 1–3.

[132] K. P. Subbu, B. Gozick, and R. Dantu, "Indoor localization through dynamic time warping," in *2011 IEEE International Conference on Systems, Man, and Cybernetics*. IEEE, 2011, pp. 1639–1644.

[133] H. Alt and M. Godau, "Computing the fréchet distance between two polygonal curves," *International Journal of Computational Geometry & Applications*, vol. 5, no. 01n02, pp. 75–91, 1995.

[134] M. Sridharan, J. Bigham, P. M. Campbell, and E. Bodanese, "Evaluation of factors affecting inverse beacon fingerprinting using route prediction algorithm," in *2019 IEEE Wireless Communications and Networking Conference (WCNC)*. IEEE, 2019, pp. 1–7.

[135] K. Liu, Y. Wang, L. Lin, and G. Chen, "An analysis of impact factors for positioning performance in wlan fingerprinting systems using ishikawa diagrams and a simulation platform," *Mobile Information Systems*, vol. 2017, 2017.

[136] V. Moghtadaiee and A. G. Dempster, "Design protocol and performance analysis of indoor fingerprinting positioning systems," *Physical Communication*, vol. 13, pp. 17–30, 2014.

[137] J. Jiao, F. Li, Z. Deng, and W. Ma, "A smartphone camera-based indoor positioning algorithm of crowded scenarios with the assistance of deep cnn," *Sensors*, vol. 17, no. 4, p. 704, 2017.

[138] J. Rapiński, D. Zinkiewicz, and T. Stanislawek, "Influence of human body on radio signal strength indicator readings in indoor positioning systems," *Technical Sciences/University of Warmia and Mazury in Olsztyn*, no. 19 (2), pp. 117–127, 2016.

[139] J. S. Turner, M. F. Ramli, L. Kamarudin, A. Zakaria, A. Y. M. Shakaff,

D. L. Ndzi, C. Nor, N. Hassan, and S. M. Mamduh, "The study of human movement effect on signal strength for indoor wsn deployment," in *2013 IEEE Conference on Wireless Sensor (ICWISE)*. IEEE, 2013, pp. 30–35.

[140] E. Della Valle, S. Ceri, F. Van Harmelen, and D. Fensel, "It's a streaming world! reasoning upon rapidly changing information," *IEEE Intelligent Systems*, vol. 24, no. 6, pp. 83–89, 2009.

[141] D. F. Barbieri, D. Braga, S. Ceri, E. D. Valle, and M. Grossniklaus, "C-sparql: Sparql for continuous querying," in *Te 18th international conference on World wide web-WWW'09*, 2009, pp. 1061–1062.

[142] D. F. Barbieri, D. Braga, S. Ceri, E. D. VALLE, and M. Grossniklaus, "C-sparql: a continuous query language for rdf data streams," *International Journal of Semantic Computing*, vol. 4, no. 01, pp. 3–25, 2010.

[143] A. Bolles, M. Grawunder, and J. Jacobi, "Streaming sparql-extending sparql to process data streams," in *European Semantic Web Conference*. Springer, 2008, pp. 448–462.

[144] D. Le Phuoc, M. Dao-Tran, A. Le Tuan, M. N. Duc, and M. Hauswirth, "Rdf stream processing with cqels framework for real-time analysis," in *Proceedings of the 9th ACM International Conference on Distributed Event-Based Systems*. ACM, 2015, pp. 285–292.

[145] E. Miller, "An introduction to the resource description framework," *Bulletin of the American Society for Information Science and Technology*, vol. 25, no. 1, pp. 15–19, 1998.

[146] P. Domingos and D. Lowd, "Unifying logical and statistical ai with markov logic," *Communications of the ACM*, vol. 62, no. 7, pp. 74–83, 2019.

[147] S. Matsumoto, R. N. Carvalho, M. Ladeira, P. C. G. da Costa, L. L. Santos, D. Silva, M. Onishi, E. Machado, and K. Cai, "Unbbayes: a java framework for probabilistic models in ai," *Java in academia and research*, p. 34, 2011.

[148] G. Civitarese, C. Bettini, T. Sztyler, D. Riboni, and H. Stuckenschmidt, "Nectar: Knowledge-based collaborative active learning for activity recognition," in *2018 IEEE International Conference on Pervasive Computing and Communications (PerCom).* IEEE, 2018, pp. 1–10.

[149] P. Chahuara, A. Fleury, F. Portet, and M. Vacher, "Using markov logic network for on-line activity recognition from non-visual home automation sensors," in *International Joint Conference on Ambient Intelligence.* Springer, 2012, pp. 177–192.

[150] R. Helaoui, M. Niepert, and H. Stuckenschmidt, "Recognizing interleaved and concurrent activities: A statistical-relational approach," in *2011 IEEE International Conference on Pervasive Computing and Communications (PerCom).* IEEE, 2011, pp. 1–9.

[151] M. Bruynooghe, T. Mantadelis, A. Kimmig, B. Gutmann, J. Vennekens, G. Janssens, and L. De Raedt, "Problog technology for inference in a probabilistic first order logic," in *ECAI 2010-19th European Conference on Artificial Intelligence*, vol. 215. IOS Press, 2010, pp. 719–724.

[152] T. Sztyler, G. Civitarese, and H. Stuckenschmidt, "Modeling and reasoning with problog: an application in recognizing complex activities," in *2018 IEEE International Conference on Pervasive Computing and Communications Workshops (PerCom Workshops).* IEEE, 2018, pp. 259–264.

[153] M. Fernandez-Carmona and N. Bellotto, "On-line inference comparison with markov logic network engines for activity recognition in aal environments," in *2016 12th International Conference on Intelligent Environments (IE).* IEEE, 2016, pp. 136–143.

[154] G. M. Santipantakis, A. Vlachou, C. Doulkeridis, A. Artikis, I. Kontopoulos, and G. A. Vouros, "A stream reasoning system for maritime monitoring," in *25th International Symposium on Temporal Representation and Reasoning*

(TIME 2018). Schloss Dagstuhl-Leibniz-Zentrum fuer Informatik, 2018.

[155] D. F. Barbieri, D. Braga, S. Ceri, E. Della Valle, and M. Grossniklaus, "Continuous queries and real-time analysis of social semantic data with c-sparql," in *ISWC 2009: Second Workshop on Social Data on the Web (SDoW2009)*, 2009.

[156] Q. Zhou, S. McLaughlin, A. J. Gray, S. Wu, and C. Wang, "Lost silence: An emergency response early detection service through continuous processing of telecommunication data streams," *arXiv preprint arXiv:1903.05372*, 2019.

[157] T. M. Do, S. W. Loke, and F. Liu, "Healthylife: An activity recognition system with smartphone using logic-based stream reasoning," in *International conference on mobile and ubiquitous systems: computing, networking, and services.* Springer, 2012, pp. 188–199.

[158] A. BakhshandehAbkenar and S. W. Loke, "Myactivity: Cloud-hosted continuous activity recognition using ontology-based stream reasoning," in *2014 2nd IEEE International Conference on Mobile Cloud Computing, Services, and Engineering.* IEEE, 2014, pp. 117–126.

[159] D. L. McGuinness, F. Van Harmelen *et al.*, "Owl web ontology language overview," *W3C recommendation*, vol. 10, no. 10, p. 2004, 2004.

[160] N. D. Rodríguez, M. P. Cuéllar, J. Lilius, and M. D. Calvo-Flores, "A survey on ontologies for human behavior recognition," *ACM Computing Surveys (CSUR)*, vol. 46, no. 4, pp. 1–33, 2014.

[161] P. Domingos, D. Lowd, S. Kok, H. Poon, M. Richardson, and P. Singla, "Just add weights: Markov logic for the semantic web," in *Uncertainty Reasoning for the Semantic Web I.* Springer, 2006, pp. 1–25.

[162] H. Poon and P. Domingos, "Sound and efficient inference with probabilistic and deterministic dependencies," in *AAAI*, vol. 6, 2006, pp. 458–463.

[163] J. H. Gennari, M. A. Musen, R. W. Fergerson, W. E. Grosso, M. Crubézy,

H. Eriksson, N. F. Noy, and S. W. Tu, "The evolution of protégé: an environment for knowledge-based systems development," *International Journal of Human-computer studies*, vol. 58, no. 1, pp. 89–123, 2003.

[164] P. Oliveira and P. Gomes, "Instance-based probabilistic reasoning in the semantic web," in *Proceedings of the 18th international conference on World wide web.* ACM, 2009, pp. 1067–1068.

[165] S. Richardson, P. Domingos, and M. S. H. Poon, "The alchemy system for statistical relational ai: User manual," 2007.

[166] G. Singla, D. J. Cook, and M. Schmitter-Edgecombe, "Tracking activities in complex settings using smart environment technologies," *International journal of biosciences, psychiatry, and technology (IJBSPT)*, vol. 1, no. 1, p. 25, 2009.

[167] M. H. Kabir, M. R. Hoque, K. Thapa, and S.-H. Yang, "Two-layer hidden markov model for human activity recognition in home environments," *International Journal of Distributed Sensor Networks*, vol. 12, no. 1, p. 4560365, 2016.