# A Novel Approach to Complex Human Activity Recognition

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# A NOVEL APPROACH TO COMPLEX HUMAN ACTIVITY RECOGNITION

by

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ABSTRACT
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Human activity recognition is a technology that offers automatic recognition of what a person is doing with respect to body motion and function. The main goal is to recognize a person's activity using different technologies such as cameras, motion sensors, location sensors, and time. Human activity recognition is important in many areas such as pervasive computing, artificial intelligence, human-computer interaction, health care, health outcomes, rehabilitation engineering, occupational science, and social sciences. There are numerous ubiquitous and pervasive computing systems where users' activities play an important role. The human activity carries a lot of information about the context and helps systems to achieve context-awareness. In the rehabilitation area, it helps with functional diagnosis and assessing health outcomes. Human activity recognition is an important indicator of participation, quality of life and lifestyle.

There are two classes of human activities based on body motion and function. The first class, simple human activity, involves human body motion and posture, such as walking, running, and sitting. The second class, complex human activity, includes function along with simple human activity, such as cooking, reading, and watching TV. Human activity recognition is an interdisciplinary research area that has been active for more than a decade. Substantial research has been conducted to recognize human activities, but, there are many major issues still need to be addressed. Addressing these issues would provide a significant improvement in different aspects of the applications of the human activity recognition in different areas. There has been considerable research conducted on simple human activity recognition, whereas, a little research has been carried out on complex human activity recognition. However, there are many key aspects (recognition accuracy, computational cost, energy consumption, mobility) that need to be addressed in both areas to improve their viability. This dissertation aims to address the key aspects in both areas of human activity recognition and eventually focuses on recognition of complex activity. It also addresses indoor and outdoor localization, an important parameter along with time in complex activity recognition. This work studies accelerometer sensor data to recognize simple human activity and time, location and simple activity to recognize complex activity.

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# CHAPTER 1

# INTRODUCTION

Automated recognition of human activities has importance across different research areas including artificial intelligence, ubiquitous and pervasive computing, human-computer interaction, human-robot interaction, rehabilitation engineering, assistive technology, health outcomes, social networking, and social sciences. There are numerous context-aware applications where users' activities play an important role. It also plays a pivotal role in designing pervasive computing systems. Human activity recognition (HAR) is an interdisciplinary research area that has been active for more than a decade, but, there are many major issues that still need to be addressed. Addressing these issues would provide a significant improvement in different aspects of the applications of the HAR in various fields.

Humans perform numerous activities throughout the day. There are two classes of activities based on body motion and functionality. The first class is simple full body motor activity, and the second class is complex functional activity. The full body motor activity considers human body motion and posture, for example, walking, sitting, running, taking the stairs, or standing. The second class, complex functional activity, deals with different functions performed by a human, for instance, reading, working on the computer, watching TV, playing tennis, cooking, or vacuuming. There has been substantial research conducted on simple human activity recognition, whereas, little research has been carried out on complex human activity recognition. Many key aspects (recognition accuracy, computational cost, energy consumption, privacy, mobility) need to be addressed in both areas to improve their viability.

Building system to recognize context from real-world observation is a challenging task. With the proliferation of location-based services (LBS), the idea of the context focuses mainly on the user's location. The combination of location and activity forms the context. This combination helps to describe context well and provides more meaningful information to make systems context-aware. The ubiquitous and pervasive computing systems focus more on providing seamless services to the user based on their context. Therefore, there is an increasing demand for localization and human activity recognition in pervasive and ubiquitous computing areas.

In rehabilitation research, human activity recognition helps to perform functional diagnosis and outcome assessment. It is also an indicator of participation, quality of life (QoL) and lifestyle. The automated recognition of human activities allows automatic health monitoring, evidence-based healthcare. It provides an objective measure for medical personnel. It can also be used for evaluation in self-care and self-management. With automatic human activity recognition, it is possible to monitor remotely and provide assistance to residents in assisted living. Such systems offer continuous monitoring and ensure the safety and well-being of its residents.

In this dissertation, we address the key aspects in both areas of human activity recognition with particular focus on complex functional activity recognition. We also address indoor and outdoor localization, one of the most influential parameters in context-awareness and complex functional activity recognition. We also describe the development of a novel complex functional activity recognition system. The time, location, and simple full body motor activity have been studied to recognize complex functional activity. In this work, we address the challenges related to 1) algorithm and system development of infrastructure-less and ubiquitous localization system for both indoor and outdoor, 2) development of a computationally inexpensive approach to recognize simple human activities from kinematic sensors, 3) development of simple human activity recognition system as a service, 4) framework and system development of complex functional activity recognition.

### 1.1 Dissertation focus

In this dissertation, we first focus on understanding the challenges in developing an automated system to recognize complex functional activities. Based on this, we then propose a complex activity recognition framework. We also describe our design and development of a smartphone based ubiquitous localization system using received signal strength indicator (RSSI) of the wireless device. The goal of this localization system is to build an infrastructure-less, energy efficient, and cost effective solution for finding indoor and outdoor locations using a smartphone. Later we focus on developing an efficient simple human activity recognition system using kinematic sensors from a smartphone. In the end, we focus on the study to recognize complex functional activities using time, location and simple human activity.

### 1.2 Dissertation Statement

It is possible to recognize simple and complex human activities unobtrusively using time, location and inertial sensor with reduced complexity and improved accuracy.

### 1.3 Research Challenges

In this dissertation, we aim to make several contributions by addressing following research challenges:

- An infrastructure-less and ubiquitous localization system for both indoors and outdoors.
- A computationally efficient technique to recognize simple human activities using the inertial sensor.
- A framework to recognize complex functional human activities.
- Evaluation of the human activity recognition approach with real data and real-life application.

### 1.4 Dissertation organization

The organization of this dissertation is as follows:

- In Chapter 2, we introduce and describe different human activities. We discuss different terminologies widely used in human activity recognition research. In this chapter, we present definition and classification of these activities with examples. Then we present the taxonomy of human activity recognition approaches that have been studied for more than a decade. Each of the approaches is discussed briefly with device, sensor, and signal used to classify activities.
- In Chapter 3, we present the mathematical models, machine learning techniques, and the foundation of the algorithmic development and analysis. In this chapter, we discuss the background mathematics and algorithm for each of the experiments. We present a brief descriptions of exponential regression,

time-delay embedding (reconstructed phase space), Gaussian mixture models, maximum likelihood classifier, Markov model, hidden Markov model, and Viterbi algorithm.

- In Chapter 4, we describe the RSSI-based localization technique for a smartphone. In this chapter, we present an extensive comparative survey of existing localization techniques based on wireless technology. Then we present the mathematics to model the location using RSSI. We describe experiments and performance comparison between mobile and fixed wireless devices. Finally, we evaluate the application of localization by developing an asset/object tracking system using the proposed approach.

- In Chapter 5, we present the simple human activity recognition system. In this chapter, we describe the objectives and challenges related to automatic recognition of simple human activity. We discuss the state-of-the-art research in simple human activity recognition. Then we present the mathematical model to capture the underlying dynamics of simple activities from accelerometer sensor data. We also present a sensor data collection tool for Android and data collection procedure. Later, we discuss the methodology and experimental details along with results. We compare proposed approach with existing work and present a quantitative analysis of efficiency with respect to time. Finally, we discuss the application of the proposed approach as a service in Android Application Framework.

- In Chapter 6, we describe the complex functional activity recognition system. In this chapter, we discuss background mathematics and data collection. Then we propose the framework to recognize complex human activities. After that, we present the data modeling and computation of HMM parameters from data. Later, we analyze experimental results for different settings and compare finding with existing approaches. Finally, we discuss findings, contribution, and applications.

- In Chapter 7, we present the summary of this dissertation. Then we discuss the contributions of the work with respect to each application area. Finally, we present the intellectual merit and broader impact of this dissertation.

## 1.5 Publications

### 1.5.1 Conferences/Journals

- **Md Osman Gani**, Amit Kumar Saha, Golam Mushih Tanimul Ahsan, Sheikh Iqbal Ahamed, Roger O. Smith, ”A Novel Framework to Recognize Complex Activity,” (IEEE COMPSAC 2017; As of the publication of this dissertation in April 5, 2017, this reference is **accepted** for publication).

- **Md Osman Gani**, Sheikh Iqbal Ahamed, Roger O. Smith, ”A Novel Framework to Recognize a Large Set of Complex Activities,” (Smart Health, Elsevier; As of the publication of this dissertation in April 5, 2017, this reference is currently **under review**).

- **Md Osman Gani**, Taskina Fayezeen, Sheikh I. Ahamed, Richard J. Povinelli, Roger O. Smith, Muhammad Arif, A. J. Kattan. ”A Novel Light Weight Smartphone based Activity Recognition using Gaussian Mixture Models of Reconstructed Phase Spaces,” IEEE Transaction on Mobile Computing, (As of the publication of this dissertation in April 5, 2017, this reference is currently **under review**).

- **Md Osman Gani**, Golam Mushih Tanimul Ahsan, Duc Do, Drew Williams, Mohammed Balfas , Sheikh Iqbal Ahamed, Muhammad Arif, Ahmed J. Kattan, ”An approach to localization in crowded area,” 2016 IEEE 18th International

Conference on e-Health Networking, Applications and Services (Healthcom), Munich, 2016, pp. 1-6.

- **Md Osman Gani**, Taskina Fayezeen, Sheikh Iqbal Ahamed, Richar J. Povinelli, ”Computationally Efficient Human Activity Modeling and its Application as a Service in Android Application Framework,” ACM HotMobile, February 2016, FL, USA.

- **Md Osman Gani**, Taskina Fayezeen, Sheikh Iqbal Ahamed, Dennis B. Tomashek, Roger O. Smith, ”Simple Activity Recognition Using Smartphone Technologies For In-Home Rehabilitation,” RESNA 2015 Annual Conference, June 2015, Denver, Colorado, USA.

- Farzana Rahman, **Md Osman Gani**, Golam Mushih Tanimul Ahsan and Seikh Iqbal Ahamed, ”Seeing Beyond Visibility: A Four Way Fusion of User Authentication for Efficient Usable Security on Mobile Devices,” 2014 IEEE Eighth International Conference on Software Security and Reliability-Companion, San Francisco, CA, 2014, pp. 121-129.

- **Md Osman Gani**, Sheikh Iqbal Ahamed, Samantha Ann Davis, Roger O. Smith, ”An Approach to Complex Functional Activity Recognition using Smartphone Technologies,” in Proceedings of RESNA 2014 Annual Conference, June 11 -15, 2014, Indianapolis, IN, USA.

- **Md Osman Gani**, Casey OBrien, Sheikh Iqbal Ahamed, Roger O. Smith, ”RSSI based Indoor Localization for Smartphone using Fixed and Mobile Wireless Node,” in Proceedings of IEEE 37th Annual Computer Software and Applications Conference (COMPSAC), July 22-26, 2013, Kyoto, Japan.

### 1.5.2 Poster

- **Md Osman Gani**, GMT Ahsan, Amit Kumar Saha, Sheikh Ahamed, ”Smart Spectacle Clip to Train and Prevent Fall,” Proceedings of the Forward Thinking Poster Session, Marquette University, WI, USA, Nov. 2016.

- Taskina Fayezeen, **Md Osman Gani**, Sheikha Iqbal Ahamed, ”mHealth System for the Patients with Arthritis,” Proceedings of the Forward Thinking Poster Session, Marquette University, WI, USA, Nov. 2015 (Best Poster Award).

- Piyush Saxena, **Md Osman Gani**, Sheikh Iqbal Ahamed, Stephen Yau, ”Situation-Aware Cyber-Human Environments for Enriched Assisted Living in,” Proceedings of the Forward Thinking Poster Session, Marquette University, WI, USA, Nov. 2014.

- **Md Osman Gani**, Duc Do, Balfas, Drew Williams, G M Tanimul, Sheikha Iqbal Ahamed, ”Ubitrack: Locating Lost Pilgrims in the Crowded Area of Makkah during Hajj,” Proceedings of the Forward Thinking Poster Session, Marquette University, WI, USA, Nov. 2014.

# Chapter 2

# HUMAN ACTIVITY AND HUMAN ACTIVITY RECOGNITION

There has been numerous research studies in the area of human activity recognition. Work on this area dates back to at least three decades. There are many terms related to human activities used in the literature. In this section, we briefly discuss important terms that have been used in the area of human activity recognition research. Though these terms are well established in respective fields [42] [38], we have seen these terms being employed in different meanings in the human activity recognition area. We also discuss the classification of human activities and state-of-the-art techniques to recognize human activities. We also present a taxonomy of HAR research approaches and briefly discuss each of the areas.

## 2.1 Terminology

- **Action:** The gesture or movement of a person is called an action.
- **Activity:** The Oxford dictionary defines the term *activity* as ”a thing that a person or group does or has done” [34].
- **Physical Activity:** According to the World Health Organization (WHO), ”physical activity is defined as any degree of physical motion or movement which is produced by skeletal muscles that involves energy expenditure” [108] [66]. According to the National Institute of Health, ”physical activity is any body movement that works your muscles and requires more energy than resting.” Examples are: walking, running, swimming, yoga, and gardening [104]. According to the Department of Health and Human Services ”2008 Physical Activity Guidelines for Americans,” physical activity is defined as the

movement that improves health [103].

- **Exercise:** A planned and structured physical activity is called exercise. Examples are: lifting weights, taking an aerobics class, and playing on a sports team [104].

## 2.2 Taxonomy of Human Activities

Lara [81] has studied the taxonomy of human activities classified by existing research studies. Other studies also have classified human activities into different classes [33]. These studies suggest that there are mainly two categories of activities, simple activity and complex activity. We define the simple activity and complex activity in the following subsection.

### 2.2.1 Simple Human Activity or Simple Activity

Simple full body motor activity, or simple human activity, or just simple activity, considers the body motion and posture while defining different activities (Figure 2.1). These include walking (Figure 2.1(a)), taking stairs (Figure 2.1(b)), sitting, standing, running (Figure 2.1(c)), lying (Figure 2.1(d)), jogging. The members of this class are differentiated only by the body motion and posture [33].

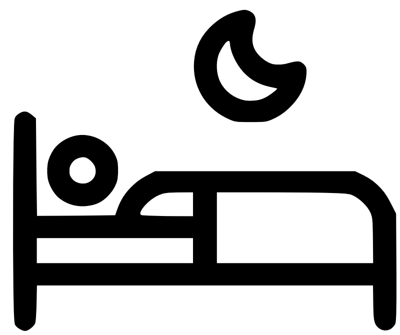
### 2.2.2 Complex Human Activity or Complex Activity

Complex functional activities are comprised of simple activity/activities and a specific function [33]. For example, when a person is reading a book (Figure 2.2(b)) it is most likely that the person is sitting somewhere (chair or couch). Here the complex activity is ”reading a book,” which is comprised of simple activity ”sitting” and the function ”reading.” Examples of complex activities (Figure 2.2) are playing soccer (Figure 2.2(a)), vacuuming, working on desk or computer (Figure 2.2(c)), brushing teeth, doing dishes, and eating dinner (Figure 2.2(d)). The specific function and related simple activity/activities differentiate the members of this class [81].

(a) Walking

(b) Taking Stairs

(c) Running



(d) Lying

Figure 2.1: Simple Human Activities, images are taken from [43]

Based on existing studies [81] [33] and the above definition, we present the taxonomy of the human activities that has been widely studied by the state-of-the-art research in the area of human activity recognition in Figure 2.3. Lara [81] suggested seven different types of activities in human activity recognition (HAR) systems. These are ambulation, daily activities, exercise, upper body, phone usage, transportation, and military. In the figure, as we go from left to right, we see the transition from simple activities to complex activities.

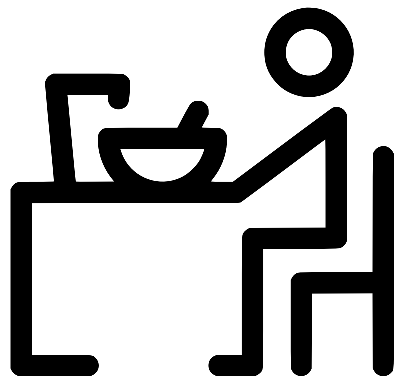
### 2.3 Taxonomy of Human Activity Recognition Approaches

There are mainly four different types of approaches used in HAR. These are: 1) computer vision-based HAR, 2) environmental sensor-based HAR, 3) wearable sensor-based HAR, and 4) time geography-based HAR. We present the taxonomy of

(a) Playing Soccer

(b) Reading Book

(c) Working on Computer



(d) Eating Dinner

Figure 2.2: Complex Human Activities, images are taken from [43]

HAR in Figure 2.4. We briefly discuss each of these in the following subsections.

### 2.3.1 Computer Vision

The computer vision approaches implement the HAR from a sequence of images or videos where the activities can be performed by one or more subjects [6] [69]. HAR is one of the promising applications in computer vision research. It requires cameras to be projected to a target region and captures images and videos [135].

### 2.3.2 Environmental Sensor

The environmental sensor approaches use sensors and signals, for example, the sound sensor on the floor, the light sensor in the room, radio frequency identification (RFID) as door tag, and signal strength of wireless devices (Wi-Fi, Bluetooth), to detect different activities [132] [101] [4].

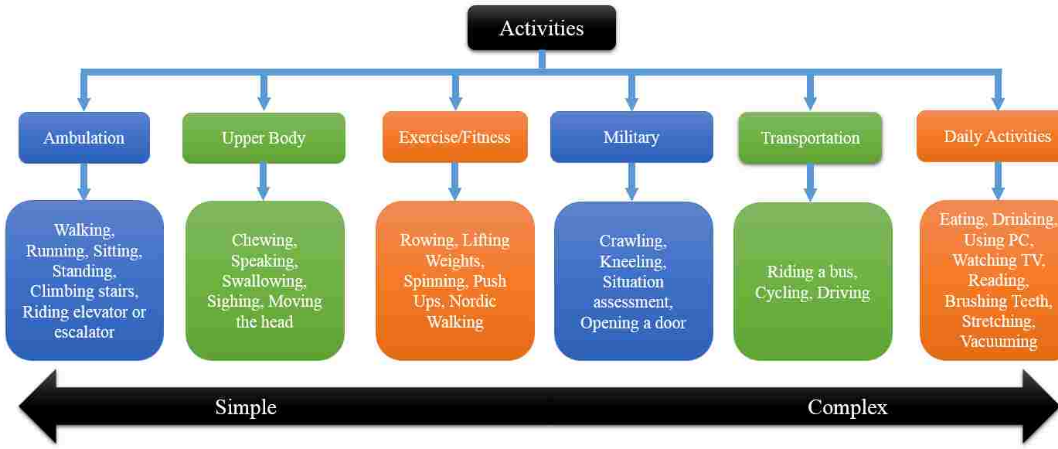



Figure 2.3: Taxonomy of Human Activities [81] [33]

### 2.3.3 Wearable Sensor

The wearable sensor approaches place kinematic sensors (accelerometer, gyroscope) on different parts of the body. It also includes the use of smartphone built-in sensors (accelerometer, gyroscope, pressure, GPS, magnetometer). The signals from these sensors are then processed to recognize activities [33] [152].

### 2.3.4 Time Geography

The time geography approaches use the time and location information to recognize human activities [29] [13]. Hagerrstrand first proposed that both time and location constraints human activities. He called it time geography [127]. Both time and location have been used separately to predict human activities.

We discuss these approaches more in detail in Chapters 5 and 6.

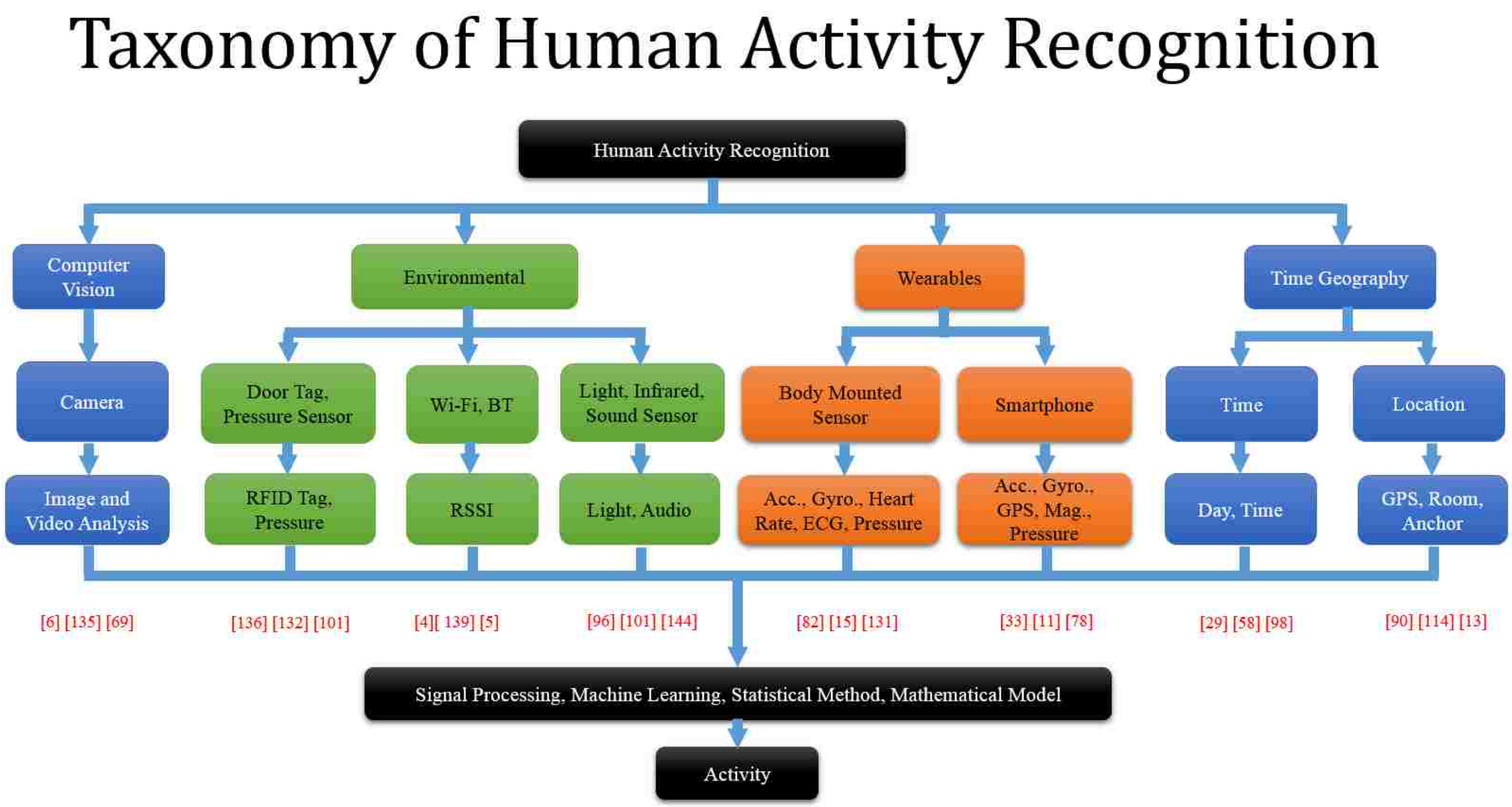



Figure 2.4: Taxonomy of Human Activity Recognition Approaches

# CHAPTER 3

# BACKGROUND

This chapter outlines the background mathematics of the approaches that is used in the remaining chapters. The exponential regression described here has application in localization (Chapter 4). The dynamical system, time-delay embedding, Gaussian Mixture Model, and Maximum Likelihood Classifier described here in this chapter have application in simple human activity recognition (Chapter 5). The Markov and Hidden Markov Model described here have used to model complex human activity recognition (Chapter 6).

## 3.1 Exponential Regression

The exponential regression is a process that finds the equation of the exponential function that best fits the given dataset (Figure 3.1). The focus of the process is the form of the exponential equation:

$$y = a * b^x \tag{3.1}$$

We have considered the following form, which is more specific form of the exponential equation (natural exponential function):

$$y = a * e^{c*x} \tag{3.2}$$

$e$ is considered the natural base of exponential functions as it is the derivative of its own.

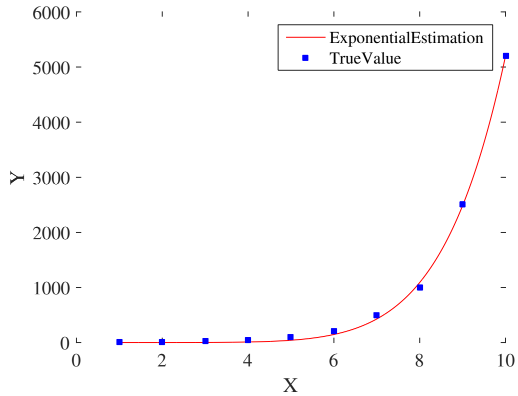



Figure 3.1: Exponential Regression

The Nelder-Mead simplex search algorithm is a popular direct search method to find minimum of the unconstrained multivariate function. This algorithm is one of the most widely used methods for nonlinear unconstrained optimization [Lagarias 1998]. This method attempts to find a minimum of a multivariate nonlinear scalar function with an initial estimate and without any derivative information. It falls under the general class of direct search methods.

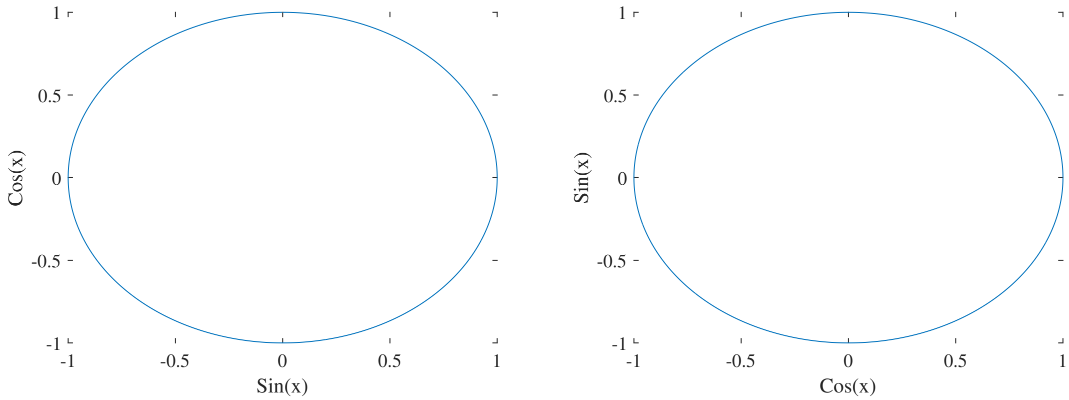
## 3.2 Delay Reconstruction of the Phase Space

### 3.2.1 Phase Space

The phase space represents all possible states of the system that evolve over time. Each point in the phase space corresponds to one possible state. The system parameters are represented as an axis of a multidimensional space (Figure 3.2).

### 3.2.2 Dynamical System

A dynamical system is a model that describes the evolution of a system over time. Theory of dynamical system attempts to understand and describe the temporal evolution of a system, which is defined in a phase space.




(a) Cos(x) vs Sin(x)

(b) Sin(x) vs Cos(x)

Figure 3.2: Phase Space

### 3.2.3 Reconstructed Phase Space

Given a time series $x$,

$$x = x_n, \quad n = 1...N, \tag{3.3}$$

where $n$ is the index and $N$ is the total number of observations. These observations are converted into state vectors according to Takens' delay embedding theorem,

$$X_n = [x_n, x_{n-\tau}, ..., x_{n-(d-1)\tau}], \tag{3.4}$$

where $\tau$ is the time delay and $d$ is the embedding dimension [128]. This process of delayed reconstruction is called time delay embedding. The newly formed state space is called Reconstructed Phase Space. This newly formed space is topologically equivalent to the original system. The time lag and embedding dimension can be estimated using different data driven approaches.

### 3.3 Gaussian Mixture Models

The Gaussian Mixture Models (GMM) is a parametric probability density function, which is a weighted sum of M Gaussian probability density function.

$$p(\chi, \lambda) = \sum_{i=1}^{M} w_i p_i(x) = \sum_{i=1}^{M} w_i \mathcal{N}(\chi, \mu_i, \Sigma_i), \tag{3.5}$$

where $M$ is the number of mixtures, $\mathcal{N}(x; \mu_i, \Sigma_i)$ is a normal distribution with mean $\mu_i$ and covariance matrix $\Sigma_i$, and $w_i$ is the mixture weight satisfy the constraint that $\sum_{i=1}^{M} w_i = 1$. The parameters of a complete parameterized Gaussian mixture is denoted by $\lambda$,

$$\lambda = \{w_i, \mu_i, \Sigma_i\} \quad i = 1, ..., M. \tag{3.6}$$

The parameters of the GMM are estimated using the Expectation-Maximization algorithm to maximize the likelihood of the data.

### 3.4 Maximum Likelihood Classifier

The Bayesian maximum likelihood classifier is defined as,

$$p(X|a_i) = \prod_{k=1}^{T} p(x_k|a_i), \tag{3.7}$$

where $p(x_k|a_i)$ is the likelihood of each point $x_k$ for each of the learned model, $a_i$ and $p(X|a_i)$ is the likelihood of $X$ given $a_i$. The maximum likelihood is computed from all the likelihood,

$$\hat{a} = \arg\max_{i} p(X|a_i). \tag{3.8}$$

### 3.5 Markov Model

The Markov Chain states that the present state has all the information that could influence the evolution of the future states. The process is a probabilistic process. The Markov property says, given the current state, future states are independent of the past states [48]. The Markov Model (MM) is a stochastic model that maintains the Markov property. It has two parameters, the initial probabilities of the states, $\pi$, and the transition probabilities between states, $A$.

### 3.6 Hidden Markov Model

The Hidden Markov Model (HMM) is a statistical MM and widely used technique in speech recognition and face recognition. It models the generative state sequences of a system from an observable sequence. HMM has three parameters, $\pi$, $A$, and $B$. The first two parameters are from MM. The third parameter, $B$, is the observation probability matrix.

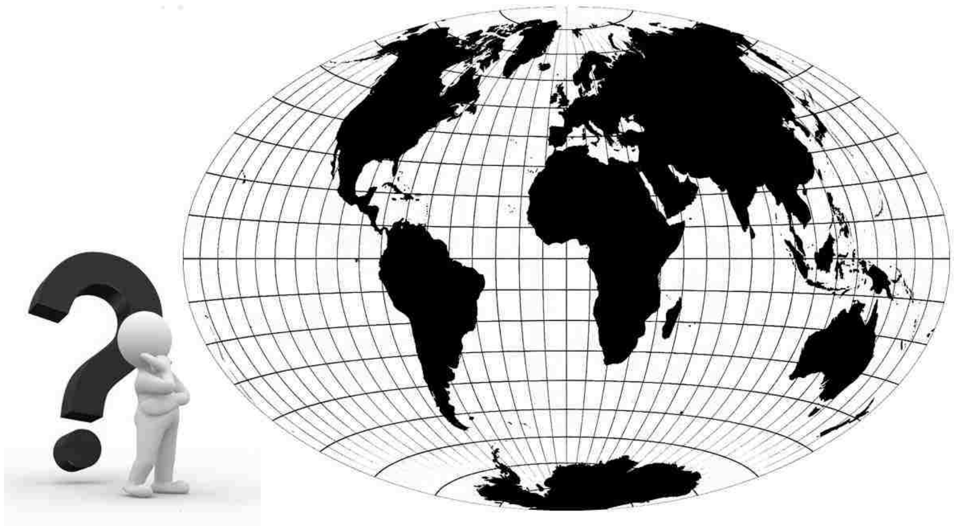
# CHAPTER 4

# INDOOR AND OUTDOOR LOCALIZATION

## 4.1 Introduction

Localization plays an important role in our everyday life (Figure 4.1). One of the developed systems for identifying location is the space-based satellite navigation Global Positioning System (GPS), which is widely used to get location and time information for military, civil and commercial users. Other localization techniques are based on different wireless networks such as Wi-Fi, ZigBee, and GSM. These techniques are used to get outdoor and indoor locations. There have been numerous location-based services (LBS) developed using GPS for the outdoor environment. Localization is used extensively in many applications such as navigation, map generation, complex activity recognition, patient identification, location tracking in hospitals, child tracking, disaster management, monitoring firefighters, indoor and outdoor navigation for humans or mobile robots, inventory control in factories, anomaly detection, customer interest observation in supermarkets, visitors interest observation in exhibitions, and smart houses [41] [46] [151] [61] [153]. These localization applications help us to solve a variety of real-life problems.

GPS has a good accuracy for outdoor localization, but, it does not offer good accuracy for indoor localization because of the unavailability and lack of reliability of signal inside buildings. It is also expensive in terms of energy and cost. Besides GPS, most of the other existing methods use fixed infrastructure to estimate location both indoors and outdoors. These methods require additional cost for the infrastructure. Also the infrastructure is stationary with respect to long-range user mobility. Hence, it is not possible to identify the location of the user accurately and sometimes it is



Where am I?

Figure 4.1: Localization: The Big Question. Images are taken from [28] and [109].

unavailable when users leave the service region. Some of these methods are adaptive, and others require training each time there is a change in the environment. Some of the approaches require additional setup time before they start working. Therefore, these methods need to recalibrate the system every time there is a change in the environment to improve their accuracy. Some of these techniques offer both indoor and outdoor localization, and others offer either one.

We have seen a huge growth in the number of smartphone users in recent years. Total shipments of smartphones in 2013 were 1004.2 million with annual growth of 38.4% percent from 2012 [134]. It reached the one billion unit mark in a single year for the first time. Most smartphones are equipped with various wireless adapters. They offer a range of useful sensors such as accelerometer, gyroscope, orientation sensor, magnetometer, barometer, GPS, Wi-Fi, and near field communication (NFC) [63]. They also have substantial computational power. Therefore, the use of the smartphone in any system eliminates the cost of additional devices and sensors.

We have worked on developing a system for localization using signal strength of wireless technology. In our work we have focused on solving problems noted in existing methods, include improving accuracy, eliminating infrastructure, reducing cost and setup time, supporting for both indoor and outdoor environment, and enhancing mobility. We have developed a mathematical model for estimating the location (both distance and direction) of a mobile device indoors and outdoors using Wi-Fi. We have used our developed model to build a localization system for smartphones (Android/iPhone). We have also implemented another approach called the fingerprint technique, to identify smartphone location using multiple mobile and fixed wireless routers.

#### 4.1.1 Contributions

In this research, we present an approach to determine the location of a mobile node using mobile and fixed wireless routers, and smartphone. Our research has the following contributions:

- An extensive comparative survey of existing localization techniques based on wireless technology
- A new approach to model the location of mobile nodes with received signal strength indicator (RSSI) of wireless devices
- Easy to use, infrastructure-less, and cost effective smartphone based localization system
- The proposed approach is ubiquitous and achieves good accuracy for both indoor and outdoor environments
- An unobtrusive system that protects user privacy
- Comparison of localization techniques with mobile and fixed wireless node (router).

### 4.2 Related Work

There have been significant research work on indoor and outdoor localization using wireless technology. These wireless technologies include Wi-Fi (Wireless Fidelity, IEEE 802.11), Bluetooth (IEEE 802.15.1), ZigBee (IEEE 802.15.4), GSM (Global System for Mobile Communications), WiMAX (Worldwide Interoperability for Microwave Access, IEEE 802.16), and RFID (Radio Frequency Identification) [63] [25] [85] [50] [117] [119] [143] [59]. These wireless technologies have been used with a number of different methods to estimate the location of the wireless device. There are several methods for estimating positioning using wireless technologies. There are three types of measurements mainly used in these techniques, a) Angle of Arrival (AOA) [85] b) Time of Arrival (TOA) and Time Difference of Arrival (TDOA) and c) Received Signal Strength Indicators (RSSI) [37]. Each of these parameters has advantages and disadvantages. In contrast with AOA and TOA/TDOA, measuring the RSSI value is simple. It is the measurement of the power of received wireless signal from the remote device, available in all existing wireless systems. Therefore RSSI based methods are preferable and easy to implement.

We can consider RSSI value as a function of distance from the source. RSSI value changes (even if the source and destination devices remain in the same position) for a number of reasons such as propagation losses, complex indoor layout, the orientation of the source and receiver, line of sight (LOS) requirement, and environmental changes. The key complexity here is that the wireless signals in an indoor environment suffer from interference and attenuation from multipath fading, reflection, channel fading, deflection, and diffraction. Due to the unpredictable behavior of this signal strength reading, estimating location with a low error rate is a challenging task.

In the last few years, researchers have proposed, simulated, and implemented many algorithms and techniques on localization using RSSI values and propagation time of wireless devices. Some of these methods are: a) Log distance path loss model [41] [151] [16], b) Trilateration [153] [10] [119], c) Multilateration [77], d) Fingerprint method [63] [120] [39], e) Centroid algorithm, f) Weighted Centroid algorithm [24] [7] [68], g) Maximum likelihood estimation (MLE) [12] [50] [68], h) K-nearest neighbors method [30] [117] [7], i) Kalman filter [41] [86], j) Particle filtering algorithm [7] [86], k) Min-Max [50] [154], l) Hidden Markov Model [57], m) Bayesian Method [120] [52], n) Artificial Neural Network [117], o) Principal Component Analysis [145] and p) Gaussian model [133] [153] [120]. Almost all of the methods use the RSSI value, a number of reference or anchor nodes (Access Point or APs), and a fingerprint map or RSSI database for the location estimation. The application of these localization techniques has a wide range of areas, including: a) indoor positioning [41] [61] [117], b) tracking moving objects [46] [151] [119] [86], c) navigation [51], d) monitoring firefighters [154], e) child tracking [143] [23], f) location based services [130], g) safety application in industrial automation [40], h) anomaly detection in wireless sensor network [142], i) locating underground miners [68], j) tracking and navigation of mobile robots [18] [51] [76], k) distance measurement [37] [133].

We have conducted an extensive survey of localization techniques in wireless technologies that use RSSI as a parameter to estimate location. We have tabulated a summary of these localization approaches in Table 4.1. It includes localization technique, algorithms or methods considered, parameters used, application of the approach, error, accuracy, and type of the experiment. The accuracy of the presented approaches varies with an approximate error between 1 meter and 5 meters.

Table 4.1: Comparison of Different Localization Approaches.

| Work | Area | Location | Algorithm | Parameters | Application | Error | Experiment |
|---|---|---|---|---|---|---|---|
| [41] | WSN | Indoor | Path Loss Model, Kalman Filter | RSSI, Beacon node | Indoor positioning | 4.85m | Real-time |
| [46] | WSN | Indoor | MAP criterion | RSSI, Anchor node, Close proximity, Line of Sight (LOS) | Tracking moving object in close proximity for medical application | Mean 0.7cm, Std Dev 4cm | Real-time |
| [151] | ZigBee | Not specified | Gaussian model, Log path loss model, Optimization algorithm | RSSI, Reference Node | Tracking multiple mobile robot | 3.38m to 5.1m | Simulation in Matlab |
| [61] | ZigBee | Not specified | Log path loss model, Antenna polarization | RSSI, Reference Node, Accelerometer | Location identification | 1.5m | Real-time |
| [153] | ZigBee | Outdoor | Gaussian model, Trilateration | RSSI, Beacon node | Localization | 1 to 5 m | Real-time |
| [63] | GSM | Not specified | Probabilistic fingerprint localization technique | RSSI, Cell information database | GSM positioning system | Improved accuracy 23.8% and 86.4% | Real-time |
| [25] | WLAN | Indoor | Radio Map | RSSI, Reference Node | Position detection | Accuracy: 32%-47% to find exact room | Real-time |
| [57] | WLAN | Indoor | Hidden Markov Model (HMM), Viterbi algorithm | RSSI, Reference APs | People location system | 50% | Real-time |

Table 4.1: Comparison of Different Localization Approaches.

| Work | Area | Location | Algorithm | Parameters | Application | Error | Experiment |
|---|---|---|---|---|---|---|---|
| [85] | WiMAX | Outdoor | Matrix Pencil for AOA | AOA, RSSI | 2D multi-user location system | ¡10m in 1Km range | Simulation in WiBro |
| [37] | WSN | Indoor, Line of sight | Adaptive Neural-Fuzzy, Inference System | RSSI, 3 Beacons | Distance measure | 2m mean | Real-time |
| [133] | WLAN | Indoor | Hop count based localization | RSSI | Distance measure | NA | Real-time |
| [30] | WLAN en-abled Smart phone | Indoor | K-Nearest neighbors, Nearest neighbors Mean, Linear Discriminant Analysis, Quadratic Discriminant Analysis | RSS, Reference APs | LBSs | Accuracy: KNN 62% NMM 58% LDA 53% QDA 56% | Real-time |
| [18] | WLAN | Indoor | Signal Strength Map, Monte Carlo Localization, Particle Filter | RSS, Reference APs | Localization of an indoor mobile robot on a map | Mean error 0.7m | Real-time |
| [83] | WLAN | Indoor | FBCM-Refinement | RSSI, Reference APs | Localization-based multimedia guide | 1.3m | Real-time |
| [120] | WLAN | Indoor | Fingerprint map, Nearest neighbors, Gaussian Method, Bayesian Method | RSSI, Reference APs | WSN | Error is less than 4m 90% of the time | Real-time |

Table 4.1: Comparison of Different Localization Approaches.

| Work | Area | Location | Algorithm | Parameters | Application | Error | Experiment |
|---|---|---|---|---|---|---|---|
| [10] | WLAN | Not specified | Triangulation method | RSSI, Reference Node | Qos | Error 5m | Real-time |
| [12] | WSN | Indoor | Maximum likelihood, Outline Rejection | RSSI | WSN ZigBee | Improves performance by 45% | Real-time |
| [50] | ZigBee | Indoor | Trilateration, Min-Max, MLE | RSSI, Reference APs | ZigBee | Mean error: 3.8, 12.21 4.79m respectively | Real-time |
| [52] | WLAN, PDA | Indoor | Fingerprint database, Euclidian distance, Delaunay-Triangulation, Bayesian Theorem | RSSI, Reference Node | WSN | Mean error: 2.91, 2.33, 2.00m respectively | Real-time |
| [16] | ZigBee | Indoor | Log distance path loss model, Global virtual calibration, Pre-wall virtual calibration, Ad-hoc calibration | RSSI, Anchor Node | WSN | Error 1.5m | Real-time |
| [36] | ZigBee | Outdoor, Indoor | Log distance path loss | RSSI, Reference Node | WSN | 40%reduced error | Real-time |

Table 4.1: Comparison of Different Localization Approaches.

| Work | Area | Location | Algorithm | Parameters | Application | Error | Experiment |
|---|---|---|---|---|---|---|---|
| [51] | ZigBee | Outdoor | Probability torus, Sequence based localization | RSSI, N Beacon node | Path driven by a robot in a map | 0.95m to 2.17m | Real-time |
| [117] | RFID | Indoor | K-Nearest neighbors, ANN (MLP) | RSSI, Beacon Node | Indoor localization | 83% | Real-time |
| [154] | ZigBee | Indoor | Min-Max | RSSI, Anchor Node | monitoring firefighters | 5m mean | Real-time |
| [119] | RFID | Outdoor | Trilateral, Path loss model | RSSI, Beacons | Track and monitor object in university area | 6.7m | Simulation in Matlab |
| [143] | GPS, Blue-tooth | Outdoor | Approximation of distance from RSSI [Y = -13.3 ln(x) - 47] | GPS, RSSI | Child tracking | Not specified | Real-time |
| [24] | WSN | Not specified | Weighted Centroid algorithm | RSSI, Beacon Node | Target localization and tracking | RMSE less than 3m | Simulation |
| [91] | WLAN | Indoor | Dominant AP's algorithm | RSSI, Reference Node | Location Based Services | Mean 3m | Real-time |
| [130] | WSN | Not specified | Log distance path loss model, Lateration estimation | RSSI, Reference Node | Anomaly Detection for WSN | Not specified | Simulation |
| [142] | WLAN | Indoor | K-nearest neighbors, Particle filter, Map filtering | RSSI, Anchor Node | WLAN | Mean 1.98m, Std Dev. 1.39m | Real-time |

Table 4.1: Comparison of Different Localization Approaches.

| Work | Area | Location | Algorithm | Parameters | Application | Error | Experiment |
|---|---|---|---|---|---|---|---|
| [7] | WSN | Indoor | Log distance path loss model, Weighted Centroid | RSSI, Anchor Node | ZigBee | Not specified | Real-time |
| [40] | WSN | Indoor | Antenna Diversity and Plausibility Filter | RSSI, Reference Node | WSN, Safety in Industrial Automation | 1 to 2.56m | Real-time |
| [86] | RFID | Not specified | Unscented Kalman and Particle Filter | RSSI, Reference Node | Tracking object | 2.2m for PF and 7.19m for UKF | Real-time |
| [68] | WSN | Under ground | Weighted minimum variance Centroid MLE | RSSI, Reference Node | ZigBee, Locate underground miners, vehicles and detect temperature | Location 20.5% distance 33.8% | Real-time |
| [23] | ZigBee | Outdoor | Piecewise linear path loss model, Min-Max | RSSI, Static Node | Park lighting control, Child tracking | RMS 3.5228 | Real-time |
| [76] | WSN | Not specified | RSSI formation control | RSSI, Beacon Node | Control mobile robot | Not specified | Simulation |
| [84] | RFID | Indoor, Outdoor | Enhancement algorithm | RSSI, Reference Node | Tracking user location | Mean 2.8m | Real-time |
| [77] | WLAN | Indoor | Multilateration with RSSI linearization | RSSI, Reference Node | WSN | 15.99m in an 50x50m area | Simulation |
| [39] | WLAN | Indoor | Time-Space Sampling Mobile device calibration | RSSI, Fingerprint database | Not specified | Not applicable | Not applicable |

Table 4.1: Comparison of Different Localization Approaches.

| Work | Area | Location | Algorithm | Parameters | Application | Error | Experiment |
|---|---|---|---|---|---|---|---|
| [110] | WLAN, RFID | Indoor | Hybrid Schema for localization enhancement | RFID tag, WLAN | WSN | 4.2m | Simulation |
| [145] | WLAN | Indoor | Adaptive Neuro-Fuzzy Interference System, Principal Component Analysis | RSSI, Reference Node | WSN | Max error 5.13m, Min error 0.25m | Real-time |
| [149] | RFID | Indoor | Radio Map | RSS, Reference Node | Indoor Localization, Improved and automate radio map construction | Not applicable | Real-time |
| [59] | WLAN | Indoor, Outdoor | jinifMap | RSSI, Reference APs | Content services with location-aware functionality | Hospital 3-5m, University 10-15m | Real-time |

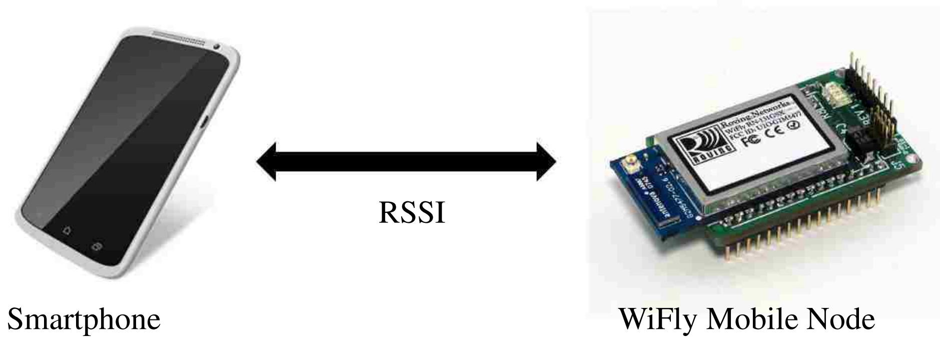



Figure 4.2: Proposed Localization Approach

## 4.3 Our Approach

We have performed two experiments with wireless device and smartphone. In the first experiment, we tried to locate a mobile Wi-Fi node using a smartphone. We have developed a mathematical model for distance and direction estimation using RSSI value. In the second experiment, we estimated the location of a smartphone using fixed and mobile wireless nodes (routers). Both approaches are described in the following subsections with experimental details and results.

### 4.3.1 Localization of Mobile Wi-Fi Node with Smartphone

In this approach, we used the RSSI value of a wireless network as the parameter to estimate the location (distance and direction) of a mobile wireless node using a Smartphone (Figure 4.2). First, we collected RSSI values for different distances. Data were collected for both indoor and outdoor environments. We then used a low pass filtering method to eliminate noise in collected RSSI, which is caused by various environmental factors. This filtering improves the usability and acceptability of the RSSI value as a parameter to estimate distance and direction. In our experiment, we used Roving Networks (now Microchip) WiFly RN-131GSX [2] as a mobile Wi-Fi router. It has the capability to create a Wi-Fi ad hoc network and also connect as a client. This battery powered device is very small and light weight.

We developed an application for data collection in Android and iOS. We recorded RSSI values of the mobile node for both indoor and outdoor environments using Android and iPhone application. These measurements were taken at distances of $10$ feet to $80$ feet between the smartphone and mobile Wi-Fi node. We stored the pair (distance, RSSI) for all the distinct locations with $2$ feet intervals. We also computed the direction, $\theta$, which is the angle between the device and true north, for each collected RSSI value. We used the accelerometer and magnetometer sensors of the smartphone to compute direction from true north. Then we used the following mathematical model to predict the distance and direction of the mobile Wi-Fi node from the smartphone.

**Mathematical Model**

We used the result from a separate experiment (RSSI value, and orientation of smartphone and wireless node) to build the mathematical model. From the experimental results, we saw that the RSSI value varies with the orientation of the mobile device and Wi-Fi node. To normalize the orientation effect we collected RSSI value, $rssi$ while rotating the smartphone by 360 degrees on the horizontal plane (Equation 4.1). The phone was placed on the hand palm and faced upward.

$$rssi = \{rssi_0, rssi_1, rssi_2, ..., rssi_n\} \quad for \quad 0 \leq \theta \leq 360. \tag{4.1}$$

Then we computed the mean value of the collected RSSI values, and stored mean RSSI value and the corresponding distance, $d$ pair for all the distances (Equation 4.2).

$$(d, rssi_{mean}) \quad where \quad rssi_{mean} = \frac{1}{n}\sum_{j=0}^{n} rssi_j \quad for \quad 0 \leq \theta \leq 360. \tag{4.2}$$

We found that rotation of the smartphone reduces the orientation effect on the RSSI value. We also found that the RSSI value is strongest, when the smartphone orientation points towards the Wi-Fi node (Line of Sight). Based on this result and

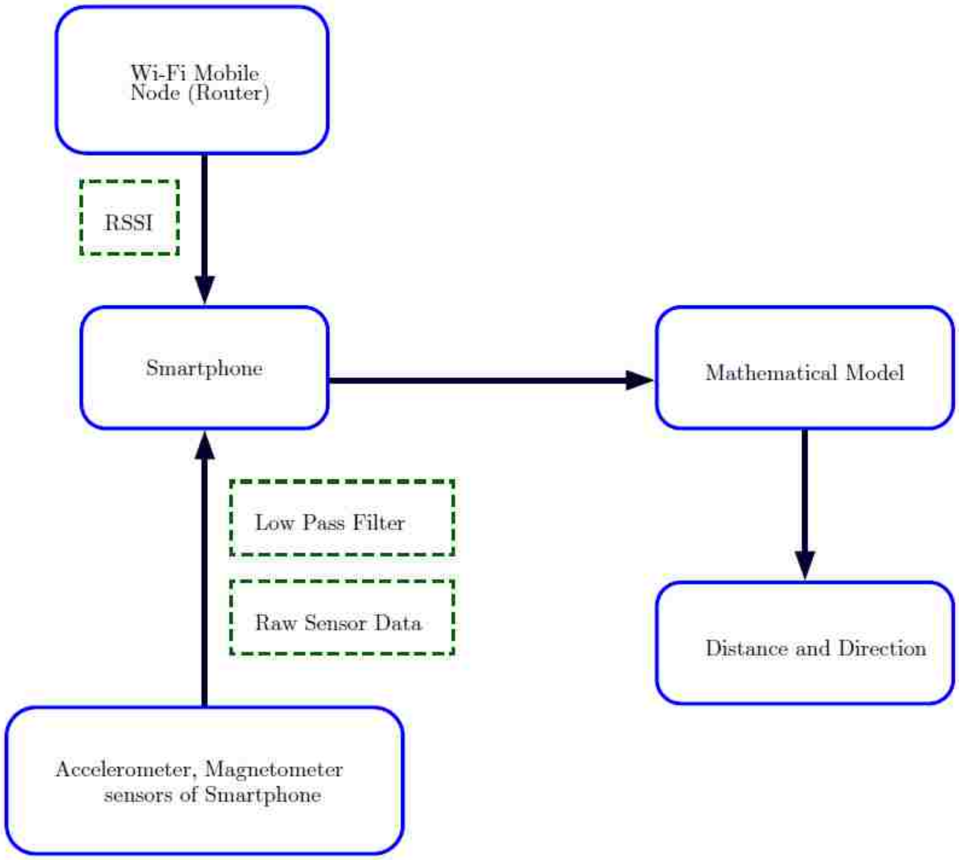



Figure 4.3: Localization of Mobile Wi-Fi Node (Router) with Smartphone.

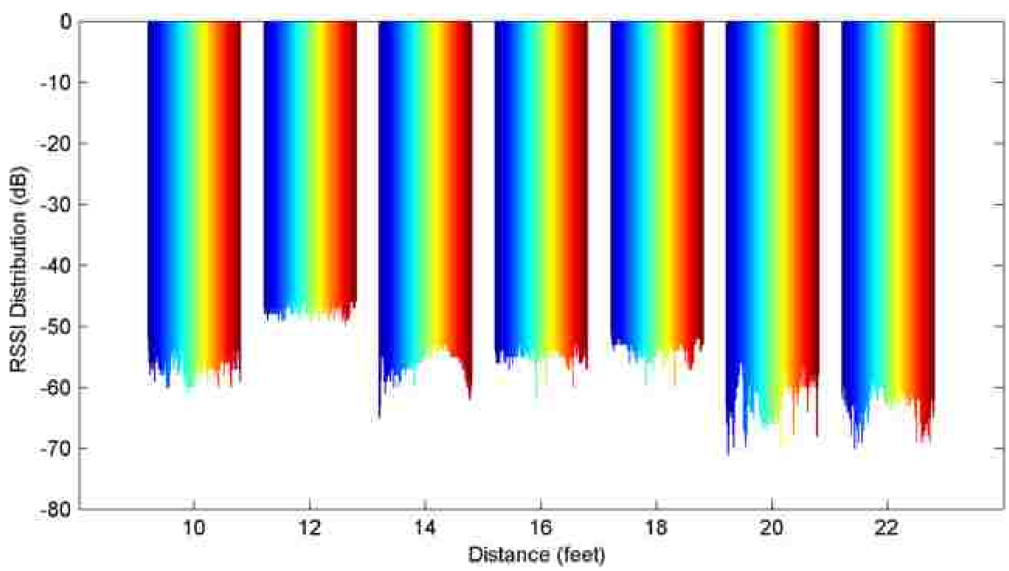



Figure 4.4: Distribution of RSSI Values Over Distance

observation, we computed the direction as the angle from the true north, for which we get the strongest (maximum RSSI value) wireless signal (Equations 4.3 and 4.4). The overall approach is shown in Figure 4.3.

$$rssi_{max} = \{rssi_j \mid rssi_j > \forall_{i!=j}^{i \in j} rssi_i\}. \tag{4.3}$$

$$direction = \{\theta_i \mid rssi_{max} = rssi_i, \quad current \quad direction \quad is \quad \theta_i\}. \tag{4.4}$$

We used filtered (low pass filter) accelerometer sensor and magnetometer sensor data to compute the heading of the smartphone. At the same time, we collected RSSI from the mobile node for each degree rotation. Then we used the mathematical model to the predict distance and direction of the mobile node from the smartphone. The distribution of the RSSI values over distances is shown in Figure 4.4.

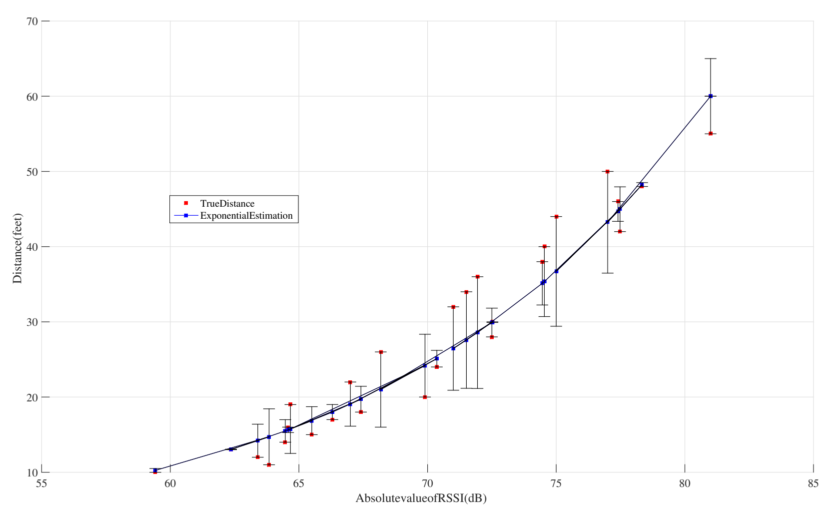



Figure 4.5: Exponential Regression for Outdoor Environment with Android Smartphone

We used exponential regression on distance and RSSI pairs using Nelder-Mead

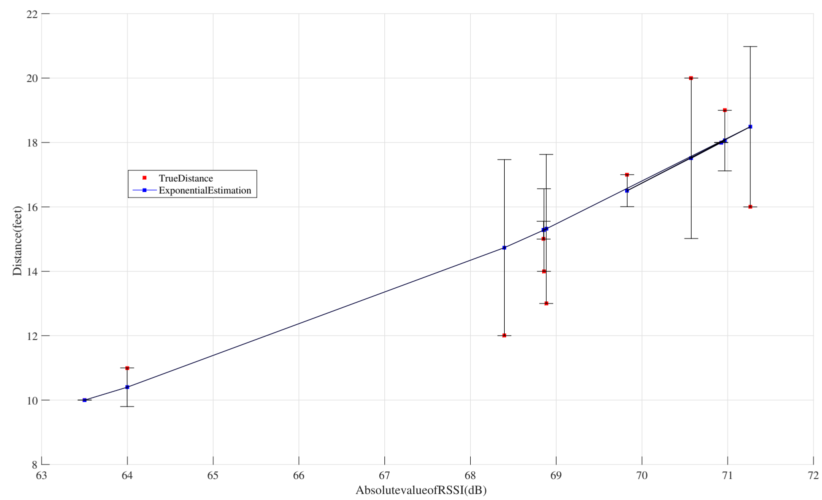



Figure 4.6: Exponential Regression for Indoor Environment with iPhone

Simplex Search method [102] [79]. As RSSI values vary with different vendors, we collected four different sets of data and used four separate regressions for the indoor and outdoor environments with Android and iPhone. We show the regression (RSSI vs. distance) for outdoor environment on Android in Figure 4.5 for distance 3 meters to 18 meters and for indoor environment on iPhone in Figure 4.6 for distance 10 feet to 20 feet. We plot both true value and exponential estimation. We have used negative value of RSSI to plot graph and find exponential equation.

**Result**

The exponential regression function was then used to estimate location from observed RSSI. We developed a working prototype on the smartphone (both Android and iPhone) using this model. We then computed the accuracy of both Android and iPhone systems for indoor and outdoor environments. We considered the distance from 10 feet to 80 feet (3 meters to 24 meters). The result is presented in Table 4.2. We also developed two different tools for data collection and location estimation.

Table 4.2: Accuracy of the Systems for Different Environment (Mobile)

| Environment | System | Error (meters) | Accuracy |
|---|---|---|---|
| Indoor | Android | <2.0 | 85% |
| | iPhone | <2.5 | 80% |
| Outdoor | Android | <1.5 | 90% |
| | iPhone | <1.8 | 90% |

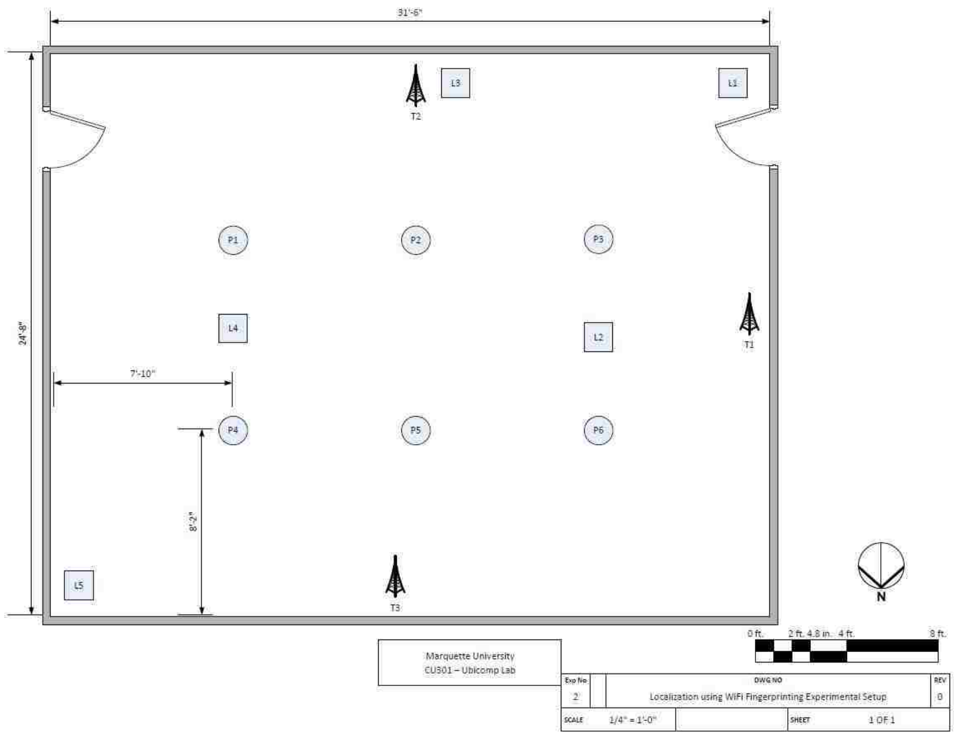
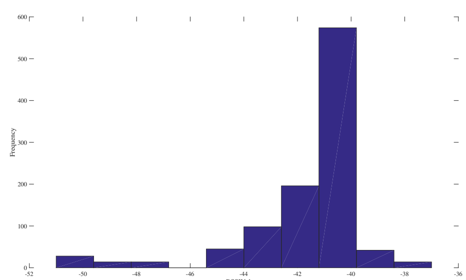



Figure 4.7: Floor Map of the Test Bed at UbiComp Lab, Marquette University

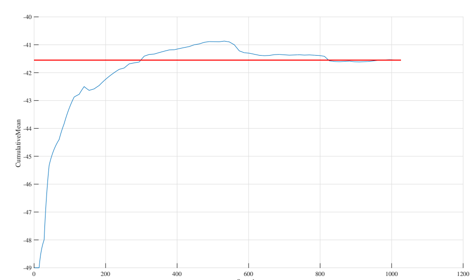
### 4.3.2 Localization of Smartphone with Wi-Fi Routers

In this approach, we tried to locate the user with a smartphone within a single, open spaced room using the previously observed RSSI values. We did the experiment in the UbiComp Lab, Marquette University (MU) 4.7. Here we imposed six different points (12 grids) inside the room. Then we placed three WiFly RN-131GSX in three separate locations. We also used the publicly available three MU Wireless routers for our experiment. The details of the experimental setup are shown in Figure 4.7. The dimensions of the UbiComp Lab are 31.6 feet by 24.8 feet. We used 12 equally spaced grids in this experiment.

We collected RSSI vectors (1 x 3) for each of the six points for both WiFly routers and MU Wireless routers. We developed a tool for Android to collect data from the wireless routers. Data collection frequency was 9-10 Hz. We collected 1000 samples for approximately 1.7 minutes. We then generated a histogram and computed cumulative mean of the collected RSSI samples. Histograms and cumulative means for four points (point 1, point 2, point 3, and point 6) are shown in Figure 4.8, Figure 4.9, Figure 4.10, and Figure 4.11 . All the cumulative means converge to certain values over time. We can see that, in almost all of the cases (Figure 4.9, Figure 4.10, and Figure 4.11) the cumulative mean value converges to the mean value at around 300 samples. Therefore we decided to collect at least 300 samples during the test phase. We created the RSSI signatures using the mean value of collected RSSI samples.



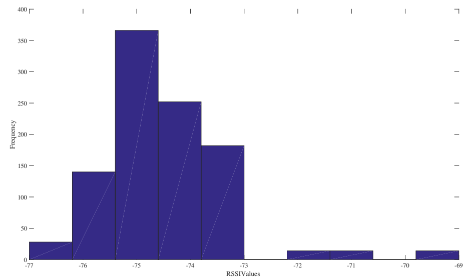
(a) Histogram



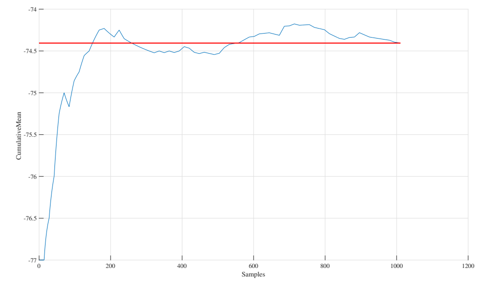
(b) Cumulative Mean

Figure 4.8: Histogram and Cumulative Mean of WiFly Tag 1 at Point 1.

We did the same experiment using three publicly available MU Wireless routers and generated the cumulative mean and histogram from RSSI samples. Like the previous experiment, using the mean RSSI of collected samples, we created RSSI signatures for each point. This signature will be compared to the observed RSSI vector during the test phase. The signature of six different points for both routers is shown in Figure 4.12 and Figure 4.13. From these two figures, we can see the difference (distance) between the signatures of these six different points. We used this property

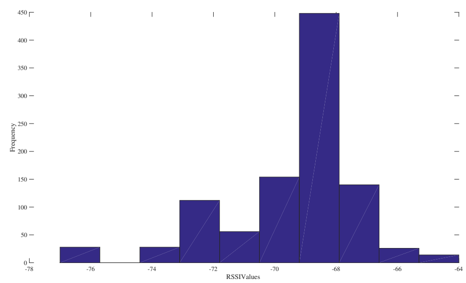



(a) Histogram

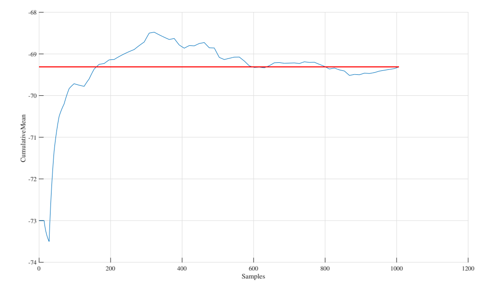



(b) Cumulative Mean

Figure 4.9: Histogram and Cumulative Mean of WiFly Tag 2 at Point 3.




(a) Histogram




(b) Cumulative Mean

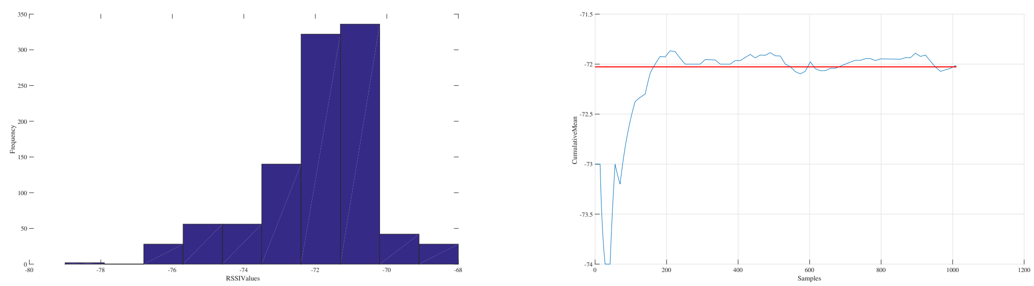
Figure 4.10: Histogram and Cumulative Mean of WiFly Tag 2 at Point 4.

(distance) to distinguish the points and predict location from observed RSSI values.

We have RSSI values, computed means and then used previously observed RSSI signatures to predict location during the test phase. We developed a tool for Android to predict locations. We predicted six different points using both WiFly and MU Wireless routers. The result of both experiments is presented in Table 4.3. We show actual locations and predicted locations for both WiFly RN 131 GSX and MU Wireless routers.

### 4.4 Evaluation

We have evaluated our system by implementing these approaches in three different scenarios.



(a) Histogram (b) Cumulative Mean

Figure 4.11: Histogram and Cumulative Mean of WiFly Tag 2 at Point 6.

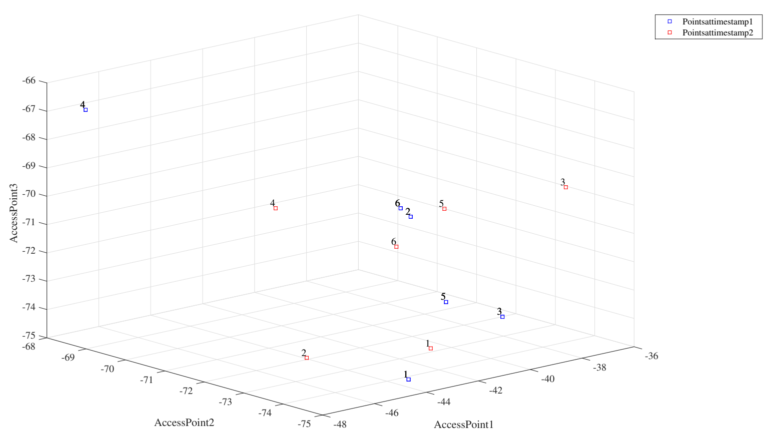



Figure 4.12: Observed RSSI Signatures of 6 Points using 3 WiFly for Two Different Dataset

### 4.4.1 Scenario 1

We developed an asset/object tracking system for smartphones using the first approach. Here the mobile node (WiFly) was integrated with the asset (target object) to be tracked. Then we developed two separate applications on Android and iOS for the smartphone to track the distance and direction of the mobile node (tracked asset). The application can find the location (distance and direction) of the mobile node. It can also trigger an alarm (paging sound) in the tracked asset so that a user can locate it using the sound. The applications also allow the user to activate a ”leash” function to keep track of the distance of the asset from the smartphone. Once the tracked asset is

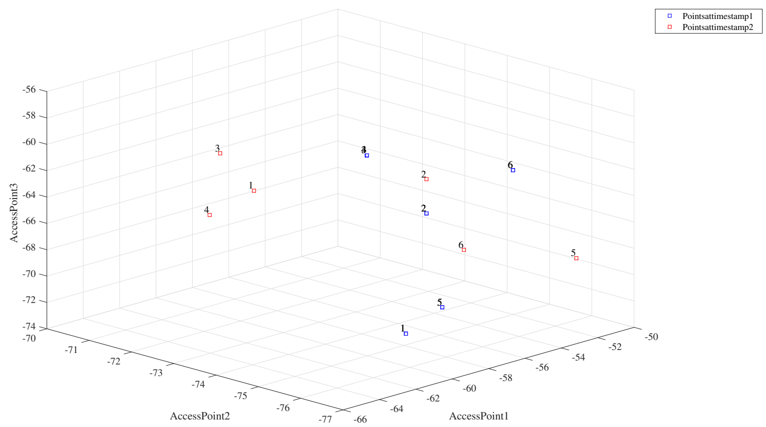



Figure 4.13: Observed RSSI signatures of 6 Points using 3 WiFly for Two Different Dataset

out of the preset perimeter (set by the user), the application triggers an alarm in the smartphone to notify its user. We used the open-source electronics prototyping platform ”Arduino-Mini” to power our developed system. We programmed the Arduino to operate continuous monitoring of WiFly shield and maintain communication with Android and iOS devices. The asset tracker (tracked device and iOS application) is shown in Figure 4.14. The Arduino hosts WiFly, buzzer, and LEDs and communicates with smartphone application through WiFly.

### 4.4.2 Scenario 2

We also evaluated our localization technique in complex activity recognition (sleeping, eating, watching TV, washing dishes, taking a shower). We have implemented our system inside an apartment to find the location of the user with respect to different rooms and anchors (bedroom, kitchen, dining, living room, lawn, couch, sink). In this approach, we used time and location parameters as input to the system. We also considered other parameters that influence human activity to create a vector of attributes. Then we trained our system by collecting these parameters for different complex activities. We observed from the experiment that the correct location

Table 4.3: Accuracy of the System for Different Environments (Fixed)

| Wireless Router | Actual Location | Computed Location |
|---|---|---|
| WiFly RN-131 GSX | Point 1 | Point 1(100%) |
| | Point 2 | Point 1(100%) |
| | Point 3 | Point 1(100%) |
| | Point 4 | Point 4(90%) |
| | | Point 1 (10%) |
| | Point 5 | Point 4(70%) |
| | | Point 6 (30%) |
| | Point 6 | Point 6(80%) |
| | | Point 4 (20%) |
| MU Wireless Access Point | Point 1 | Point 1(70%) |
| | | Point 5 (30%) |
| | Point 2 | Point 3(40%) |
| | | Point 1 (30%) |
| | | Point 5 (30%) |
| | Point 3 | Point 3(100%) |
| | Point 4 | Point 4(70%) |
| | | Point 6 (30%) |
| | Point 5 | Point 5(80%) |
| | | Point 1 (20%) |
| | Point 6 | Point 6(80%) |
| | | Point 5 (20%) |

of the user tells us more about the ongoing complex activities. The errors in the location led us to predict wrong complex activity. Therefore localization plays an important role in this application.

### 4.4.3 Scenario 3

We are also evaluating our localization system in a crowded place where people might get lost. The Hajj is the fifth pillar of Islam and an annual Islamic pilgrimage of Muslims to Mecca. Hajj is a one-time mandatory religious duty for


(a) Tracker Module


(b) Tracker Application

Figure 4.14: Asset Tracker Module and iOS application

Muslims who are physically and financially capable of undertaking the pilgrimage [31] [105]. It is considered to be the largest annual gathering in the world. More than 3 million people performed the Hajj in 2012 [1]. As pilgrims, in a new and crowded area, it is very easy to get lost. Every year there have been report of lost pilgrims, mostly elderly, despite placement of clear signs [105]. We have started working on building a system using the technique described that could be used by millions of users in Mecca during Hajj. The key motivation here is to assist pilgrims to find a place, their companions, or the hotel where they reside. It will also help emergency teams to find lost pilgrims. The system will feature several services including, 1) pilgrim's current location, 2) location of pilgrim's companion, 3) emergency response, 4) location tracking, and 5) indoor mapping. The location will be estimated based on the available resources (Wi-Fi, GPS, or Kinematic sensors) shown in Figure 4.15. We are also working on developing a computational model for step-by-step navigation using Wi-Fi signals and inertial sensor (accelerometer, gyroscope) fusion.

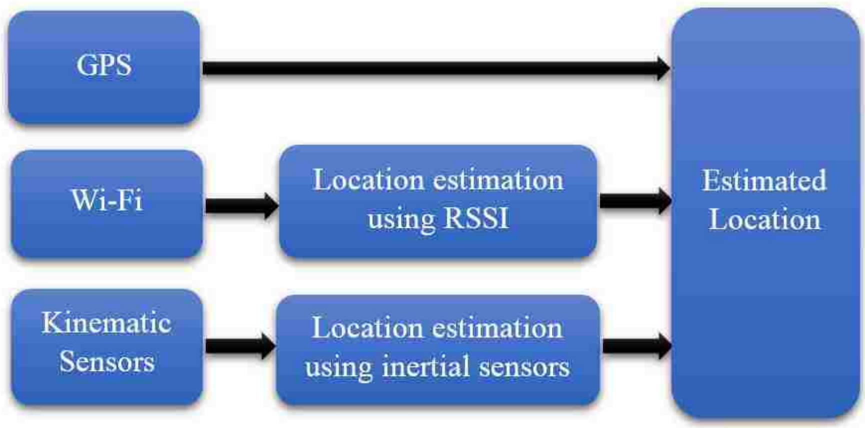



Figure 4.15: Location Estimation based on Available Resources.

### 4.5 Discussion

The goal of this research is to design and develop an infrastructure-less intelligent ubiquitous localization system, which will able to detect the location of the user both indoors and outdoors with a high accuracy using wireless technology. In our first approach, we performed an experiment to find the location of a mobile node with a smartphone. We achieved good accuracy without using any infrastructure. We found that we were able to predict user locations with an error less than 2 meters in Android and in less than 2.5 meters in iPhone for both indoor and outdoor environments. We achieved even better accuracy (less than 1.5 meters for Android and less than 1.8 meters for iPhone) for outdoor environments only. Thus the proposed approach works slightly better in the outdoor environments than in indoors. We think this is because of the complex indoor layout and presence of different household goods. From Table

4.1, we can see most of the approaches use infrastructure to achieve this level of accuracy (errors are between 1 meter and 5 meters). We were able to achieve the same accuracy without using any trilateration or reference nodes. This reduces the cost and complexity of the system. Another advantage of this system is that it can be used in both indoor and outdoor environments.

We did the experiment in real-time to test the performance of the system. We also evaluated our localization approach. We used the first approach to design and develop an object/asset tracking system (for both Android and iPhone). We used our second method in an activity recognition system. To localize a smartphone with a wireless router we achieved 80% accuracy for 5 out of 6 different locations with MU Wireless routers. However, we have low accuracy (30% to 40%) for mobile nodes or WiFly routers. We decided to use fixed routers (like MU Wireless routers) to find different anchors (rooms and locations of objects like couch and sink) inside buildings and apartments.

Though we achieved a good accuracy in the first experiment, we achieved less accuracy in the second experiment. We achieved better accuracy with a fixed wireless router than with a mobile wireless router in the second experiment. We think that a battery powered mobile wireless router is more vulnerable to the environment, which influences RSSI by a large factor. We also think that modeling RSSI with the orientation and environmental changes will be helpful for better prediction. Also, automatic map generation using smartphones will be helpful for better navigation and will require less setup time.

### 4.6 Conclusion

We achieved a good localization accuracy (compared to the approach presented in Table 4.1) for the first approach without using any infrastructure. We also evaluated our proposed system using the implementation in two different applications. Use of kinematic sensors of smartphone with this approach can be used to develop indoor and outdoor navigation systems. We plan to work on the second approach to improve the accuracy with both fixed and mobile nodes. We think the inclusion of publicly available parameters (like cellular network information, nearby wireless devices) in the system, which is available within the range, can accelerate accuracy of the system. Creation of an RSSI map database considering orientation and environmental changes will be helpful for the fingerprint approach. We are working on tracking specific users in a highly crowded area where GPS signal may be weak or even unavailable. We are also working on a group-tracking mechanism that can be applied when a group member appears to get lost in a crowded area. Other members of the team will be immediately notified and receive an estimation of the missing member's location. We will integrate inertial sensor data with this localization technique, to develop a mathematical model and build a system for both outdoor and indoor localization. This system will be used by millions of users in Mecca, where there have been thousands of reported cases of pilgrims getting lost during Hajj, the annual Islamic pilgrimage.

## 4.7 Related Publications

### 4.7.1 Publications

- **Md Osman Gani**, Golam Mushih Tanimul Ahsan, Duc Do, Drew Williams, Mohammed Balfas , Sheikh Iqbal Ahamed, Muhammad Arif, Ahmed J. Kattan, ”An approach to localization in crowded area,” 2016 IEEE 18th International Conference on e-Health Networking, Applications and Services (Healthcom), Munich, 2016, pp. 1-6.

- Farzana Rahman, **Md Osman Gani**, Golam Mushih Tanimul Ahsan and Seikh Iqbal Ahamed, ”Seeing Beyond Visibility: A Four Way Fusion of User Authentication for Efficient Usable Security on Mobile Devices,” 2014 IEEE Eighth International Conference on Software Security and Reliability-Companion, San Francisco, CA, 2014, pp. 121-129.

- **Md Osman Gani**, Casey OBrien, Sheikh Iqbal Ahamed, Roger O. Smith RSSI, ”Indoor Localization for Smartphone using Fixed and Mobile Wireless Node,” in Proceedings of IEEE 37th Annual Computer Software and Applications Conference (COMPSAC), July 22-26, 2013, Kyoto, Japan.

#### 4.7.2 Poster

- **Md Osman Gani**, Duc Do, Balfas, Drew Williams, G M Tanimul, Sheikha Iqbal Ahamed, ”Ubitrack: Locating Lost Pilgrims in the Crowded Area of Makkah during Hajj,” Proceedings of the Forward Thinking Poster Session, Marquette University, WI, USA, Nov. 2014.

# CHAPTER 5

# SIMPLE HUMAN ACTIVITY RECOGNITION

## 5.1 Introduction

Human activity recognition is important in many research areas such as pervasive computing, machine learning, artificial intelligence, human computer interaction, medicine, rehabilitation engineering, assistive technology, social networking, and the social sciences [121], [125], [81]. Substantial research has been conducted to recognize human activities. One of the most significant and challenging tasks for pervasive computing systems is to offer correct and appropriate intelligence about peoples activities and behaviors [81]. Activity recognition systems are being used extensively to monitor elderly people with dementia and people in rehabilitation [94]. The functional status of a person is an important parameter in the area of assisted living and elderly care. This status is described mainly by the activity of daily living (ADL) [60]. Also, it can be used to offer context-aware services to the smartphone users like suitable application selections and content recommendation [87].

In everyday life, we perform numerous activities that occur both indoors and outdoors [90]. We categorize these activities into two classes. The first class is simple full body motor activity, and the second class is complex functional activity [33]. Simple activities include walking, running, standing, sitting, lying, climbing upstairs or downstairs, and jumping. Complex activities include brushing teeth, taking a shower, cooking, washing dishes, driving, watching TV, reading a book, playing tennis, and swimming [81]. Humans can easily distinguish activities by observing them, but creating an automatic system to identify a particular activity from a large set of human activities is a challenging task [75].

We used smartphones to capture these activities. They offer a range of useful sensors such as accelerometers, gyroscopes, orientation sensors, magnetometers, barometers, GPS, Wi-Fi, fingerprint, and near field communication (NFC) [150]. Smartphones also have substantial computational power. Hence, use of the smartphone in the human activity recognition system eliminates the cost of additional devices and sensors [80]. Most smartphones have built in tri-axial accelerometer sensors, which measure acceleration along the x, y and z-axes. The key challenge is to use the accelerometer sensors to model full body human motor activities. In this chapter, we present a smartphone based human activity recognition system using Gaussian mixture models (GMM) of reconstructed phase spaces (RPS). Our approach uses raw accelerometer sensor data from one single axis to recognize 11 different activities including walking, walking upstairs and downstairs, running, standing, and sitting. We investigated the use of dynamical system and chaos theory to capture and then recognize the underlying dynamics of different human activities.

We evaluated our proposed system using two datasets (collected dataset and a publicly available dataset) of acceleration measurements of 11 activities. We collected accelerometer data for 10 different activities. The activities were performed by ten different participants who carried a smartphone in their pocket. We collected another dataset from UCI Machine Learning repository. It has accelerometer and gyroscope data for 6 activities performed by 30 participants. Both datasets were divided into training and testing sets. The training dataset was only used to train the system, while test datasets were used to test the accuracy.

We implemented our system in two different case studies. One case study took place in a rehabilitation clinic for remote monitoring, where the patients daily activities are reported to a cloud server from their smartphone. Physicians could access and assess patients activities based on the assigned task and daily routine. The other case study took place in the Hajj, the fifth pillar of Islam, an annual pilgrimage of muslims to Makkah, Saudi Arabia [27]. The purpose was to track pilgrims' location based on their activities when they get lost.

The summary of the contributions of this research include:

- Use of time-delay embedding or reconstructed phase space to capture underlying dynamics of the human body motion for different activities from smartphone accelerometer
- Statistical learner that learns the underlying dynamics of the human activities and maximum likelihood classifier to recognize those activities
- An alternative approach to widely used machine learning techniques to recognize human activities from kinematics sensors (specifically accelerometer)
- Activity recognition system with a very good accuracy across 11 activities
- Computationally inexpensive approach to activity recognition by using only one accelerometer axis
- Evaluation of the approach using collected dataset and publicly available human activity dataset
- Deployment of the system in two different case studies: Daily activity monitoring of patients in a rehabilitation clinic, and 2) 1) Location tracking of pilgrims using their activity information
- Published collected human activity dataset on public domain to enhance research in this area

This chapter is organized as follows. The related research is discussed in section 5.2. The background is discussed in section 5.3. The data collection process is presented in section 5.4. The method is discussed in section 5.5. The details of the experiments including training, testing, and results are discussed in section 5.6. The contributions are discussed in section 5.7. Finally the conclusions are presented in section 5.8.

## 5.2 Related Research

There has been extensive research focused on automated machine recognition of human activity [90], [6], [146], [147], [132] [74] [139]. Use of computer vision has been one approach [6]. Computer vision approaches implement automatic human activity recognition from a sequence of images or videos where activities are performed by one or more persons. Other research has used environmental sensors like the sound sensor on the floor, the light sensor in the room, radio frequency identification (RFID) as a door tag or wearable kinematic sensors like the accelerometer, and the gyroscope by placing them on different parts of the body [96], [132], [15], [113] [123]. The wearable device based systems are very expensive. These systems lack applicability on mobile devices due to high computational cost and excessive energy consumption. Therefore, there is a need for special attention to energy consumption and computational cost when designing systems to recognize human activities using mobile devices [94]. One of the disadvantages of the wearable activity recognition system is that the may users face discomfort using the wearable devices. There is a risk of losing and forgetting the devices [94].

An alternative approach leverages the increasingly ubiquitous smartphone. Compared to computer vision or wearable sensor approaches, smartphones offer many advantages. Smartphones do not require additional infrastructure, are unobtrusive, and have good and rapidly increasing computational power [33], [21], [53], [152]. Most smartphone based approaches have focused on recognizing simple human activities such as walking, running, standing, walking up stairs, walking down stairs, sitting, and climbing. Some researchers also considered recognition of more complex functional activities like brushing teeth, cleaning dishes, and vacuuming the floor [81]. The overview of the smartphone based human activity recognition system is shown in

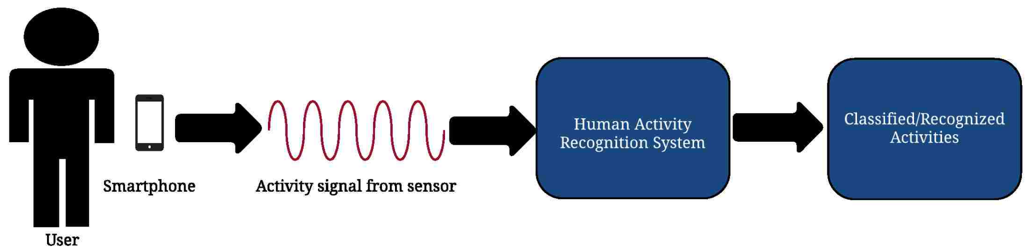



Figure 5.1: Overview of the Smartphone-based Human Activity Recognition System

Figure 5.1 [125]. Different activity signals are collected from the smartphone sensors. The signals are then processed to train a human activity recognition system and tested to recognize different activities. The approaches vary based on data preprocessing, number and type of sensors, mathematical models, and implementations. These systems output the classified human activities.

There has been a widespread use of machine learning techniques in wearable and smartphone based human activity recognition. One of the most common approaches is to extract statistical and structural features ( time-domain features: mean, standard deviation, maximum, minimum, correlation [125] [93], [78], frequency-domain features: Fourier transform [15], Discrete Cosine transform [8], and principal component analysis (PCA) [55]) from raw sensor data and then to use classification algorithms like logistic regression [78], multilayer perceptron [17], support vector machine (SVM) [55], [71], decision tree [67], k-nearest neighbors [96], naive Bayes [131], hidden markov model (HMM) [155] [125], [81] [11] [113]. Gaussian mixture models have also been used to model human activities [124], [111]. Most of these approaches require extensive computation to extract feature, train model, and recognize activity class. It increases power consumption on mobile and wearable devices, which limits the long-run activity recognition [146]. The memory and computational complexity of the activity recognition system depends on the number of sensors, sampling frequency, number of extracted features, size of the activity cycle, and mathematical model [81]. Yan discussed the effect of the sampling frequency and classification features on energy consumption [146]. We discussed the number of sensor, sampling frequency, and size of the activity cycle used in different studies in the following subsection.

The activity cycle is a set of time series observations (sensor data) that contains a complete execution of an activity pattern. The system wont be able to determine the performed activity if the time series observation does not contain a complete activity cycle [94]. There are different strategies to select this window or segment so that it contains necessary time series observation [15] [33]. Kwapisz used a 10 second window (comprises of 200 samples) from cell phone accelerometer at a sampling frequency of 20 Hz [78]. The authors argued that it was an adequate amount of time to capture several repetitions of the performed activities. They performed their experiment with 10 and 20 second windows and found the 10 second segment produced a better outcome. Reiss used a 5 second window at a sampling frequency of 100 Hz from three body mounted sensors (mounted to the dominant arm, chest, and foot) [115]. Lee used a smartphone accelerometer signal window of 5 seconds (60 samples) [87]. In some research work, the activity window included some percentage overlap of the immediate neighboring activity window [15] [60] [65]. Bao used a window of 512 samples (6.7 seconds of data) with 50% overlap to extract time and frequency domain features from 5 body mounted bi-axial accelerometer sensors [15]. Ravi used a single tri-axial accelerometer (worn near pelvic region) to form an activity window of 256 samples (5.12 seconds of data) with 50% overlap at a sampling frequency of 50 Hz [113]. Hong also extracted features from a 256 sample window overlapped with 128 samples (50% overlap) [60]. Inoue recognized real nursing activities for a whole day by extracting features from a window of 5 seconds, overlapping every 2.5 seconds [65].

Most of the existing research has focused on generalized activity recognition model to recognize unseen activities [78] [21]. Lockharty and Weiss discussed the impact of personalized model and generalized model in smartphone-based activity recognition [140]. They also discussed the benefits of the personalized or individualized activity recognition models [92]. They showed that the personalized models performed better than generalized models. The generalized models were unable to classify activities with good accuracy. They experimented with six activities (walk, jog, stair, sit, stand, and lie) using widely used classification algorithms (decision tree, random forest, instance-based learning, neural networks, naive Bayes and logistic regression). The participant carried the android smartphone in their pocket. The 3 axes accelerometer sensor data were used to extract 43 statistical features. The personal model showed an average accuracy of 97% compared to the average accuracy of the hybrid model of 88%, whereas their combination provided even lower average accuracy of 70%. They showed that in order to improve the accuracy of the generalized models, it is better to get data from more users than to obtain more data from the same set of users.

There has been some work using dynamical system theory and chaos theory along with machine learning techniques. Frank et al. used a wearable device (Intel mobile sensing platform (MSP) [26] ) that contained a tri-axial accelerometer and a biometric pressure sensor [71]. The device was clipped onto a belt at the side of the hip. They used three axes acceleration to form a single measure of magnitude. The series of acceleration magnitude were used to reconstruct phase space. They used principle component analysis (PCA) to extract features (9 largest eigenvalues) from the phase space. These 9 features along with gradient of biometric pressure were used to train and test a Support vector Machine (SVM) for 5 activities performed by 6 participants. They achieved an accuracy of 85%. Kawsar developed an activity recognition system using accelerometer and gyroscope sensor data from the smartphone, and pressure sensor data from the shoe [73]. They used decision tree, Shapelet based classification [148] and time-delay embedding based classification. The experiments were performed using only 4 activities (running, walking, sitting, and standing). They achieved 88.64% classification accuracy using the Shapelet based classification with pressure sensor data from the left shoe which took 3.3 seconds. This is a very expensive system with respect to time. They achieved 100% classification accuracy using the time-delay embedding with one pressure sensor data from the left shoe. They did not include the number of participants in the study, which has significant impact on the classification accuracy. Also, they did not perform their experiment with the other widely tested activities like walking upstairs and walking downstairs. Most of the existing approaches have lower accuracy in differentiating between these two activities and the walking activity [62] [15] [81]. In our approach, we used only one-axis acceleration from the smartphone to capture underlying dynamics of the activities by reconstructing the phase space. We learned Gaussian mixture models from underlying dynamics to classify 11 activities performed by 40 participants placing the smartphone in two different body positions.

## 5.3 Background

A dynamical system is a model that describes the evolution of a system over time. It describes the temporal evolution of a system to capture the system's dynamics. A phase space represents all possible states of the system that evolve over time. The dynamics is the map that describes how the system evolves. Theory of dynamical systems attempts to understand and describe the temporal evolution of a system, which is defined in a phase space.

### 5.3.1 Reconstructed Phase Space

We use the representational capability of RPS to capture the underlying dynamics of the system from time series observations (accelerometer sensor data). The

RPS is topologically equivalent to the original system [128]. Given a time series $x$,

$$x = x_n, \quad n = 1...N, \tag{5.1}$$

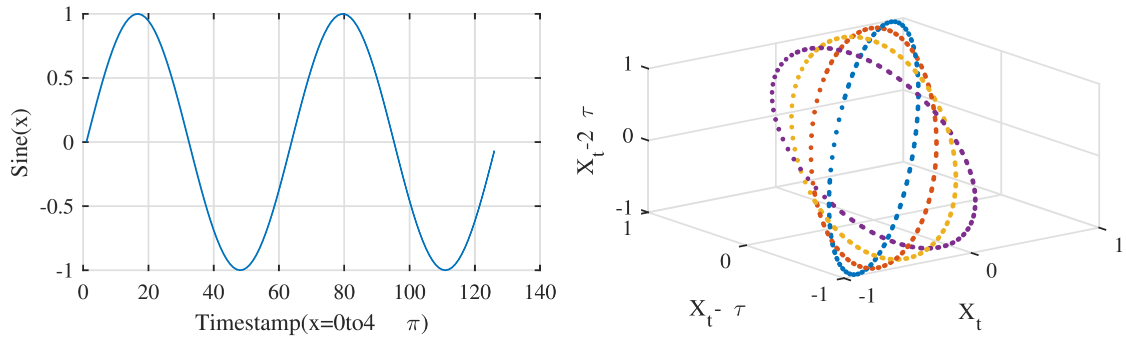
where $n$ is the index and $N$ is the total number of observations. We observe a sequence of scalar measurements in a time series that depends on the state of the system. We convert these observations into state vectors. These vectors are formed according to Takens delay embedding theorem,

$$X_n = [x_n, x_{n-\tau}, ..., x_{n-(d-1)\tau}], \tag{5.2}$$

where $\tau$ is the time delay and $d$ is the embedding dimension [128], [141], [122]. This time-delay embedding reconstructs the state and dynamics of the unknown system from the observed measurements. This time delayed embedding of the time series is called the *reconstructed phase space*. The reconstructed space is topologically equivalent to the original system. It preserves the dynamics of the underlying dynamical system if certain assumptions are made. The embedding dimension $d$ needs to be greater than twice the box counting dimension of the original system [112]. For most of the system where $d$ is unknown, $d$ is estimated using the false nearest-neighbor technique. The dimension of the RPS can be reduced using appropriate selection of the time lag. Though embedding theorems say nothing about the time lag, one of the data driven approaches to find a reasonable estimate of the time lag is to use the first minimum of the automutual information [72].

### 5.3.2 Gaussian Mixture Models

We use Gaussian Mixture Models (GMM) to learn the underlying distribution of the dynamics represented by the RPS. We represent each activity class model using a GMM. The GMM is a parametric probability density function, which is a weighted




(a) Sine Curve for Value of $x$ from 0 to $\pi$

(b) Phase Spaces of the Sine Curve for the Dimension, $d = 3$ and Time Lags, $\tau$ = 3 (Blue), 5 (Orange), 7 (Yellow), and 9 (Purple)

Figure 5.2: Sine Curve and its Phase Plot

sum of $M$ Gaussian probability density function defined as [116],

$$p(\chi, \lambda) = \sum_{i=1}^{M} w_i p_i(x) = \sum_{i=1}^{M} w_i \mathcal{N}(\chi, \mu_i, \Sigma_i), \tag{5.3}$$

where $M$ is the number of mixtures, $\mathcal{N}(x; \mu_i, \Sigma_i)$ is a normal distribution with mean $\mu_i$ and covariance matrix $\Sigma_i$, and $w_i$ is the mixture weight satisfy the constraint that $\sum_{i=1}^{M} w_i = 1$. The parameters of a complete parameterized Gaussian mixture is denoted by $\lambda$,

$$\lambda = \{w_i, \mu_i, \Sigma_i\} \quad i = 1, ..., M. \tag{5.4}$$

The parameters of the GMM are estimated using the Expectation-Maximization (EM) algorithm to maximize the likelihood of the data [100]. The EM algorithm begins with an initial model $\lambda$ and then estimate a new model $\bar{\lambda}$ at each iteration, where $p(X|\bar{\lambda}) \geq p(X|\lambda)$ for a sequence of training vectors, $X = x_1, x_2, ..., x_T$. Parameters are estimated using the following formulas:

$$
\begin{aligned}
{\mu_m}' &= \frac{\sum_{t=1}^{T} p_m(x_t)x_t}{\sum_{t=1}^{T} p_m(x_t)}, \\
{\Sigma_m}' &= \frac{\sum_{t=1}^{T} p_m(x_t)(x_t-\mu_m)^T(x_t-\mu_m)}{\sum_{t=1}^{T} p_m(x_t)}, \\
{w_m}' &= \frac{\sum_{t=1}^{T} p_m(x_t)x_t}{\sum_{t=1}^{T}\sum_{m=1}^{M} p_m(x_i)}.
\end{aligned} \tag{5.5}
$$

### 5.3.3 Maximum Likelihood Classifier

A Bayesian maximum likelihood classifier computes likelihoods on each point $x_k$, from each of the learned model, $a_i$ using the following likelihood function:

$$p(X|a_i) = \prod_{k=1}^{T} p(x_k|a_i). \tag{5.6}$$

Once all the likelihoods are computed then the maximum likelihood class, $\hat{a}$ (i.e. classification) is found:

$$\hat{a} = \arg\max_i p(X|a_i). \tag{5.7}$$

## 5.4 Data

Wearable kinematics sensors, such as accelerometer and gyroscope, have been widely used in activity recognition systems. Smartphone platforms offer application frameworks and libraries to access the sensor data, such that it is easy to access and collect motion data from the smartphones. Thus, smartphones provide a powerful mobile system with integrated sensors, inexpensive software development, and without the need for additional hardware. Practically, users are more comfortable carrying a smartphone than wearing multiple sensors on their body. We used two different datasets (one through data collection procedure and another publicly available human activity dataset) to perform the experiment. Both datasets contained raw data from the built-in accelerometer sensor of the smartphone. The data were collected placing the smartphone in four different positions (pant pocket, waist, table, and beside cupholder (inside car)). The activities performed and phone placement are shown in Table 5.1.

Table 5.1: Activities and Smartphone Placement

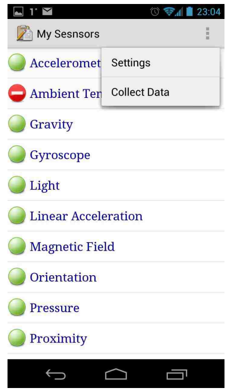
| **Activity** | **Phone Placement** |
|---|---|
| Walking | Pocket and Waist |
| Walking Downstairs | Pocket and Waist |
| Walking Upstairs | Pocket and Waist |
| Running | Pocket and Waist |
| Standing | Pocket and Waist |
| Sitting | Pocket and Waist |
| Lying | Waist |
| Elevator Down | Pocket |
| Elevator Up | Pocket |
| Driving | Pocket and Cupholder |
| Baseline | Table |

### 5.4.1 Development of the Data Collection Tool

We developed a data collection tool, ***UbiSen*** (Ubicomp Lab Sensor Application), in Android, to collect sensor data from smartphones. It shows the list of available and unavailable sensors in green and red colors respectively. It can collect data from all available sensors simultaneously. We used multi-threading technique to parallelize the operation and separate data collection process from the main thread. It provides more precise sensor data at each timestamp.

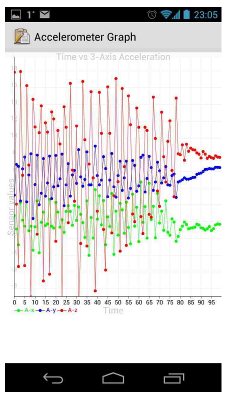
The developed tool is generic. It can be used to collect data from a specific set of sensors. The frequency can be specified from the settings of the application. The data collection process can be labeled. It offers a stop watch feature to start and stop the data collection process. The recorded data can be exported as a CSV (comma separated value) file. The screenshots of the data collection tool is shown in Figure 5.3.


(a) List of Available and Unavailable Sensors

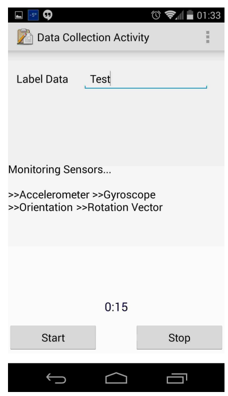



(b) Settings and Data Collection

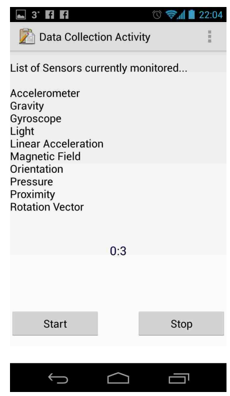

(c) Sensor Information and Raw Data



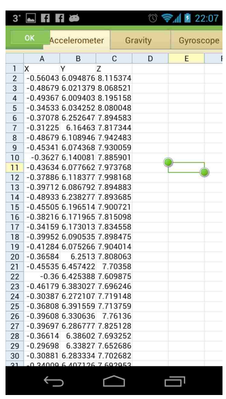

(d) Sensor Data Visualization



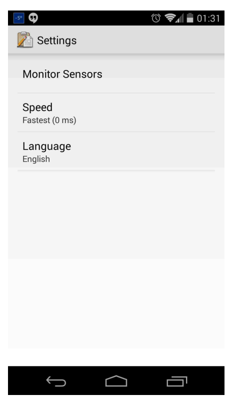

(e) Label Data



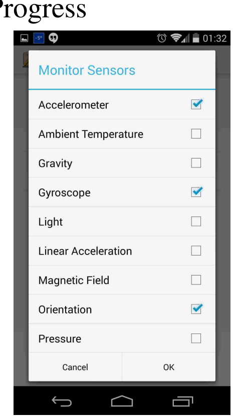

(f) Data Collection Progress




(g) Exported Data in Excel




(h) Settings Window

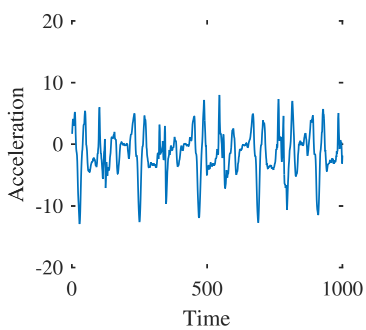



(i) Sensor Selection for Data Collection

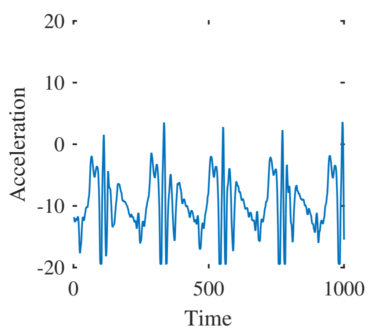
Figure 5.3: UbiSen (Data Collection Tool) Functionality

### 5.4.2 Data Collection

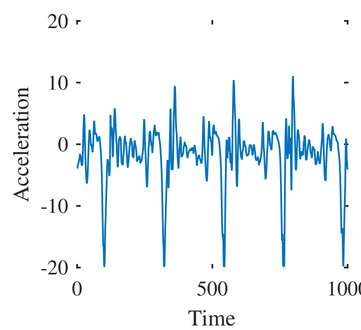
We collected accelerometer sensor data for different activities using UbiSen (Ubicomp Lab Sensor Application for Android). We used a Google Nexus 5 smartphone running Android OS 5.0. The participants placed the phone in their front pant pocket. They performed eight simple activities: walking, walking upstairs, walking downstairs, running, sitting, standing, elevator up and elevator down. We also collected sensor data during driving and when the phone was placed at a fixed place like on a table. For the driving activity, the phone was placed inside the pant pocket and also beside a cupholder. Sun discussed different aspects of the activity recognition system varying mobile phone positions and orientations [126]. The accelerometer sensor data along the three axes for the walking activity is shown in Figure 5.4. Here three different axes have three different but repetitive patterns. The accelerometer sensor data along the y-axis for all the activities are shown in Figures 5.5 - 5.9.




(a) Acceleration along X-axis



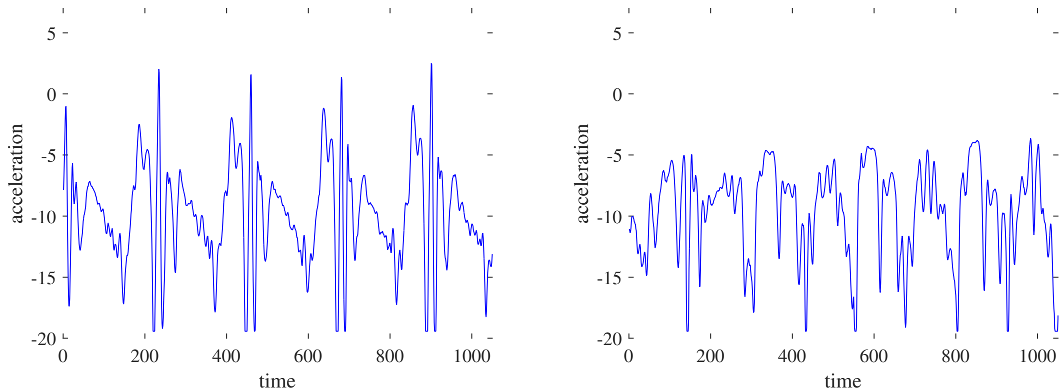

(b) Acceleration along Y-axis




(c) Acceleration along Z-axis

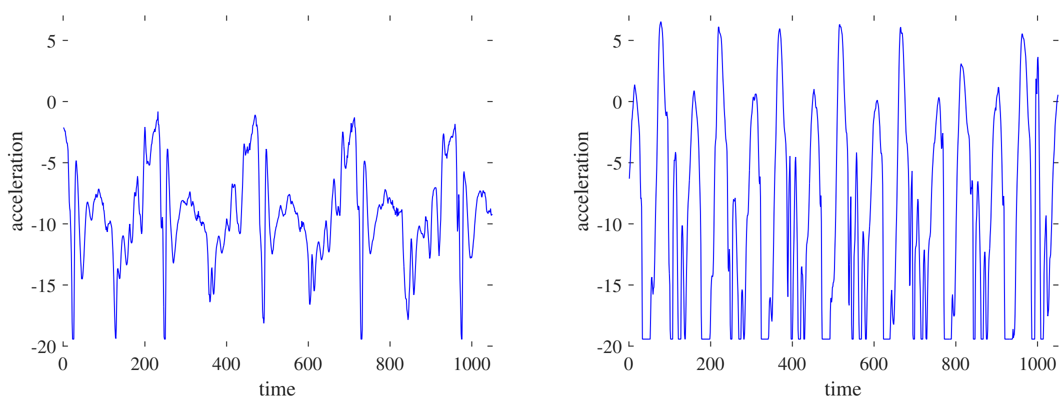
Figure 5.4: Acceleration along Three Axes for Walking Activity.

There were 10 participants (age ranges between 20-35, both male and female) in the data collection event. Each participant performed 10 activities in an uncontrolled environment. Each activity was performed for a different time duration. Walking, running, standing, sitting, and phone placed at table (baseline) were performed for 2-3 minutes. Walking upstairs, walking downstairs, elevator up, and elevator down were performed for 1-2 minutes. Driving data were collected for approximately 10-15 minutes. In total, we have 3 hours and 20 minutes of sensor data for 10 different activities performed by the participants.



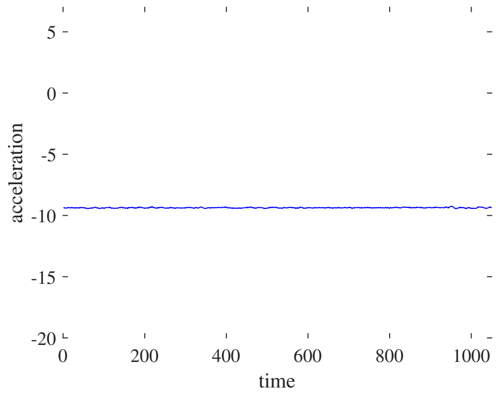

(a) Walking (b) Walking Down Stairs

Figure 5.5: Accelerometer Sensor Data along the Y-axis for Walking and Walking Down Stairs.

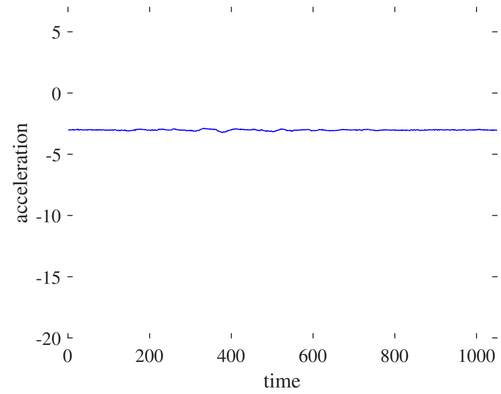



(a) Walking Up Stairs (b) Running

Figure 5.6: Accelerometer Sensor Data along the Y-axis for Walking Up Stairs and Running.

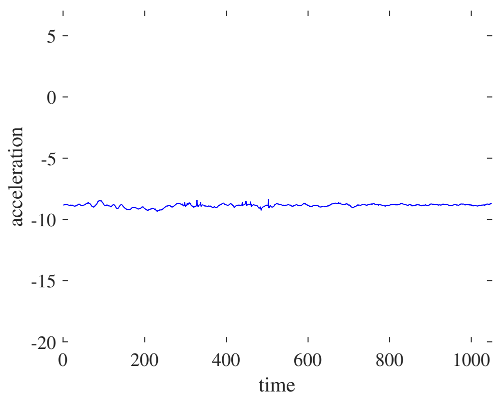



(a) Standing

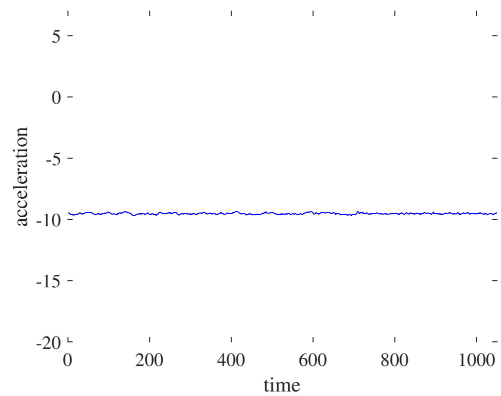



(b) Sitting

Figure 5.7: Accelerometer Sensor Data along the Y-axis for Standing and Sitting.




(a) Elevator Down

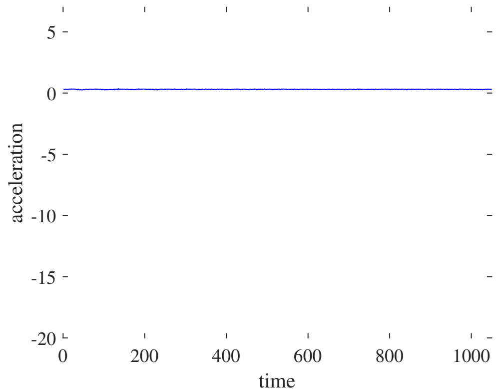



(b) Elevator Up

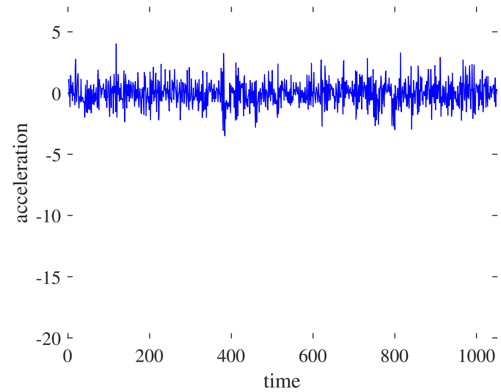
Figure 5.8: Accelerometer Sensor Data along the Y-axis for Elevator Down and Up.

### 5.4.3 Public Dataset

We utilized dataset *Human Activity Recognition Using Smartphone Data Set* from the UCI Machine Learning Repository [9]. The data were collected from a group of 30 participants within an age range of 19-48 years. Each participant wore a smartphone (Samsung Galaxy S II) on the waist and performed six activities: walking, walking upstairs, walking downstairs, sitting, standing, and lying down. The accelerometer and gyroscope sensor data were captured at a rate of 50Hz. The noise




(a) Phone Placed at Table (Baseline)




(b) Driving

Figure 5.9: Accelerometer Sensor Data along the Y-axis for Baseline and Driving.

filters were applied to preprocess the raw sensor data. The Butterworth low-pass filter was used to separate gravity from the acceleration signal. The dataset has been partitioned randomly into training (70%) and testing (30%) sets.

## 5.5 Method

We briefly discuss the process of training and testing the human activities in the following subsections. An overview of both phases is shown in Figure 5.10.

### 5.5.1 Training

The first step was to build RPS from accelerometer data for each activity using time lag and embedding dimension. We estimated the time lag and embedding dimension using the techniques discussed in section 5.3. The time lag was estimated for each activity signal using the first minimum of the automutual information. Once all the time lags were estimated for each activity, then a time lag was selected for the RPS using the mode of the histogram of all estimated time lags. The global false nearest-technique was applied on each activity signal to calculate embedding dimension for RPS. Again, once embedding dimensions for all the signals were calculated, then an embedding dimension was selected for the RPS as the mean of all

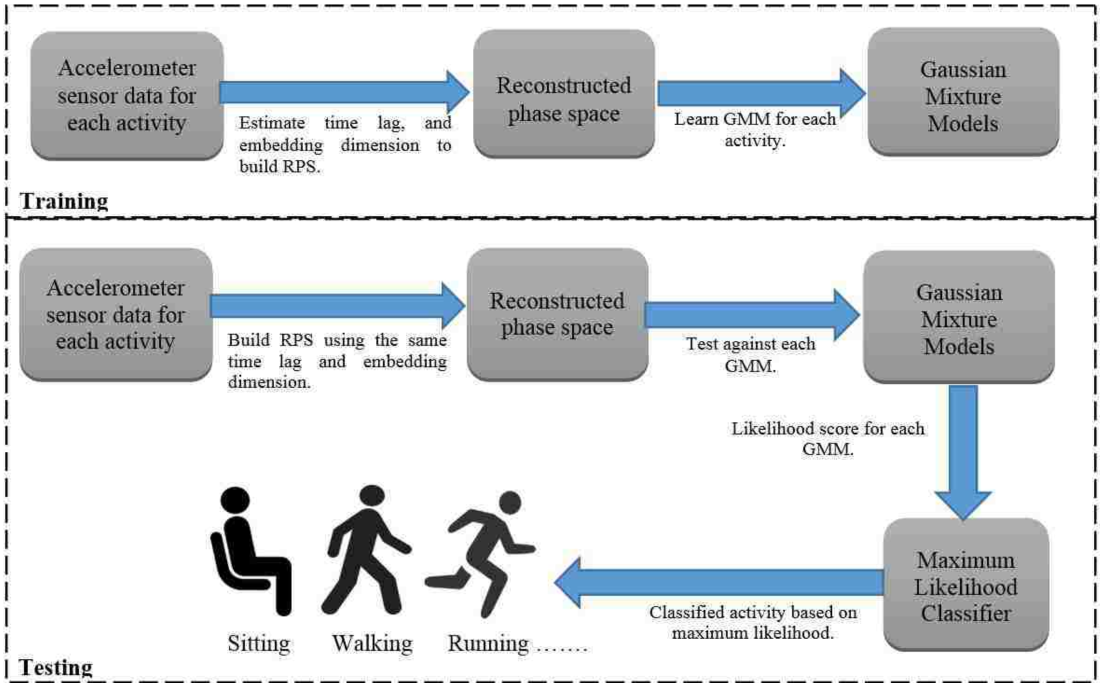



Figure 5.10: Overview of Training and Testing Phases of the Proposed Approach.

calculated dimensions. The mode and mean were taken so that most of the activity signals were able to unfold completely in the RPS. Once time lag and embedding dimension were selected, then we built RPS for each signal.

Once the RPS was built, we learned a GMM probability distribution for each activity signal class. Each GMM represented the corresponding model for the activity class. Thus, we had an array of models after the completion of the training phase. The size of this array is equal to the number of activity class.

### 5.5.2 Testing

To test activity signal, we created RPSs from the raw accelerometer sensor data using the same time lag and embedding dimensions (estimated in training phase). Then we tested the RPS against all the GMMs (created in training phase). It gave us likelihood probability for each activity model. Bayesian maximum likelihood classifier was used to classify test signal as classified or recognized activity. This is done using the activity model class with the highest likelihood. The system outputs test signal as one of the classified activities.

We evaluated our system with quantitative assessment. The k-fold cross validation helped us to evaluate accuracy where k was the number of data partitions. It helped us to generalize the statistical analysis and overcome problems like over fitting of the algorithm on the training set. We also varied the system's parameter to analyze its robustness.

### 5.6 Evaluation

We evaluated our approach using both the collected and publicly available datasets. We used an individualized model to experiment with the collected dataset and a generalized model for the public dataset. We used Matlab and Weka machine learning toolbox to perform the experiment. We tested our approach using both dataset and time-domain features with classification algorithms using the first dataset. We discuss the experimental details and results in the following subsections.

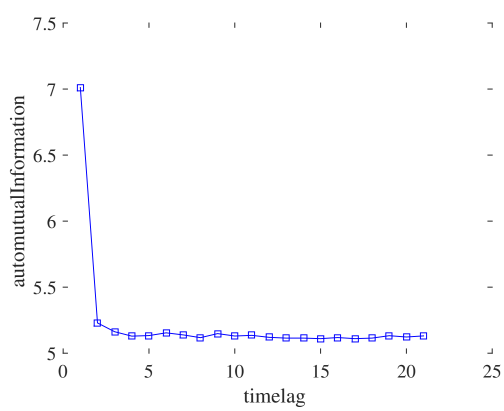
#### 5.6.1 Experiment with Our Approach

We analyzed accelerometer sensor data (3 axes) for all the activities. We observed acceleration along different axes. We observed different patterns along these axes for different activities. Even when we looked only at the acceleration along the y-axis (as shown in Figures 5.4 - 5.9), we also saw that there was a uniquely distinguishable pattern for each of the different activities. The challenge was to build the model to capture the dynamics of the activities from this acceleration along the y-axis and differentiate one from another. We discuss training and testing phases in the following subsections in detail.

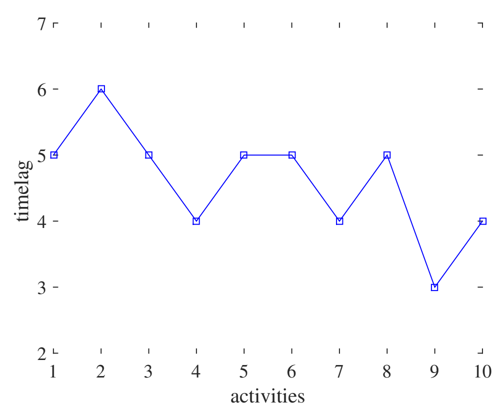
**Training**

We used the raw sensor data along the y-axis to build reconstructed phase space with appropriate time lag and embedding dimension. We partitioned data into different activity cycles (number of partitions, $k = 40$) each containing 300-600 samples.

During the data collection process we recorded videos of the footsteps. We selected the sample size by comparing activity (walking, walking upstairs, walking downstairs, and running) cycles with synchronized video observations for each of the activities and the corresponding sensor values at the same time. We selected the sample size to ensure that it contained more samples than the largest activity cycle. We also analyzed the effect of sample size on the system's performance. To build the RPS, we took one subject from each of the different activity classes. Then we computed automutual information for different time lags. The first minimum of the automutual information was used to estimate the time lag for each activity class. The graph in Figure 5.11(a) shows the automutual information of "walking upstairs" activity for different time lags. Here the first minimum of the automutual information was found for time lag value 5.



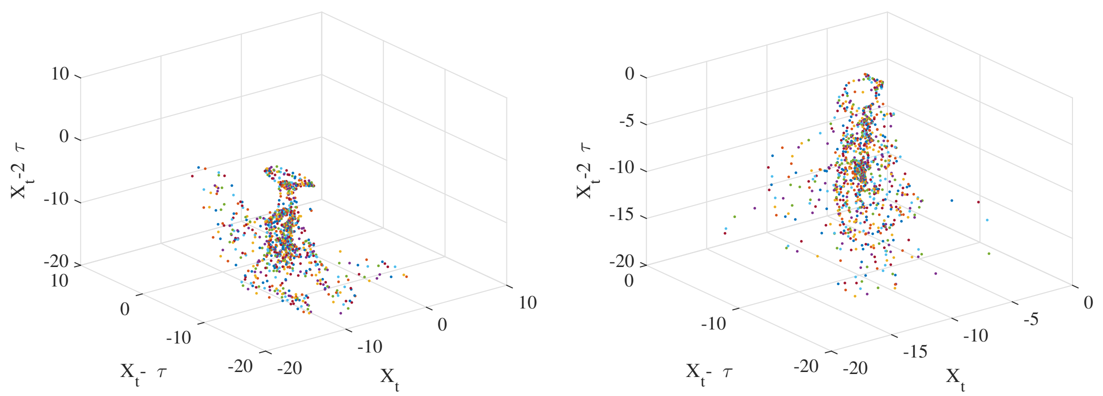

(a) Automutual Information




(b) Time Lags

Figure 5.11: Time Lag Estimation for Walking Activity.

We computed the time lag for all the activity classes. The mode of these time lags was used to estimate time lag for RPS as shown in Figure 5.11(b) for all the activities. We found time lag $\tau = 5$ in this process. Then we used this estimated time lag value to estimate embedding dimension. We computed percentage of false nearest-neighbors to determine the embedding dimension for each activity class. We took the mean of all calculated embedding dimensions to select embedding dimension for the RPS. We estimated the embedding dimension to be $d = 6$. We used these estimated values of time lag and embedding dimension to build RPS for each activity class. The RPSs for walking, walking downstairs, walking upstairs, running, sitting, and phone placed at table build with time lag, $\tau = 5$ and embedding dimension, $d = 6$ are shown in Figures 5.12, 5.13, 5.14, 5.15, and 5.16. The difference in underlying dynamics between the activities is represented by these RPSs. We used RPSs for each activity class to learn GMMs.



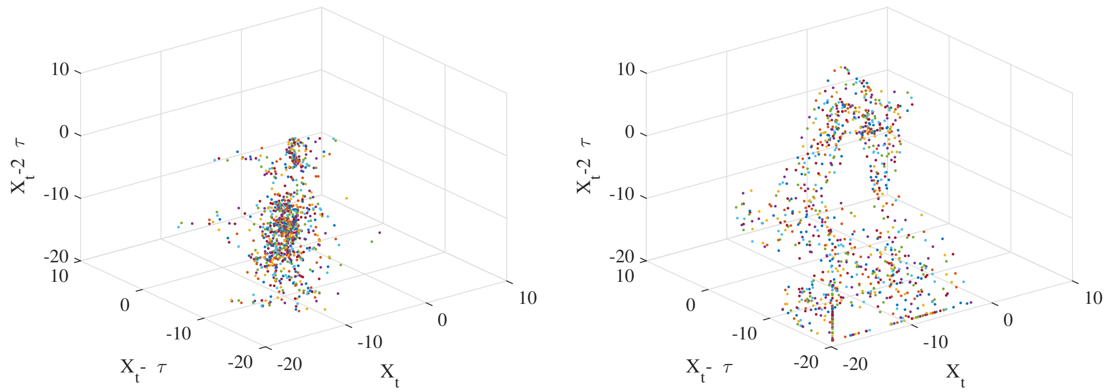

(a) Walking

(b) Walking Down Stairs

Figure 5.12: RPS for Time Lag, $\tau = 5$, and Embedding Dimension, $d = 6$ for Walking and Walking Down Stairs.

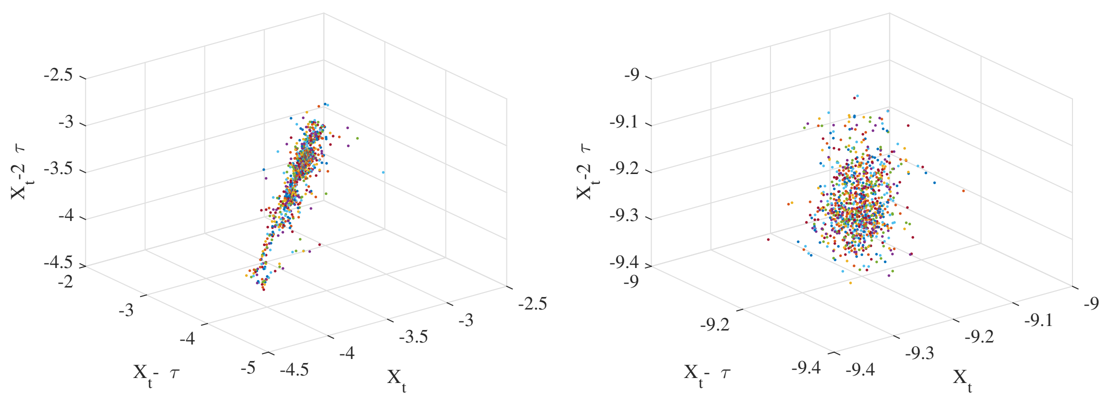
**Testing**

We evaluated all the subjects for each activity using each of the activity models (GMMs). At first the RPSs were generated using the same time lag and embedding dimension we used in the training phase. These RPSs were then tested against each of the activity class models. We estimated the likelihood of the RPSs against GMMs. We used m = 5 mixtures for GMM. We also changed the number of mixtures to see its effect on the system's performance. For each single subject of data, we computed all the likelihood probability (log probability) for each activity class model. Then we used a maximum likelihood classifier to identify the corresponding subject as one of the




(a) Walking Up Stairs (b) Running

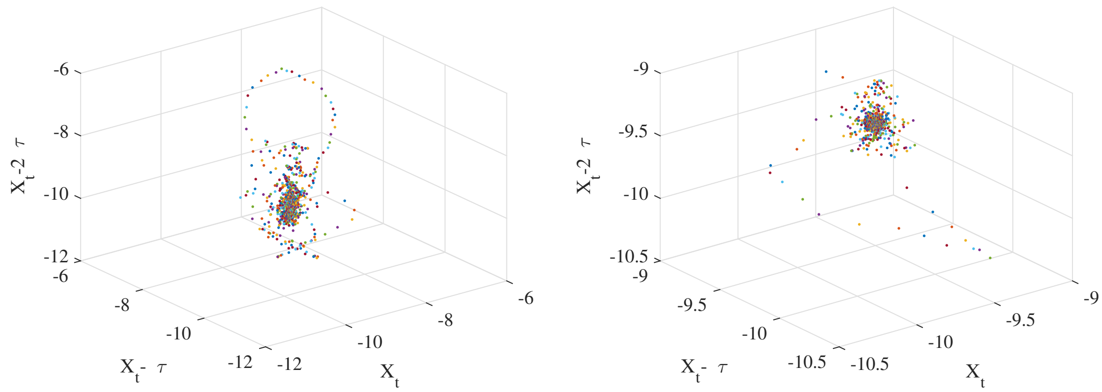
Figure 5.13: RPS for Time Lag, $\tau = 5$, and Embedding Dimension, $d = 6$ for Walking Up Stairs and Running.




(a) Standing (b) Sitting

Figure 5.14: RPS for Time Lag, $\tau = 5$, and Embedding Dimension, $d = 6$ for Standing and Sitting.

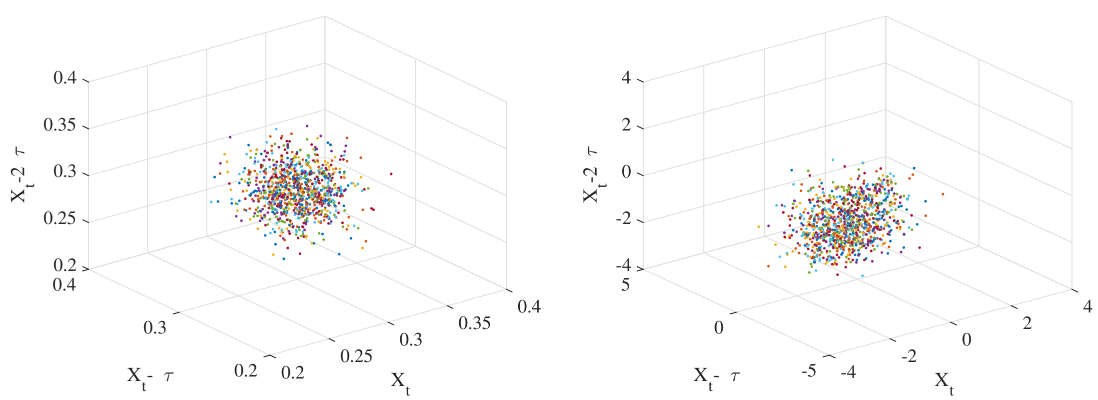
human activities. The classifier takes all the likelihood probabilities and outputs the activity class associated with the maximum probability. We used 10-fold cross validations to validate accuracy of the system. We took nine partitions at a time to train the system. The 10th one along with the training partitions were used to test the performance.




(a) Elevator Down

(b) Elevator Up

Figure 5.15: RPS for Time Lag, $\tau = 5$, and Embedding Dimension, $d = 6$ for Elevator Down and Up.




(a) Phone Placed at Table (Baseline)

(b) Driving

Figure 5.16: RPS for Time Lag, $\tau = 5$, and Embedding Dimension, $d = 6$ for Baseline and Driving.

### 5.6.2 Experiment with Time-Domain Features and Classification Algorithms

We performed experiments with time-domain features and classification algorithms used by state-of-the-art human activity recognition systems [88] [32] [33] [123]. We used following time-domain features: *1) Mean, 2) Max, 3) Min, 4) Standard Deviation, 5) Variance*, representing mean, maximum, minimum standard deviation, and variance of activity cycle, respectively.

The features were extracted from each subject (as discussed in the previous section) for all the activities. The feature vector was formed using the features. We used the feature vector to train and test different classification algorithms. We analyzed the performance of the classification algorithms tabulated in Table 5.2.

Table 5.2: Classification Algorithms

| **Family** | **Classifiers** |
|---|---|
| Decision Tree | Classification and Regression Trees |
| Beyasian | Bayesian Network, Naive Bayes |
| Artificial Neural Networks | Multilayer Perceptron |
| Maximum Margin Classifier | Support Vector Machine |
| Instance based | k-Nearest Neighbors |
| Rule based classifier | Decision Table |
| Regression | Logistic Regression |
| Classifier Ensembles | Bagged Trees, Random Forest |

#### 5.6.3 Experiment with Time and Frequency Domain Features

We performed experiments with time and frequency domain features used in [9] for each axis acceleration. We extracted 60 features for each axis and used Decision Tree, SVM, Weighted KNN, Bagged Trees along with SVM with Gaussian Karnel (technique used in [9]) to perform the experiment.

#### 5.6.4 Results

We present quantitative evaluation of the system in this subsection. The confusion matrix for all the activity classes are also presented. Here for each row, the corresponding true activity class is the positive class and the rest of the activity classes were considered as the negative class. To describe the performance, we obtained the following terms from the confusion matrix:

- True Positives (TP) is the number of positive activity classes that were classified as positive.

- False Positives (FP) is the number of negative activity classes that were classified as positive.

- True Negatives (TN) is the number of negative activity classes that were classified as negative.

- False Negatives (FN) is the number of positive activity classes that were classified as negatives.

Then, we computed the performance for all the activity classes from using these terms as follows:

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN}. \tag{5.8}$$

**Collected Dataset**

There were $10$ participants, and for each of the activities, we took $40$ partitions into consideration; therefore we complied a total of 400 instances for each class of activity. We used individual activity models for each of the participants. We changed different parameters of the model to test its robustness. The confusion matrix is shown in Table 5.3. All 400 instances in each row were classified correctly. We also performed experiments with the rest of the data (not included in the $40$ partitions) and found similar results.

Table 5.3: Confusion Matrix for the Individualized Model of Collected Dataset using Proposed Approach

| | | Predicted Class | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | Activity | Walking | Downstairs | Upstairs | Running | Sitting | Standing | Elevator Down | Elevator Up | Baseline | Driving |
| True Class | Walking | 400 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| | Downstairs | 0 | 400 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| | Upstairs | 0 | 0 | 400 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| | Running | 0 | 0 | 0 | 400 | 0 | 0 | 0 | 0 | 0 | 0 |
| | Sitting | 0 | 0 | 0 | 0 | 400 | 0 | 0 | 0 | 0 | 0 |
| | Standing | 0 | 0 | 0 | 0 | 0 | 400 | 0 | 0 | 0 | 0 |
| | Elevator Down | 0 | 0 | 0 | 0 | 0 | 0 | 400 | 0 | 0 | 0 |
| | Elevator Up | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 400 | 0 | 0 |
| | Baseline | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 400 | 0 |
| | Driving | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 400 |

We changed the size of the training set from 1000 samples to 3000 samples and increased the size of each activity cycle from 200 samples to 600 samples. For each combination we tested system accuracy. The performance of the system for all the configurations is shown in Figure 5.17. The performance increased as we increased the size of the training set and activity cycle. We observed that most of the activities had cycle length around 260-270. The incorrect partitioning of the activity cycle did not contain enough evidence for respective activity class. Hence, the system was unable to capture the underlying dynamics of the activity. Thus increasing the size of activity cycle helped each cycle to contain enough information about the activity class. The accuracy of the system was consistent when the activity cycle contained enough information and the model wss trained with the underlying dynamics.

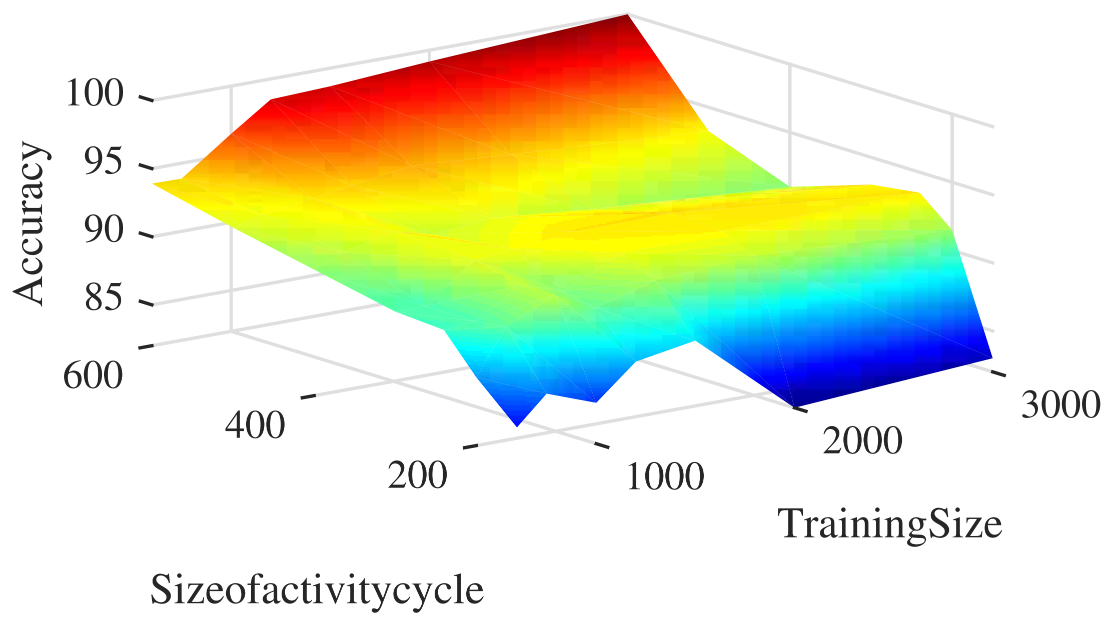



Figure 5.17: Performance of the System with Respect to Number of Sample in Training Set and Activity Cycle.

We also changed the number of mixtures for GMMs from $m = 1$ to $m = 7$. We combined this change in a number of mixtures with change in size for each activity cycle discussed above. The performance of the system for all the configuration is shown in Figure 5.18. The performance was stable with 100% accuracy for all the configurations having at least activity cycle size of 300 and 5 mixtures. We observed that the system was unable to classify activity cycle with number of mixtures less than or equal to 3, even though activity cycle contained enough evidence ($size = 300$ to $size = 600$). Therefore the number of mixtures was not enough to maximize the likelihood of the RPS.

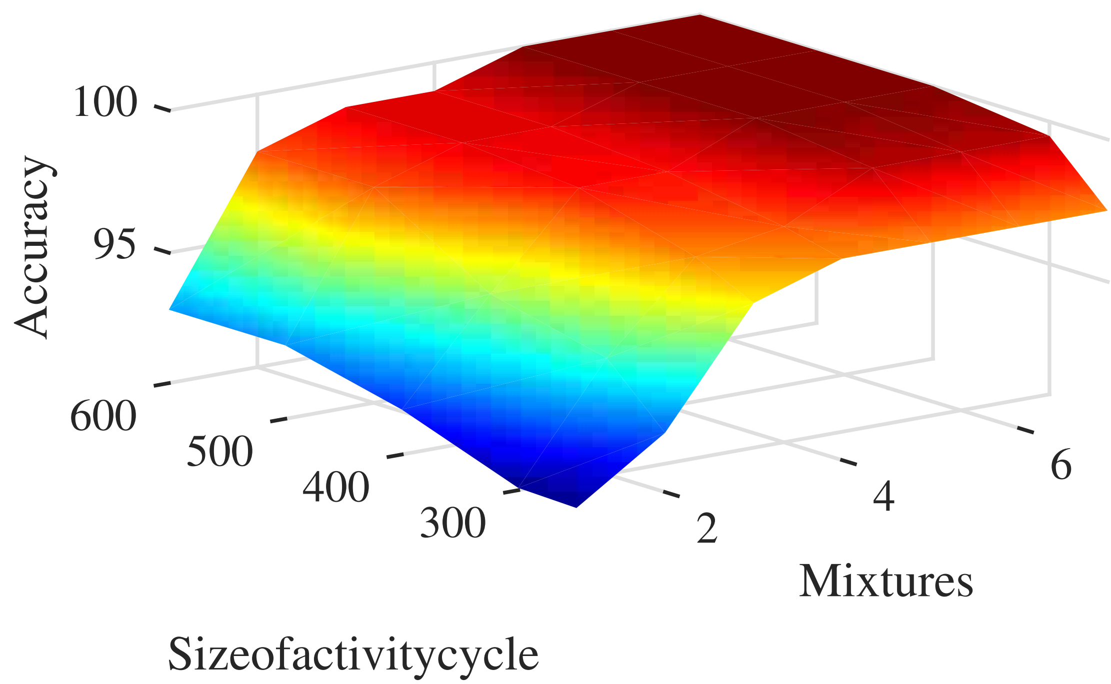



Figure 5.18: Performance of the System with Respect to Number of Gaussian Mixtures and Size of Activity Cycle

The performance of the classification algorithms using time-domain features is shown in Figure 5.19. The acronyms used in the figure are as follows: a) Our: Our Approach, b) BT: Bagged Trees, c) LR: Logistic Regression, d) RF: Random Forest, e) DTb: Decision Table, f) W-KNN: Weighted K-Nearest Neighbors, g) SVM, h) Artificial Neural Network, i) NB: Naive Bayes, j) BN: Bayesian Network, and k) DT: Decision Tree. We tested 10 classification algorithms using 5 time-domain features for individual model. We achieved 90%-91% accuracy for Bayes Network, Naive Bayes, Multilayer Perceptron, SVM, KNN, and Bagged Trees. We had accuracy of above 83% for other classification algorithms. Compared to these approaches, our system achieved an accuracy of 100%. Our system was able to classify all the activities from y-axis acceleration with 100% accuracy. We have shown the models are able to capture the underlying dynamics when activity cycle contains enough information about activity. The classification algorithms are not very successful with the above mentioned extracted time-domain features from the same activity cycle.

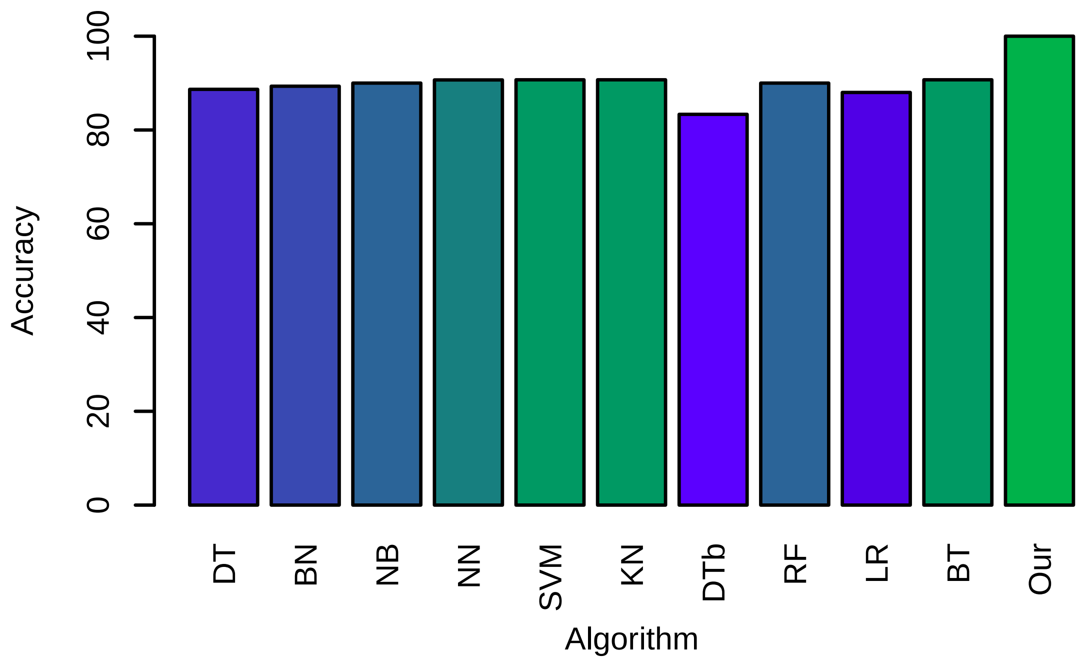



Figure 5.19: Algorithm Performance using 1-Axis Acceleration (Our Dataset)

**Public Dataset**

We applied our approach on the public dataset. We used generalized model of each activity for all the participants. The confusion matrix for this experiment is shown in Table 6.4. The accuracy of the system is 90%. Here for each row, the corresponding true activity class was the positive class and rest of the activity classes were considered as negative class. We also compared our work with Anguita [9] using 60 time and frequency domain features and presented those results in Figure 5.20. Our

Table 5.4: Confusion Matrix for the Generalized Model of Public Dataset using Proposed Approach

| | | Predicted Class | | | | | |
|---|---|---|---|---|---|---|---|
| | Activity | Walking | Downstairs | Upstairs | Standing | Sitting | Lying |
| True Class | Walking | 278 | 37 | 55 | 0 | 0 | 0 |
| | Downstairs | 33 | 297 | 0 | 0 | 0 | 0 |
| | Upstairs | 30 | 15 | 255 | 0 | 0 | 0 |
| | Standing | 0 | 0 | 0 | 361 | 19 | 0 |
| | Sitting | 0 | 0 | 0 | 5 | 402 | 0 |
| | Lying | 0 | 0 | 0 | 6 | 0 | 409 |

approach achieved the highest level of accuracy compared to other approaches and the approach used in Anguita [9].

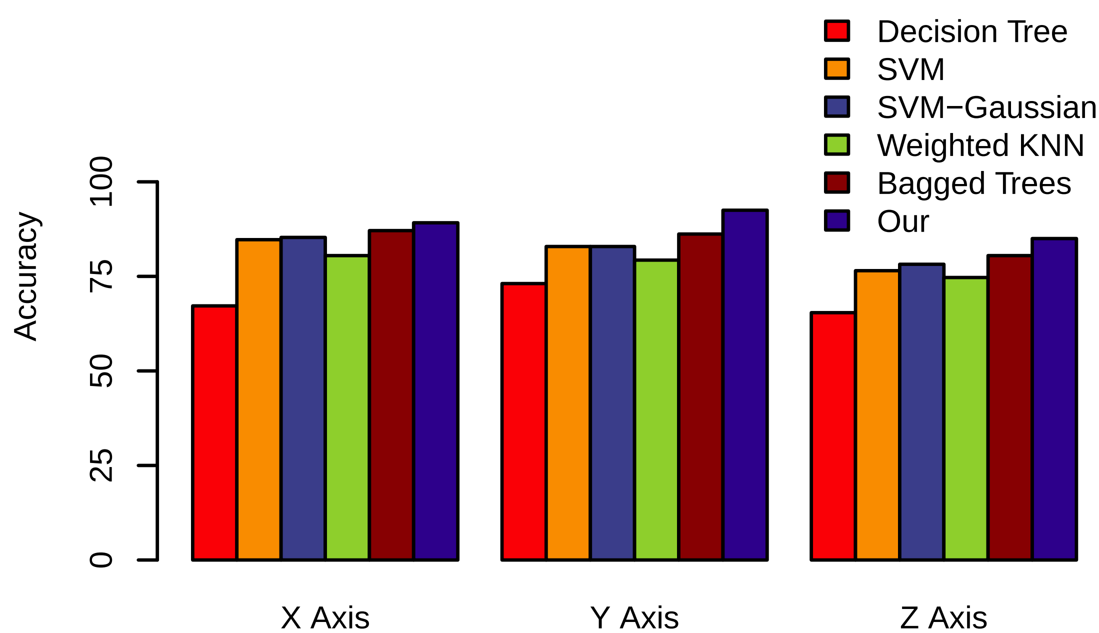



Figure 5.20: Performance of Algorithms using 1-axis Acceleration (UCI Dataset) [9]

### 5.7 Discussion

We have presented a human activity recognition system for smartphones. Here we leveraged the built-in accelerometer sensor to identify users current activity. For the first dataset of 10 participants, out of 10 activities, we achieved 100% accuracy for all the activities. We used individualized models for each of the participants. We extracted 5 time-domain features from the same dataset and applied 10 classification algorithms. We achieved the largest accuracy of 91% using these techniques. We also compared (Figure 5.19) our work with Anguita [9] using 60 time and frequency domain features. We present a comparative analysis of our work with state-of-the-art techniques in Table 5.5. We compare activities, methodology, sensors, extracted features, no of subjects, and performance for each of the works. Compared to the existing approaches, we achieved a very good accuracy for the personalized model even with a less amount of data. This gives us the opportunity to easily create a high accuracy personalized activity recognition model. We also presented time required to build RPS and extract time and frequency domain features from the acceleration signal of sample size 128 and 600, shown in Figure 5.21. The time required to extract features (7 features and 66 features respectively) is 3 to 4 times higher than building RPS. Also, the time to recognize activity class is fast, taking an approximate time of 0.0715 milliseconds.

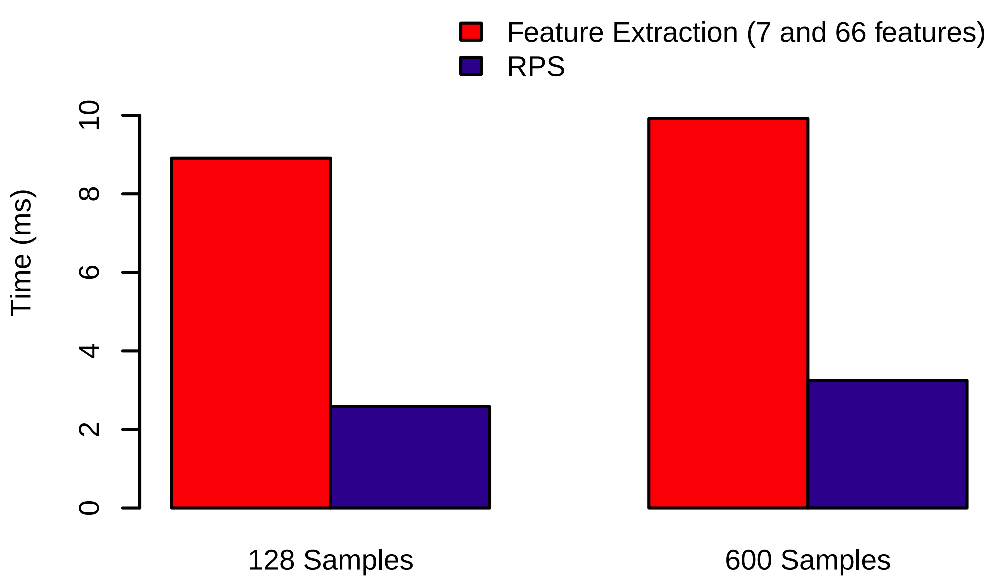



Figure 5.21: Time Required to Extract Features and Build RPS

Table 5.5: Comparison of Representative Past Works on Activity Recognition

| **Work** | **Activities** | **Methodology** | **Sensors** | **System** | **Features** | **Subjects** | **Accuracy** |
|---|---|---|---|---|---|---|---|
| [32] | Gait, 3 speed walking | Cross DTW, SVM, BN, RT, MLP | 3 axis Acc | Smartphone | 24 | 25 | 99%, 81.9%, 89.3% [1] |
| [88] | 5 | MOE, GLCT | 3 axis Acc, Orn, Mag, Light, Prox | Smartphone | 22 | Unknown | 91.7%, 92.56% [2] |
| [11] | 5 | HMM, SVM | 3 axis Acc | Smartphone | 106 | 12 | 90.8%, 88.1%, 95.2% [3] |
| [22] | 6 | Random Forest | 3 axis Acc | 1 Wearable | 20 | 14 | 94% |
| [15] | 20 | DT | 2 axis Acc. | 5 Wearables | 40 | 20 | 84% |
| [113] | 8 | NB, SVM, kNN, DT, Plurality Voting | 3 axis Acc | 1 Wearable | 12 | 2 | 73% to 99% [4] |
| [9] | 6 | SVM | 3 axis Acc, Gyr | Smartphone | 561 | 30 | 96% |
| [78] | 6 | ST, LR, ML NN | 3 axis Acc | Smartphone | 43 | 29 | 83% [5] |
| [14] | 6 activities, 6 transitions | kNN, SVM, GMM, RF, HMM, k-Means | 3 axis Acc, Gyr, Mag | 3 Wearables | 168 | 6 | 99%,83% [6] |
| [129] | 2 activities, 4 transitions | HMM | 1 Axis Acc | Wearable | 6 to 20 | 3 | 70% to 80% |
| Our | 11 | RPS, GMM, MLE | 1 axis Acc. | Smartphone | RPS | 40 | 100%, 90% [7] |

[1] Walking(Individualized: 99%, Generalized: 81.9%) Gait: 89.3%. [2] Dateset 1: 91.7%, Dataset 2: 92.56%.
[3] Mean 90.8% (Known location), 88.1% (Unknown location), highest 95.2% (pocket). [4] Varies in different settings.
[5] Mean [6] Supervised: 99%, Unsupervised: 83% [7] Individual: 100%, Generalized: 90%
[8] Acronyms: DTW: Dynamic Time Warping, MLP: Multilayer Perceptron, Acc: Accelerometer, MOE: Mixture-of-Experts, GLCT: Global-local co-training, Orn: Orientation, Mag: Magnetometer, Prox: Proximity, Gyr: Gyroscope.

For the second dataset, we applied our approach and used a generalized model. However, the system was able to classify 6 different activities of 30 participants with an accuracy of 90%. We achieved 99% accuracy for sitting and lying activity, and 95% for standing. The overall accuracy increased to 95% when we increased the number of samples in the activity cycle. When we used individualized models the system was able to classify the activities with an accuracy of 100%. Hence, our approach was able to recognize 11 different activities for 40 different users varying the smartphone placement between the pocket and waist. This is only using the observation from one single axis accelerometer data for personalized models.

The walking, walking upstairs, and walking downstairs are classified with an accuracy of 75%, 90%, and 85% respectively. It looks like the system is unable to fully capture dynamics for these three activities. When we looked at the misclassified instances, we saw that all the misclassified instances were classified between these three activities interchangeably. Also by observing RPSs for these activities we saw that they have a similar dynamics. It means, when we placed the smartphone on the waist, these three showed similar dynamics based on the acceleration along y-axis. We considered grouping these three activities as one activity, named ”walk”, and then classifying it. We found that the system is able to classify the walk activity with 100% accuracy.

We think that the representational capabilities of time-delay embedding (RPS) captures the underlying dynamics well from the time series acceleration. The higher dimensional representations also helps GMM to learn well from RPS. Compared to existing approaches where the goal is to extract time and frequency domain features to learn signal patterns, this approach (RPS+GMM) focuses on understanding underlying dynamics, which describes the temporal evolution of the activities that evolve over time. The better RPS understands underlying dynamics, the better GMM learns. This achieves higher accuracy compared to existing approaches.

In this chapter, we investigated the performance and applicability of the dynamical systems and chaos theory in the smartphone based human activity recognition system. We also used time-delay embedding or reconstructed phase space to capture underlying dynamics of the human body motion for 11 different activities from smartphones accelerometer sensor. Most of the proposed and existing approaches use three axes acceleration along with other sensors (3-axes gyroscope, pressure, magnetometer) values to recognize activities. In contrast to these approaches, we only used one axis acceleration to recognize activities. This reduces the computational and memory complexity of the system by reducing the size of data (from 3-7 time series to 1 time series) that needs to be processed. Moreover, most of the machine learning techniques require extensive computation and occupy large memory because of the large number of attributes that are present in the feature vectors [81]. Building RPSs are less complex and less expensive than these techniques, Figure 5.21. The time required to extract features is a couple magnitude higher than building RPS. This is very helpful for implementation of the system on the smartphone. We also reduced computational and memory complexity by considering a small sample size. We used a statistical learner to train captured underlying dynamics in the RPSs and used maximum likelihood classifier to classify activities.

Human activity recognition plays a very important role in many research areas and applications. Therefore, a support system, which will provide information about current activity of the user by hiding all the complex details behind activity recognition, is a time demanding service for these areas. We have implemented the proposed activity recognition system in the Android application framework as a service (Figure 5.22). The applications from the application layer and other services from the application framework can register to get the activity information.

We implemented our system (as android application) in two different case

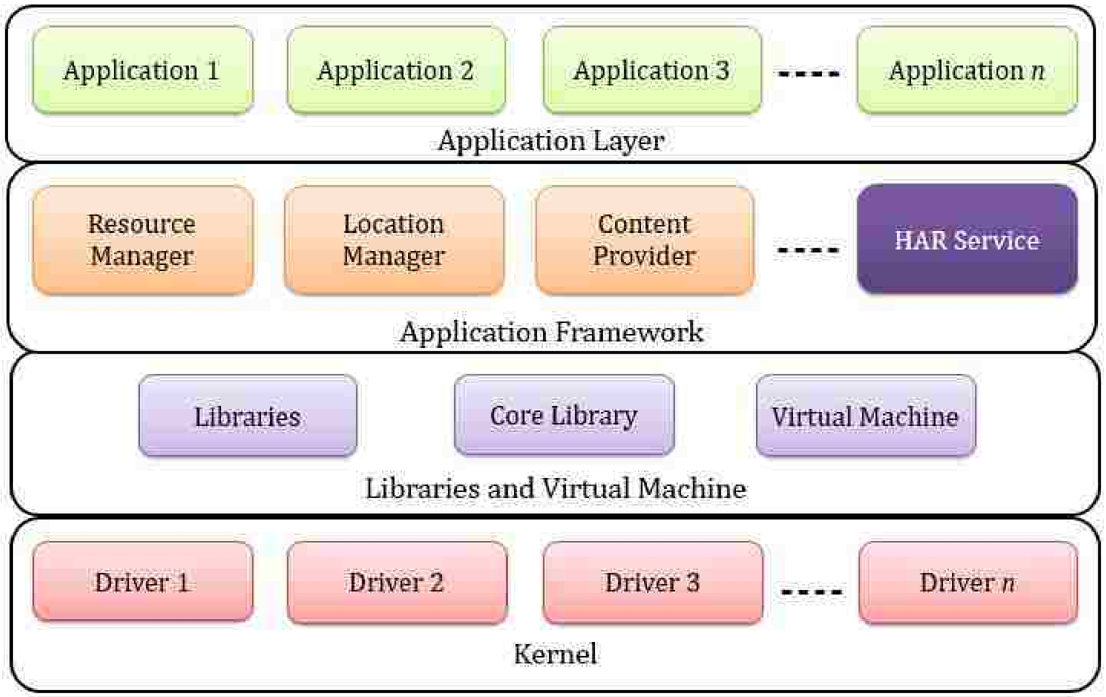



Figure 5.22: Human Activity Recognition as a Service in Android

studies: 1) a rehabilitation clinic, to track patients daily activities, and assess assigned task and daily routine, 2) the Hajj, to track pilgrims' location based on their activities. We used Android platform for the implementation. We have published our dataset on a public domain website to enrich human activity dataset and accelerate research in this area.

### 5.8 Conclusion

We experimented with an alternative approach to extensively use machine learning techniques in human activity recognition from kinematics sensors (accelerometer) and achieved a high accuracy. We also investigated the performance of the proposed approach using collected and publicly available human activity recognition datasets. We presented a comparative study and an analysis. Application of the proposed system in wearable sensor based activity recognition can be researched further. The analysis of the experience and results from the case studies can be a future work.

The functional or complex activities comprise of a simple activity and a particular function. For example, when a person is reading a book, it is most likely that the person is sitting somewhere. We developed this simple activity recognition system to expand our work on the complex activity recognition system (we discuss it in next chapter), where this simple activity will be considered as one of the inputs beside location and time to predict functional activities.

## 5.9 Related Publications

### 5.9.1 Publications

- **Md Osman Gani**, Taskina Fayezeen, Sheikh I. Ahamed, Richard J. Povinelli, Roger O. Smith, Muhammad Arif, A. J. Kattan, ”A Novel Light Weight Smartphone based Activity Recognition using Gaussian Mixture Models of Reconstructed Phase Spaces,” IEEE Transaction on Mobile Computing, (As of the publication of this dissertation in April 5, 2017, this reference is currently **under review**).

- **Md Osman Gani**, Taskina Fayezeen, Sheikh Iqbal Ahamed, Richar J. Povinelli, ”Computationally Efficient Human Activity Modeling and its Application as a Service in Android Application Framework,” ACM HotMobile, February 2016, FL, USA.

- **Md Osman Gani**, Taskina Fayezeen, Sheikh Iqbal Ahamed, Dennis B. Tomashek, Roger O. Smith, ”Simple Activity Recognition Using Smartphone Technologies For In-Home Rehabilitation,” RESNA 2015 Annual Conference, June 2015, Denver, Colorado, USA.

### 5.9.2 Poster

- **Md Osman Gani**, Golam Mushih Tanimul Ahsan, Amit Kumar Saha, Sheikh Ahamed, ”Smart Spectacle Clip to Train and Prevent Fall,” Proceedings of the

Forward Thinking Poster Session, Marquette University, WI, USA, Nov. 2016.

- Taskina Fayezeen, **Md Osman Gani**, Sheikha Iqbal Ahamed, ”mHealth System for the Patients with Arthritis,” Proceedings of the Forward Thinking Poster Session, Marquette University, WI, USA, Nov. 2015 (Best Poster Award).

# CHAPTER 6

# COMPLEX HUMAN ACTIVITY RECOGNITION

## 6.1 Introduction

Automated recognition of human activities has importance across different fields such as pervasive computing, artificial intelligence, human-computer interaction, human-robot interaction, rehabilitation engineering, assistive technology, health outcomes, social networking, and social sciences [121], [125], [81]. Human activity recognition (HAR) is an interdisciplinary research area that has been active for more than a decade. Despite the length of time researchers have investigated HAR, there are still many major issues that need to be addressed. There are numerous context-aware applications where user activities play an important role. HAR also plays a pivotal role in pervasive computing systems [81]. HAR systems are also being used in monitoring people in assisted living, elderly care, and rehabilitation [94] [60].

Humans perform numerous activities in their everyday life. Existing studies suggest two classes of activities based on body motion and functionality [33]. The first one is simple full body motor activity; the second one is complex functional activity. Full body motor activity considers body motion and posture, for example, walking, sitting, or running. The functional activity class deals with different functions performed by the subject, for example, reading, working on computer, or watching TV. Existing research defines these two classes of activities with different terminologies. Also, the boundaries of these classes are not well defined [33].

Performing activities of daily living (ADLs) and instrumental activities of daily living (IADLs) are an important part of living a healthy independent life [89], [99]. These activities cover a wide range, such as self-care, meal preparation, bill paying, and entertaining guests. Virtually every rehabilitation therapist and program focuses on these types of activities as outcome goals. The ability to perform ADLs and IADLs are important indicators both for those recovering from a newly acquired disability, as well as for those at risk for decline, either through chronic, physical or mental impairments (i.e., ALS, MS, Parkinsons, Alzheimers), and may act as early indicators of disease or illness [19]. Disruptions in the routine of ADLs can be an indicator of either lack of success in rehabilitation or significant decline in function, and act as an important indicator of a return to or decrease in the quality of life (QoL) [138], [70]. These disruptions in routine are often used as indications that help diagnose, treat, and document the outcomes of services for people with a wide variety of disabilities including psychological impairments, such as depression and dementia [20], [45], [95]. Additionally, older adults may perform activities despite decreases in functional capacity. However, a threshold of declined functional performance may be reached, at which time assistance may be necessary [3].

Substantial research has been conducted on simple human activity recognition (HAR), whereas, less research has been conducted on complex human activity recognition [81]. However, there are many key aspects (recognition accuracy, computational cost, energy consumption, privacy, mobility) that need to be addressed in both areas to improve their viability. We propose a novel complex activity recognition framework where the time, location, and simple full body motor activity are used to recognize complex functional activity. To the best of our knowledge, this is the first approach to consider simple activity as an influential parameter in the recognition process of complex activities. Also, ours is the first approach to consider a large number of complex activities.

We evaluated our proposed system using a dataset of 51 unique complex activities. We collected data of time, location, simple activity, and complex activity. The data was collected from 3 subjects, 2 male and 1 female, 2 subjects for 3 weeks and 1 subject for 2 weeks, in total of 56 days of data. The out-of-sample experiment shows that the approach achieved an accuracy of above 97% for all the subjects over 51 unique complex activities. The goal of developing this system is to implement it in two different scenarios. One setting is in a rehabilitation clinic for remote activity monitoring of patients and elderly people; we have two locations, one in the USA and one in Taiwan. The other setting is in the Hajj [97], to track pilgrims when they get lost and provide emergency services if needed.

The summary of the contributions of this research include:

- Propose a novel framework to recognize complex human activity.
- Evaluate the proposed framework with real human activity data of 56 days.
- Activity recognition system with a very good accuracy across 51 unique complex activities.
- Comparative analysis with existing works.
- Publish complex human activity dataset on the public domain to enhance research in the area of complex HAR.

This chapter is organized as follows. The related research is discussed in section 6.2. The background is discussed in section 6.3. The proposed approach is discussed in section 6.4. The data collection is presented in section 6.5. The experimental details are discussed in section 6.6. The contributions are discussed in section 6.7. Finally, the conclusions are presented in section 6.8.

### 6.2 Related Work

We discussed the classification of activities, taxonomy of state-of-the-art human activity recognition approaches and activities studied by those approaches in Chapter 2. In Chapter 5, we discussed human activity recognition approaches in detail, including computer vision approach, environmental sensor-based approach, and wearable sensor-based approach. We presented machine learning based methodologies used in different approaches. In this section, we discuss the approaches in detail.

#### 6.2.1 Computer Vision

Computer vision approaches implement the HAR where the activities can be performed by one or more subjects [6] [69]. Cameras are used as sensors to capture an image or a sequence of images (video). These images and videos are then analyzed to recognize activities and gestures. There are many applications for the computer vision approach, especially in security and interactive applications [81]. Applications include surveillance and interaction with video games. One of the main advantage of this approach is it can be used to recognize a wide range of gestures and activities.

There are some disadvantages with this approach, including privacy, mobility and computational complexity. Recording video or capturing images may violate user privacy. Due to the fixed location of the camera, the approach lacks mobility or pervasiveness. The recognition of objects and actions from the image or a sequence of images require good computational power, thus making it computationally expensive.

#### 6.2.2 Environmental Sensor

Environmental sensor based approaches use different sensors throughout the environment to capture signals about surroundings to recognize activity [132] [101]. Sensors include sound sensor, light sensor, RFID, wireless devices (Wi-Fi, Bluetooth), and pressure sensor [5] [144]. The sensors are placed at different locations. Sound and pressure sensors are on the floor, light sensors in the room, RFID attached to different objects (faucet, door, glass, drawer, medication container), and wireless devices placed in different rooms. Signals from these devices are analyzed to recognize a wide range of activities. It can be used to recognize activities in home settings.

This approach lacks mobility and applicability as it is unable to recognize activities not involving placed sensors or if the sensors are out of reach. Thus, environmental sensor approaches are unable to recognize any outdoor activities. It also requires high costs to setup and maintain a large set of sensors.

### 6.2.3 Wearable Sensor

The wearable sensor based approaches tries to capture human body motion using kinematic and other sensors [33] [152]. Sensors used in this approach include accelerometer, gyroscope, magnetometer, orientation, pressure, location (GPS) [82]. There are approaches where physiological signals (heart rate, electrocardiogram (ECG)) are captured to recognize activities. Sensors are attached to different parts of the subject's body to capture body motion and physiological parameters. Beside this, smartphones have built-in sensors, which are also used to recognize activities. The subject carries the smartphone and built-in sensors capture motion. Another set of wearable devices are wrist-worn devices, like the smart watch and fitness tracker. These devices are equipped with kinematics sensors, heart rate sensors and other sensors to capture motion and physiological parameters.

This approach has been used widely to recognize simple human activities, energy expenditure, workout, and a small set of complex human activities. Placement of the sensors on different parts of the body may make it uncomfortable for the user and lacks viability for real-life applications. Besides, these body worn sensors require computational power and connectivity that compromises device batteries. It is also not possible to recognize activities if the subject does not carry their smartphone or wear wrist-worn devices. Another problem with the smartphone-based approach is that different users carry smartphones in different locations (pant pocket, belt, backpack, hand) making it more complicated.

### 6.2.4 Time Geography

In the time geography approach, the time and location are used to recognize human activities [29] [98] [114]. Both time and location have been used separately to predict human activities. Importantly, the literature has examined the use of time and location data to predict activity. Hagerstrand was early to propose that human activities were constrained not only by location, but also by time, which he called ”time geography” [127]. He also recognized individual differences and emphasized the importance of the individual as the unit of study in human activity [29]. As humans we are creatures of habit and tend to follow the similar routines based on various cycles. Such cycles include circadian rhythms, weekly schedules, seasonal events and annual holidays. Prediction of what a person is doing based on their individual time schedules is quite plausible when both location and time are known. The better granularity of the time/activity linked data increases the confidence level of the deduction. This method of location and time based activity deduction is currently used in such diverse fields as environmental health [35], wildlife monitoring [49], and traffic systems analysis [58].

The time information is easily available to any computing device, while the location information requires the use of technologies discussed in Chapter 4. Outdoor locations are easier to find while indoor locations lack accuracy and reliability. The more accurate locations are obviously better for activity recognition.

## 6.3 Background

In this section, we discuss the background of the mathematical model used to model complex activity data and perform the experiment. We discuss the data modeling in section 6.6.

### 6.3.1 Markov Model

The Markov Chain (MC) is a stochastic process with the Markov property. The Markov property is that, given the current state, future states are independent of past states [48] [47]. Therefore, only the information of the current state influences the evolution of the future process. A MC is a sequence of random variables $X_1, X_2, ...$, defined by

$$\begin{aligned} &Pr(X_{n+1} = x | X_n = x_n, ..., X_1 = x_1) \\ &= Pr(X_{n+1} = x | X_n = x_n). \end{aligned} \tag{6.1}$$

The values of $X_i$ constitute a finite set called the state space of the MC, denoted by

$$S = \{1, 2, 3, ..., N-1, N\}. \tag{6.2}$$

The state $S_t$ denotes the state at the time instant $t$ and ranges over the set $S$. The Markov Model (MM) has two parameters, $\pi$ and $A$, the initial probabilities of the states and the transition probabilities between the states. The initial probability, $\pi_i$, is the probability that the value of the state will be $i$ at time $t$. The transition probability, $A_{ij}$, is the probability of the transition from the state $i$ at time $t$ to the state $j$ at time $t+1$. Therefore,

$$\begin{aligned} \pi_i &= Pr(S_t = i), \quad i \in \mathbb{S}. \\ A_{ij} &= Pr(S_{t+1} = j | S_t = i), \quad i, j \in \mathbb{S}. \end{aligned} \tag{6.3}$$

### 6.3.2 Hidden Markov Model

The Hidden Markov Model (HMM) is a statistical MM with the system being modeled as a Markov process. HMM is used to model the generative state sequences that can be characterized by an underlying process that generates an observable sequence [48]. It can be used to find the unobserved sequence of hidden states from the respective sequence of the related observation. HMM has been used for modeling and analyzing time series data. It has been applied in many areas including automatic speech recognition, natural language processing, and face recognition. The HMM is defined by three parameters, $\pi$, $A$, and $B$, where, $\pi$ and $A$ are the parameters that form the MM. The other parameter, $B$, is the observation matrix, where each entry in the matrix represents the probability of a specific observation given that the system is in a particular state at a particular time. Therefore,

$$B = \{b_j(k)\}, where \quad b_j(k) = P(v_k \quad at \quad t|S_t = j), \tag{6.4}$$

the probability of $v_k$ being the observation given that the system is in state $j$ and $v_k$ is the member of the set $V$, the discrete set of possible observations. $\lambda$, where $\lambda = (A, B, \pi)$, is used to denote the HMM. The observation symbol observed at time $t$ is denoted by $O_t$.

**Applications of HMM**

HMMs are used to solve three main problems:

- Given the HMM, $\lambda$, compute the probability of occurrence of the observation sequence $O$, $P(O|\lambda)$.
- Given the HMM, $\lambda$, compute the state sequence, $I$, so that the joint probability of the observation and state sequence, $P(O, I|\lambda)$, are maximized.
- Adjust the parameters of the HMM to maximize the $P(O|\lambda)$ or $P(O, I|\lambda)$

We discuss the modeling of the complex activity with the application of HMM in section 6.6.

## 6.4 Our Approach

Most of the complex activities are influenced by the time and location at which they occur. Time and location provide vital information about the ongoing activity. For example, when a person is sitting in the dining room at night, it is most probable that the person is eating dinner. Here the time ”night,” and the location ”dining room” provide us very useful information to identify that the person is eating his/her dinner. Beside time and location, simple activity also provides us essential information about the complex activity. In the previous example, simple activity ”sitting” helps to determine complex activity. We propose a novel system to predict complex functional activity of the user. Here we use time, location, and identified simple activity as input to the system. These inputs are used to develop a mathematical model.

### 6.4.1 Proposed Framework

We propose a novel system to predict complex activity based on time, user location and simple human activity (Figure 6.1). Simple activities provide influential information about complex activities. We use smartphone to collect sensor data and recognize simple activities. With smartphone, activities can be recognized indoors and outdoors as long as the user carries it. We leverage Wi-Fi signals to find indoor locations and Wi-Fi and GPS to find outdoor locations. Time is readily available in most computing systems.

Besides Wi-Fi based localization and smartphone based simple activity recognition, any other approach can be used to get the location and simple activity information. The main goal of the framework is to use time, location, and simple activity information to recognize complex activity.

To the best of our knowledge, this is the first approach that considers simple activity as a parameter to predict complex activity. The assumption is that the incorporation of this vital parameter in the recognition system with time and location information helps to recognize complex activities.

## 6.5 Data

One of the most challenging tasks in the area of HAR research is to collect real data from subjects [81]. We discuss the data collection process in the following subsection.

### 6.5.1 Data Collection

We collected real human activity data from three subjects. The subjects included two men and one woman. Our goal is to collect data consisting of time,

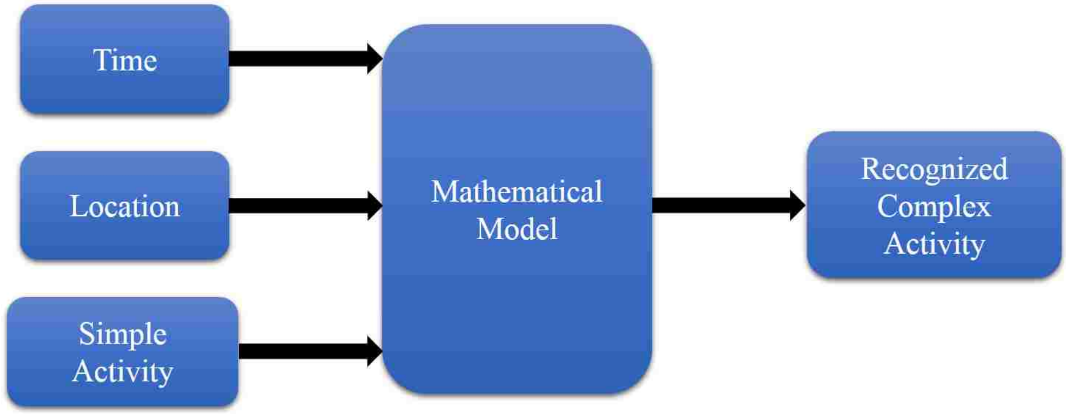



Figure 6.1: Complex Human Activity Recognition Framework

Table 6.1: Snapshot Of The Complex Activity Dataset

| Time | Room | Anchor | SA | CA |
|---|---|---|---|---|
| 7:05 | bedroom | bed | lying | wake up |
| 7:20 | bathroom | shower | standing | showering |
| 8:10 | kitchen | counter | standing | make coffee |
| 12:33 | dining room | table | sitting | eating lunch |
| 16:26 | door | front door | walking | returning home |
| 18:45 | living room | recliner | sitting | playing games |

location, simple activity, and complex activity of the subjects throughout the day. In this data collection process, for each of complex activity, we collected time of the complex activity, location where the activity is performed with a specific anchor whenever possible, duration of the complex activity, corresponding simple activity, and the performed complex activity. We have collected data from two of the subjects for three weeks (21 days), and data from the other subject for two weeks (14 days). In total, we have 56 days of data. We show the snapshot of the data in Table 6.1. The first column contains the time complex activity performed. The second and third columns contain the location data, in two parts. The first part is the room inside the apartment or house. The second part has more precise location inside the room with respect to different household stuff and object anchors such as bed, sofa, chair, sink etc. The fourth column lists the simple activity (SA) that has been performed. The fifth

Table 6.2: Set of Simple Activities, Room and Anchor Level Locations

| Room | Anchor | SA |
|---|---|---|
| Bedroom | Bed | Sitting |
| Bathroom | toilet | Standing |
| Kitchen | Sink | Walking |
| Front Door | Counter | Lying |
| Dining Room | Dining Table | - |
| Living Room | Chair | - |
| Porch | Shower | - |
| Garage | Dresser | - |
| Laundry Room | Refrigerator | - |
| - | Couch | - |
| - | Door | - |
| - | Hamper | - |

column contains the performed complex activity (CA). We also collected the duration of the performed activities.

The set of simple activities, room level locations, and anchor level locations for subject 1 are shown in Table 6.2. These are listed in first, second, and third columns respectively. Here we have 9 room level locations, 12 anchor level locations, and 4 simple activities. The other two subjects also have a similar set of locations and simple activities.

### 6.5.2 Kasteren Human Activity Dataset

We also collected a complex human activity dataset [137] from the public repository available for research. The data were recorded in a three-room apartment with one subject performing everyday activities. 14 state-change sensors were installed at different locations of the apartment. These included doors, cupboards, refrigerator, and toilet-flush. The data were collected for a period of 4 weeks or 28 days, with a total of 245 activities recorded. It contains time of the activity, sensor event, and activity.

Activities were annotated by the participant. Recorded activities were 1) leave house, 2) toileting, 3) showering, 4) sleeping, 5) preparing breakfast, 6) preparing dinner, and 7) preparing a beverage. These activities are used to assess cognitive and physical capabilities of elderly in healthcare. The assessment is based on Katz ADL index.

### 6.6 Evaluation

We evaluated our proposed framework with the collected complex activity data. The nature of the problem of complex human activity recognition falls in category 2 of the applications of HMM. Here the observation sequence, $O$, is the combination of time, location, and simple activity. The state sequence, $I$, corresponds to the sequence of the complex activities performed by the subject. In this case, we want to find the most likely state sequence (complex activities) for a given observation sequence, $O = O_1, O_2, ..., O_T$ and a HMM, $\lambda = (A, B, \pi)$. We have used the Viterbi algorithm [48] to find the hidden state sequence (complex activities) using the maximum likelihood. This algorithm can be interpreted as a graph search where the vertices are the states of the HMM. We discuss the data modeling and building HMM parameters in the following subsections.

#### 6.6.1 Data Modeling

We modeled the collected data to work with the HMM. We describe the data modeling process in this section. The idea was to form unique observations $(O_t)$ from the combination of time, location, and simple activity and unique states $(S_t)$ using the complex activities.

**Time**

The dataset contains a specific time instant for each complex activity in the format of ”hour:minute,” more specifically ”hh:mm.” Our goal was to minimize number of observations in the set. Therefore, we grouped every 15 minutes to the same time group. We start from ”00:00” and for every 15 minutes we formed a time group till ”23:59.” In total, we have 96 different time groups.

**Location**

The location information has two parts: location with respect to the house/apartment and location within the room with respect to anchor/object. We combined both of them together to form a combined location. For example, for the second subject, we found 10 different locations inside the house. These included bedroom, dining room, kitchen, living room, laundry room, etc. Also, we identified 19 different anchors, which include couch in the living room, sink in the kitchen, table in the dining room, etc. We combined both locations to form a location groups. In theory, there were 190 location groups possible for the first subject.

**Simple Activity**

The simple activities were also recorded during the data collection. These include walking, running, sitting, standing, lying. We treated each activity as it is.

**Complex Activity**

We considered each of the complex activities as the state of the system. For the first subject, we have in total 43 unique complex activities. These unique complex activities form the set of states, $S$. The other two subjects have 37 and 51 unique complex activities, respectively.

After forming the time groups and location groups, we combined them with the simple activity to form the unique observations. In total, we have 250 unique observations for the first subject. Using these 250 unique observations we built the observation set $O$.

### 6.6.2 Experiment

We used the modeled data to compute the parameters of the HMM. We computed the transition matrix, $A$, and the initial probability matrix, $\pi$, from the set of states $S$. We also computed the observation matrix, $B$, from the set of states, $S$, and observation set, $O$. Each entry in the observation matrix has the probability of the respective observation (combined group of time, location, and simple activity) given the state (complex activity) of the system.

### 6.6.3 Experiment with Kasteren Dataset

In this experiment, we used time and location information to recognize complex activities. We modeled data following the same procedure described in the previous section. We present the result of the experiment in the following subsection.

### 6.6.4 Result

We used individualized model to experiment with the dataset. We built three different models (HMM) for three subjects. We used Matlab to perform the experiment. For each subject, we used Algorithm 6.2 to build the parameters of each of the models. Once the model was ready, we applied Viterbi algorithm to find the hidden state sequence (complex activities) for the given observation sequence (time, location, and simple activity). The Viterbi algorithm computes the most likely sequence of complex activities from the given model (initial probability of complex activities, transition probability of complex activities, and observation probability matrix of observations (time, location, simple activity) and complex activities).

We present the quantitative evaluation of the system in this subsection. The accuracy of the system recognizing the subject-wise complex activities are presented in Figure 6.3. This accuracy was achieved using all the input parameters (time, room level location, anchor level location, and simple activity). We tabulated the number of activities and corresponding system accuracy in Table 6.3. From the table we can see that the accuracy of the system for the subject 1, subject 2, and subject 3 are 97.59%, 98.39%, and 97.89% respectively.

In the second experiment, using the Kasteren dataset, we achieved an accuracy of 98.51%. This accuracy was achieved using time and location information.

```
Matrix CA contains the complex activities, S is the set of states, and O is the set of observations
numberOfStates ← size of S
numberOfObservations ← size of O
π ← array[numberOfStates]
for i = 1:numberOfStates do
    π(i) = sum(i == CA)
end for
π ← π./(length of O)
A ← array[numberOfStates, numberOfStates]
for i = 2:numberOfObservations do
    A(CA(i-1), CA(i)) = A(CA(i-1), CA(i)) + 1
end for
for i = 1:numberOfStates do
    sumOfAiRow = sum(A(i, :))
    A(i, :) = A(i, :)./sumOfAiRow
end for
B ← array[numberOfStates, numberOfObservations]
for i = 1:numberOfObservations do
    B(CA(i), O(i)) = B(CA(i), O(i)) + 1
end for
for i = 1:numberOfStates do
    sumOfBiRow = sum(B(i, :))
    B(i, :) = B(i, :)./sumOfBiRow
end for
```

Figure 6.2: Build Hidden Markov Model Parameters Procedure

Table 6.3: Subject-wise Number of Activities and Corresponding System Accuracy

| Activities/Subject | Our Dataset | | | Kasteren dataset |
|---|---|---|---|---|
| | Woman 1 | Man 1 | Man 2 | Subject 1 |
| Number of unique activities | 37 | 43 | 51 | 7 |
| Accuracy of the system | 97.59% | 98.97% | 97.89% | 98.51% |

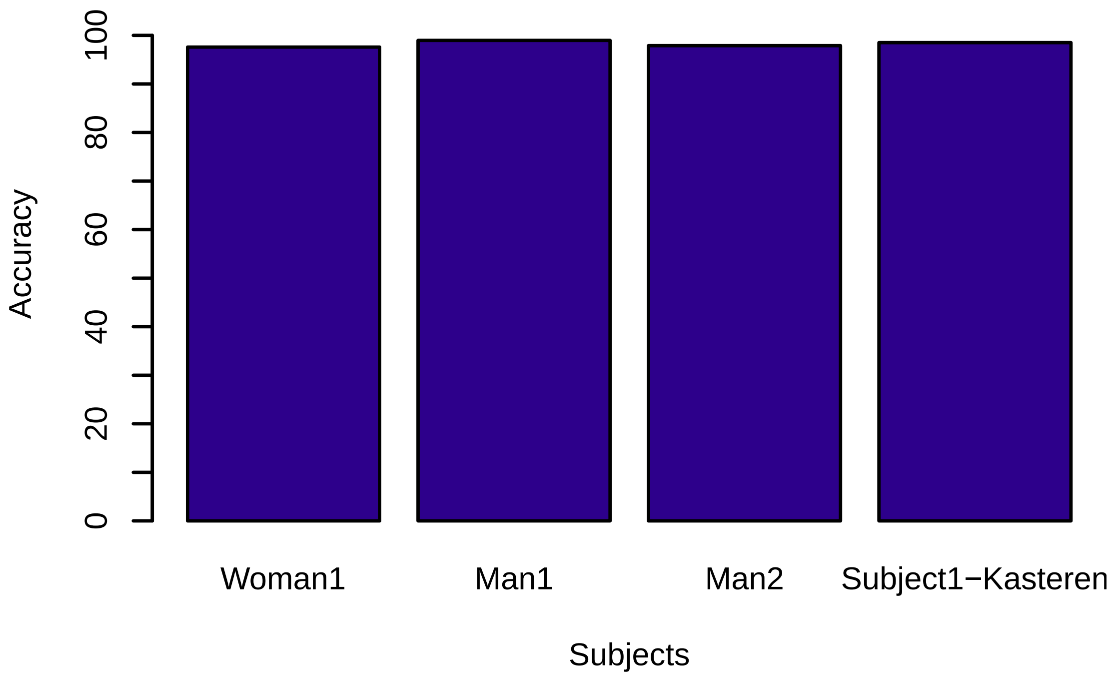



Figure 6.3: Comparison of Accuracies for All Subjects.

Table 6.4: Subject and Activity-wise Classification Result

| Subject | Man1 | | | Man 2 | | | Woman 1 | | |
|---|---|---|---|---|---|---|---|---|---|
| Total Activities | 485 | | | 855 | | | 747 | | |
| Misclassified | 5 | | | 18 | | | 18 | | |
| Unique Activities | 43 | | | 51 | | | 37 | | |
| Unique Misclassified | 2 | | | 10 | | | 7 | | |
| Misclassified Activities | Activity | Wrong | Total | Activity | Wrong | Total | Activity | Wrong | Total |
| | Personal Hygiene | 2 | 24 | Cleaning Dishes | 3 | 34 | Cleaning Dishes | 4 | 63 |
| | Cleaning Dishes | 3 | 27 | Eating Lunch | 1 | 18 | Eating & Watching TV | 1 | 9 |
| | - | - | - | Food Preparation | 2 | 68 | Knitting | 2 | 15 |
| | - | - | - | Getting a Drink | 1 | 22 | Leaving Home | 1 | 27 |
| | - | - | - | Getting a Snack | 1 | 17 | Sitting (Window) | 1 | 3 |
| | - | - | - | Leaving Home | 4 | 29 | Talking over phone | 1 | 8 |
| | - | - | - | Putting Dishes | 1 | 16 | Watching TV | 8 | 67 |
| | - | - | - | Resting | 1 | 14 | - | - | - |
| | - | - | - | Soaking Dishes | 1 | 4 | - | - | - |
| | - | - | - | Watching TV | 3 | 63 | - | - | - |

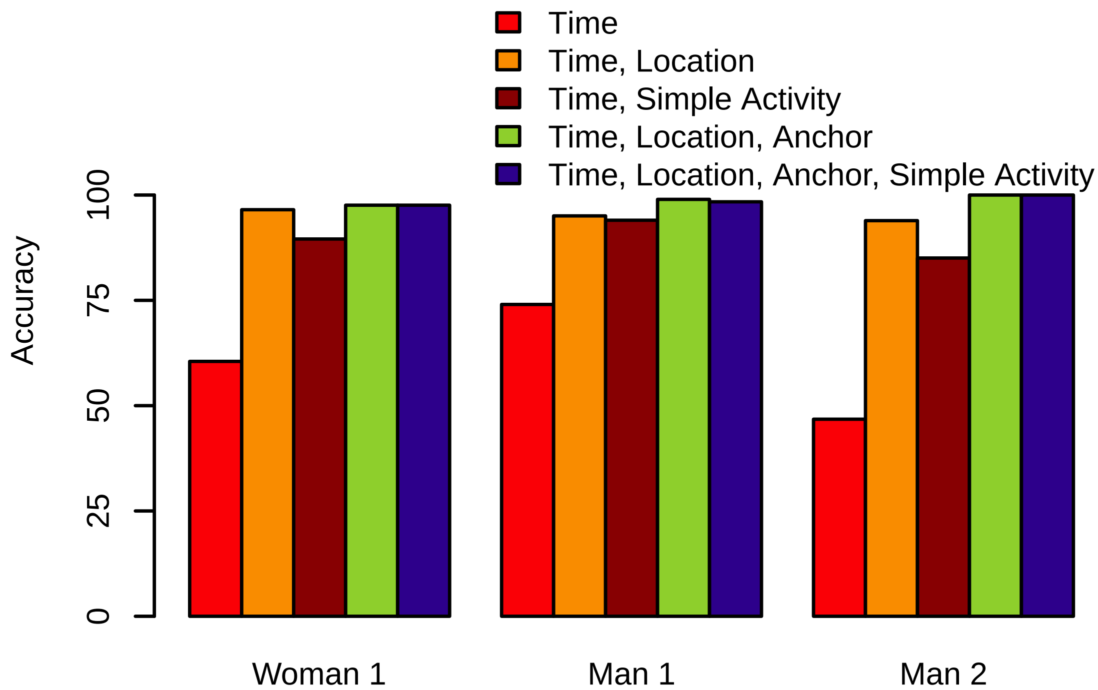



Figure 6.4: Comparison of Accuracies for All Subjects Varying Input Parameters.

We also performed experiments varying input parameters (time, room level location, anchor level location, and simple activity). The accuracy of the system recognizing the subject-wise complex activities are presented in Figure 6.4 and Table 6.5. We saw the lowest accuracy (60%, 74% and 46% for woman1, man1, and man2 respectively) of the system with only *time* parameter as input. When we added room level location with the time information in input, we observed that the accuracy increased to 93%. The inclusion of anchor level location (with time and room level location) makes it go above 97%. Inclusion of simple activity with the other three inputs produce the same level of accuracy. It seemed like simple activity did not provide any additional information; however, when we used only time and simple activity information the accuracy goes above 85% (89.5%, 94% and 85% for woman1, man1, and man2 respectively). Therefore, we concluded that the simple activity does contain vital information about the complex activity. Also, we can offset location information with the simple activity information when the location is unavailable or unreliable.

Beside individualized model, we also performed experiments where the models are trained with one subject and tested by other two subjects. We observe that the performance of the model depends on the regularity and similarity of the activities performed by the subjects. There are also other constraints like difference in room level locations and anchor level locations.

Table 6.5: Recognition Accuracies Varying Parameters

| **Subject** | **T** | **TR** | **TS** | **TRA** | **TRAS** [1] |
|---|---|---|---|---|---|
| Woman 1 | 59.71 | 96.52 | 89.56 | 97.59 | 97.59 |
| Man 1 | 73.81 | 95.05 | 94.02 | 98.97 | 98.97 |
| Man 2 | 46.67 | 93.92 | 85.73 | 97.89 | 97.89 |

[1] Acronyms: T: Time, TR: Time, Room Level Location, TS: Time, Simple Activity, TRA: Time, Room Level Location, Anchor, TRAS: Time, Room Level Location, Anchor, Simple Activity.

We present the subject and activity-wise classification result in Table 6.4. The first four rows have the total number of activities and unique activities for each subject along with respective number of misclassified activities. We present the activity-wise total and misclassified instances in the following eight rows for each subject. For each subject, we present the activity, total and number of misclassified instances in each row. We see that in most of the cases, the number of misclassified activity is lower than the total occurrence of the respective activity.

### 6.6.5 Analysis

In this experiment, we had four parameters, 1) time, 2) room level location, 3) anchor level location, and 4) simple activity. We tried all possible combination of these inputs taking combination of 1, 2, 3, and 4 parameters, one combination at a time, respectively. We represent each of the parameters with their initials (T, R, A, and S). There are 15 possible combinations, 4 single parameter inputs, 6 double parameter

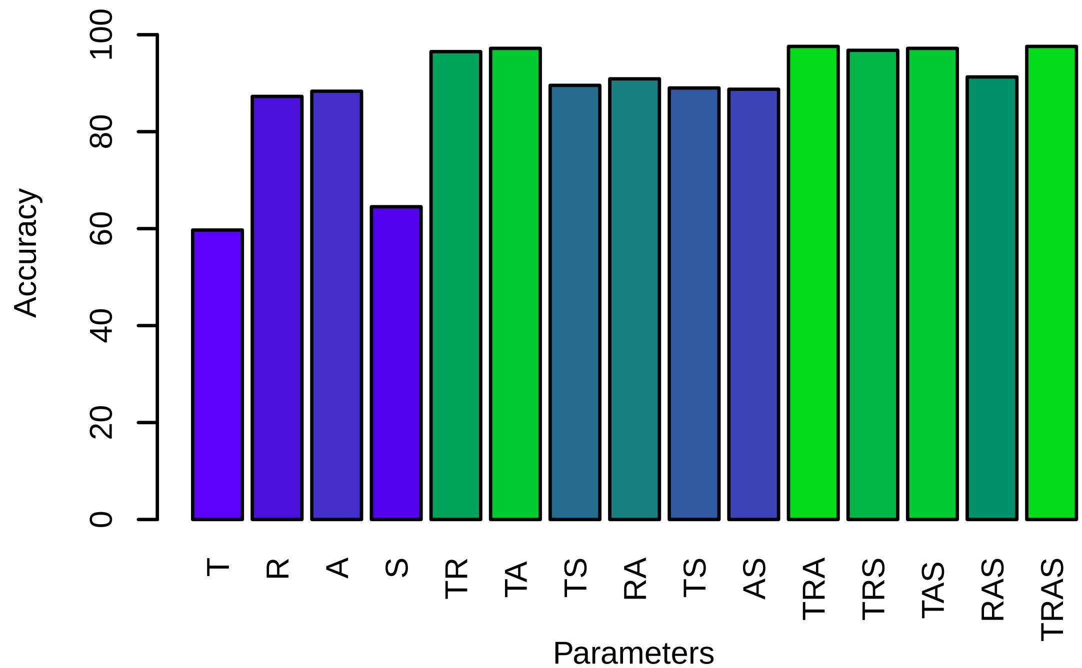



Figure 6.5: Accuracy for Woman1 Varying Input Parameters

inputs, 4 triple parameter inputs, and 1 tetra parameter input. We combined the initials to represent corresponding combination. The results of the experiments are presented in Table 6.6. Each row contains results for individual subjects and each column contains results for one combination of the parameters. The corresponding graph for this result is shown in Figure 6.8 to visualize the comparative performance. We also present subject wise performance in Figures 6.5, 6.6, and 6.7.

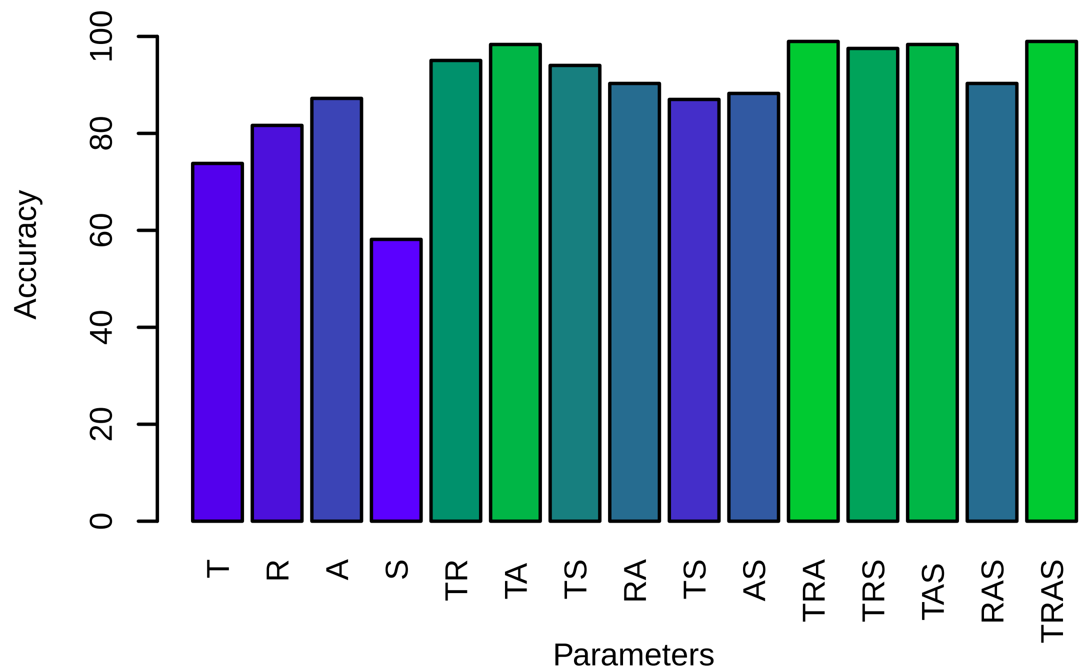



Figure 6.6: Accuracy for Man1 Varying Input Parameters

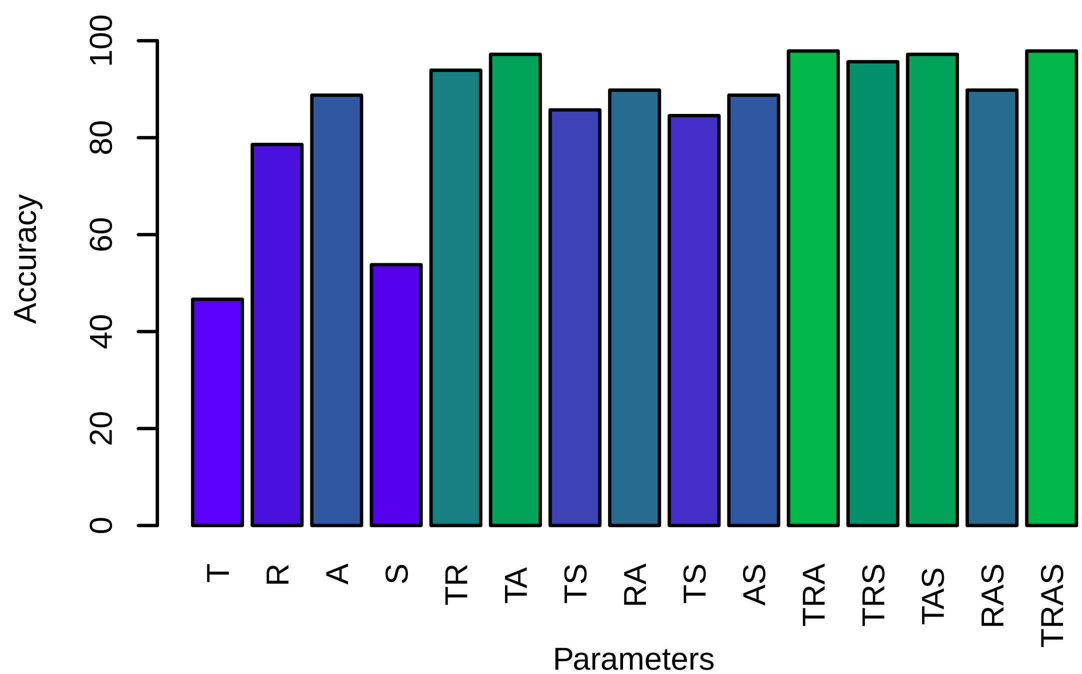



Figure 6.7: Accuracy for Man2 Varying Input Parameters

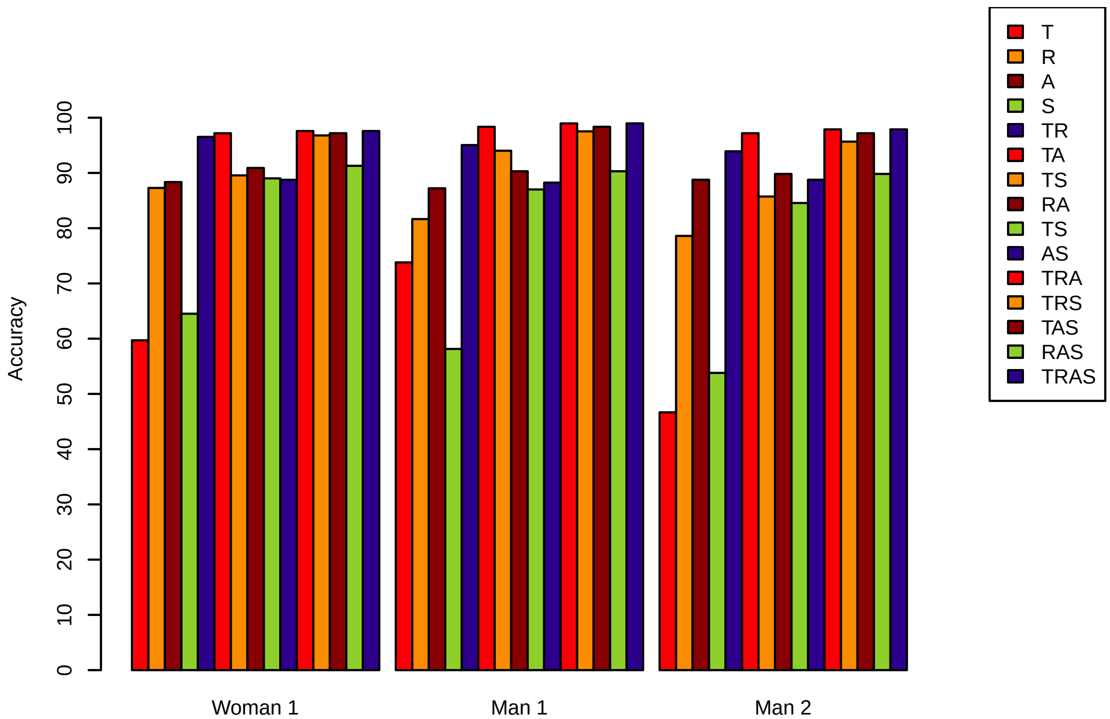



Figure 6.8: Subject-wise Comparison of Accuracies Varying Input Parameters

Table 6.6: Recognition Accuracies for All Combination of Parameters

| Subject | T | R | A | S | TR | TA | TS | RA | RS | AS | TRA | TRS | TAS | RAS | TRAS [1] |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Woman 1 | 59.71 | 87.28 | 88.35 | 64.52 | 96.52 | 97.19 | 89.56 | 90.90 | 89.02 | 88.76 | 97.59 | 96.79 | 97.19 | 91.29 | 97.59 |
| Man 1 | 73.81 | 81.65 | 87.22 | 58.14 | 95.05 | 98.35 | 94.02 | 90.31 | 87.01 | 88.25 | 98.97 | 97.53 | 98.35 | 90.31 | 98.97 |
| Man 2 | 46.67 | 78.60 | 88.77 | 53.80 | 93.92 | 97.19 | 85.73 | 89.82 | 84.56 | 88.77 | 97.89 | 95.67 | 97.19 | 89.82 | 97.89 |

[1] Acronyms: T: Time, R: Room Level Location, A: Anchor, S: Simple Activity.

We observe that for each subject, the combinations of the input parameters showed similar recognition performance. The time information alone produced the lowest accuracy, while the combinations of time, room level location, and anchor level location produced higher accuracy. When we look at the performance for location and combination of locations, it is between 80% to 90%. Once we add the time information to the locations, the accuracy goes up to highest accuracy. Therefore, time information does carry a lot of information about the complex activity. Again, with just simple activity input, it achieved an accuracy between 53% to 64%. Once we added the time information with the simple activity information, the accuracy went up by a lot, and is between 85% to 94%. Therefore, time information again helped to achieve a good accuracy with simple activity recognition. The combination of time and simple activity was able to recognize complex activities with a high accuracy.

Human activities vary with location. It is more likely to do kitchen activities while in the kitchen and personal hygiene activities while in the bathroom. The more accurate location information we can get, the better result for the activity recognition. The location information was relatively hard to get with a reliable accuracy. If we considered room level location and anchor level location, we had to place a large set of sensors through-out the home to get an accurate estimation of the location. With wireless signal based approaches the indoor localization was less reliable and lacked accuracy. Anchor level locations were even harder to get with a good accuracy than room level locations. Therefore, it is not helpful to use location information with an unreliable localization system. As location influences complex activities a lot, a small error in the input will produce erroneous recognition.

On the other hand, the simple activity information was relatively easy to get from different devices (smartphone, body worn sensors, smart watch, fitness tracker). Therefore, even when the location information was unavailable or unreliable, it is possible to recognize complex activities with an accuracy up to 94%. It is remarkable that simple activity information and time help to recognize a large set of complex activities. Simple activity alone can not recognize complex activity with high accuracy. We observed that the set of simple activity is relatively small. Also, the same simple activity maps to a large number of complex activities. Therefore, there is a large number of possible complex activities for a single simple activity. Thus, it is harder to get complex activity information from just simple activity information.

Human activities also vary with time. There are some activities people do only in the morning, some only in the evening or at night. Some activities happen in a sequence, one after another, while others happen in a periodic manner. Some activities happen over a long period of time. Therefore, time carries a lot of information about the ongoing activity. The time information helped both location and simple activity to recognize complex activities. In this experiment, we only used the simplest form of time information.

Beside simple time information, we also collected two other time information, duration of the activity and the day of the week. We also performed experiment with duration information. In this experiment, we divided duration information (in minutes) in to twelve levels to minimize number of observations in HMM. We used bar plot to analyze the duration information and find the range of duration levels (Table 6.7). We used this duration level (D) information to perform experiment. The duration level has been used both alone and with other parameters to form observation. The experimental result for Man1 is presented in Figure 6.9.

We observe that the time and duration information alone produced the lowest accuracy, while the combinations of time and duration produced higher accuracy (95.46%). Also, when we add the duration information to the locations and simple activity, the accuracy increases. Therefore, time information does carry a lot of information about the complex activity. Again, with just simple activity input, it achieved an accuracy between 58% . Once we added the time and duration information with the simple activity information, the accuracy went up by a large factor, and produces 98.35%. Therefore, time and duration information helped to achieve a high accuracy with simple activity recognition. In general, the incorporation of duration information increases the accuracy of the complex activity recognition.

Table 6.7: Duration Ranges and Levels

| **Time (minutes)** | **Level** |
|---|---|
| 0 to 1 | 1 |
| 1 to 2 | 2 |
| 2 to 5 | 3 |
| 5 to 10 | 4 |
| 10 to 15 | 5 |
| 15 to 20 | 6 |
| 20 to 30 | 7 |
| 30 to 60 | 8 |
| 60 to 120 | 9 |
| 120 to 180 | 10 |
| 180 to 240 | 11 |
| 240 and above | 12 |

There is other time information, for example, timestamp, one-step sequence (sequence of activities with respect to time), multi-step sequence, day of the week, day of the month, season, weekend, holiday, or day to day regularity. We only used 1st order time information in this experiment. These are time, and one-step sequence. We did not use other second order time information. Still, we achieved a pretty good accuracy. The influence of the other time information in complex activity recognition needs to be investigated.

The occupation of time and space tells a lot about the human activity. With the proliferation of sensors and related technologies, most previous research ignored time information to recognize complex human activities. Prior work also missed the

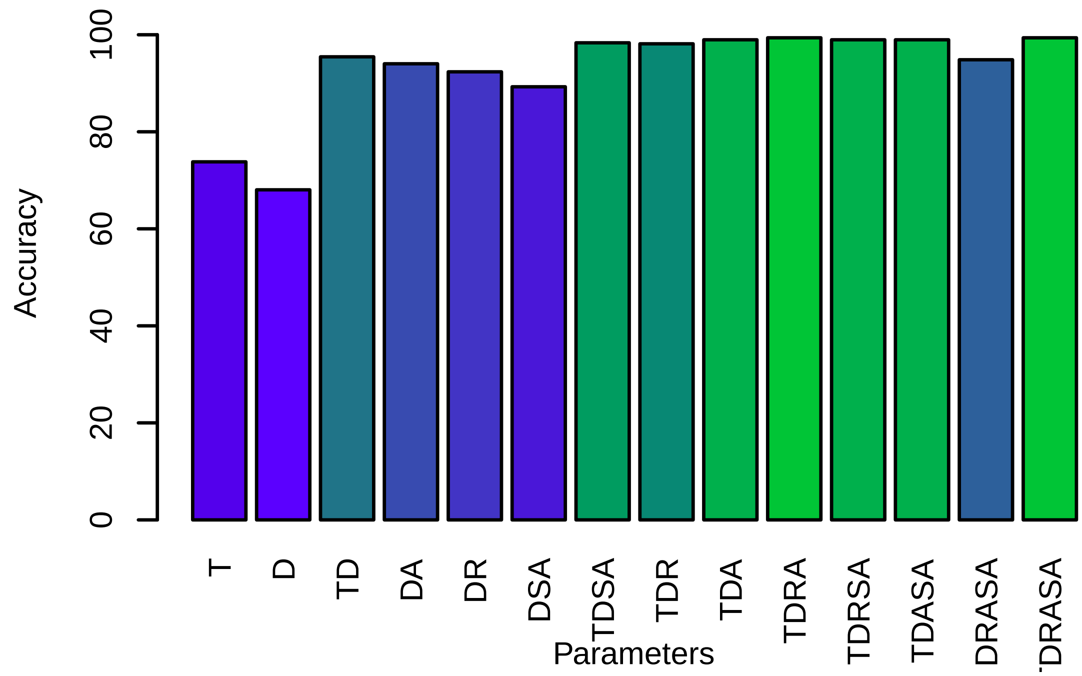



Figure 6.9: Accuracy for Man1 Varying Parameters Inclduing Duration

opportunity to leverage multi-level time information. The combination of time and other technologies may lead to better recognition of human activities.

## 6.7 Discussion

### 6.7.1 Contributions

We have presented a novel framework for complex activity recognition. We have also evaluated our proposed system using 56 days of real data from 3 subjects. The dataset consisted of 51 unique complex activities. We modeled the time, location, and simple activity to develop the mathematical model. We presented the experimental details and results of the experiments. The developed model classifies this large set of complex human activities with a very high accuracy of above 97%. The model can leverage simple activity information to recognize complex activities. The effects of absence of location and simple activity information have been presented. We also evaluated the proposed system using a public dataset. It classified a set of 7 complex human activities collected over 28 days with an accuracy of 98.51%.

We have compared our work with existing work in Table 6.8. For each work, we presented the number of activities it studied in the first column (simple activity (SA), complex activity (CA)) and total number of instances in the second column. The third column contains the total time duration of the data set. The fourth and fifth column presents the methodologies and different sensors used in the studies. The seventh column has the number of subjects that participated in the study. The last column contains the accuracy of the system. Our work has used 2087 number of instances of 51 unique complex activities and achieves an accuracy of above 97%.

Table 6.8: Comparison with Existing Works

| Work | # of activity | Total activities | Duration | Methodology | Sensors | # of subjects | Accuracy |
|---|---|---|---|---|---|---|---|
| [137] | 8 CA | 245 | 4 weeks | HMM, Conditional RF | 14 location sensors | 1 | 79.4 Class accuracy |
| [136] | 14 CA | 318 | 12 weeks | Hidden Semi MM, SMCRF | 25 sensors (reed switch, BT, IR, float, mercury contact) | 2 | Highest precision:75.3 & recall: 84.7 |
| [107] | 7 CA | - | - | HMM, EM, Bayesian | 25 sensors (reed switch, BT, IR, float, mercury contact) | 3 | Highest F-measure: 0.8 |
| [33] | 5 SA, 10 CA | - | - | MLP, NB, DTb, K-Start | Acc., Gyro., Smartphone | 10 | Over 50% for CA, 93% for SA |
| [15] | 3 SA, 17 CA | - | 160 hours | DTb, C4.5, NB, IBL | 5 Acc. sensor | 20 | 84% |
| [118] | 16 CA | - | 3 weeks | Context Driven Activity Theory | Acc., Smartphone, BT, RFID, GPS | 2 | 95.73% |
| Our | 51 CA | 2087 | 8 weeks | HMM, Viterbi | Acc., WiFi | 3 | above 97.58% |

### 6.7.2 Novelty

To the best of our knowledge, this is the first system to recognize complex human activities using time, location, and simple activity. Also, this is the first system to recognize a large number of complex human activities. The dataset used in this experiment was made publicly available to enhance the research in the area of HAR. We have extensively studied previous work in the area of HAR and presented the definition of simple activity and complex activity along with the related terminologies. We also presented the taxonomy of the approaches in HAR.

### 6.7.3 Applications

We have developed this system to implement in two different case studies. The first one in the rehabilitation clinics and elderly care (one in USA, and another in Taiwan), to track the patients' daily activities. The reported activities will be evaluated by a rehabilitation specialist to assess the assigned task and daily routine. The second one is in the Hajj, where millions of Muslims gather annually for the pilgrimage. The goal is to track pilgrims based on their activities and provide emergency services if needed.

## 6.8 Conclusions

Human activity recognition has an important role in many research areas and their applications. We have presented taxonomy of the human activities and human activity recognition approaches. We proposed a novel framework to recognize complex human activities. We collected real complex activity data from three subjects for a total of 56 days. We used HMM and Viterbi algorithm to model and recognize activities. We achieved a very good accuracy of above 97% for a large number of activity sets. The system achieved upto 94% accuracy with just time and simple activity information. The comparison of other approaches with this dataset can be a future work. Also, other datasets can be used to evaluate the proposed system.

## 6.9 Related Publications

### 6.9.1 Publications

- **Md Osman Gani**, Amit Kumar Saha, Golam Mushih Tanimul Ahsan, Sheikh Iqbal Ahamed, Roger O. Smith, ”A Novel Framework to Recognize Complex Activity,” (IEEE COMPSAC 2017; As of the publication of this dissertation in April 5, 2017, this reference is **accepted** for publication).

- **Md Osman Gani**, Sheikh Iqbal Ahamed, Roger O. Smith, ”A Novel Framework to Recognize a Large Set of Complex Activities,” (Smart Health, Elsevier; As of the publication of this dissertation in April 5, 2017, this reference is currently **under review**).

- **Md Osman Gani**, Sheikh Iqbal Ahamed, Samantha Ann Davis, Roger O. Smith, ”An Approach to Complex Functional Activity Recognition using Smartphone Technologies,” in Proceedings of RESNA 2014 Annual Conference, June 11 -15, 2014, Indianapolis, IN, USA.

### 6.9.2 Poster

- Piyush Saxena, **Md Osman Gani**, Sheikh Iqbal Ahamed, Stephen Yau, ”Situation-Aware Cyber-Human Environments for Enriched Assisted Living,” in Proceedings of the Forward Thinking Poster Session, Marquette University, WI, USA, Nov. 2014.

# CHAPTER 7

# CONCLUSION

## 7.1 Summary

In this dissertation, we describe how we developed a mathematical model and systems for indoor and outdoor localization. We used received signal strength indicator (RSSI) as a parameter to model location with distance. We evaluated the localization system by developing an asset tracking system. We also developed a computationally efficient approach to recognize simple human activity. Theory from chaos and nonlinear system along with Gaussian mixture model was used to capture, understand and learn underlying dynamics of the simple human activities. We proposed a framework to recognize complex human activities using time, location and simple activity information. Hidden Markov Model was used to evaluate the framework with real data.

There is much opportunities for future research to advance the knowledge in this area. In simple human activity recognition, application of the time-delay embedding method in wearable sensor-based activity recognition can be researched further. The analysis of the experiment and results from the case studies can be a future work. In complex human activity recognition, the comparison of other approaches with the collected dataset can be a future work. Also, other datasets can be used to evaluate the proposed system.

## 7.2 Contributions

The major contribution of this research work is in algorithm development, system design, framework development, and evaluation with real data. In this section we summarize the contributions of this dissertation. These contributions are discussed with respect to each of the application areas.

### 7.2.1 RSSI based Indoor Localization for Smartphone using Fixed and Mobile Wireless Node

Today with the widespread use of mobile computing, wireless technology, smartphones and diverse related services, different localization techniques have been developed. One of the widely used space-based satellite navigation system is Global Positioning System (GPS). It has a high rate of accuracy for outdoor localization. But the service is not available inside buildings. Also other existing methods for indoor localization have low accuracy. In addition, they require fixed infrastructure support. In this work, we presented an extensive survey on existing localization techniques in wireless technology. We proposed a novel approach to solve indoor localization, which also works well outside. We have developed a mathematical model to estimate location (both distance and direction) of a mobile node (router) using wireless technology. We have presented our results and it shows that we can achieve good accuracy (an error less than 2.5 meters) on smartphones (Android and iOS). We have evaluated the developed system in different applications.

### 7.2.2 Asset Tracking System for Smartphone

We have developed an asset/object tracking system for smartphones using the first approach. Here the mobile node (WiFly) is integrated with the asset (target object) to be tracked. We have developed two separate applications in Android and iOS for the smartphone to track the distance and direction of the mobile node (tracked asset). The application can find the location (distance and direction) of the mobile node. It can also trigger an alarm (paging sound) in the tracked asset so that user can locate it using the sound. We have used the open-source electronics prototyping platform ”Arduino-Mini” to power our developed system.

### 7.2.3 Data Collection Tool

We developed a data collection tool, ***UbiSen*** (Ubicomp Lab Sensor Application), in Android, to collect sensor data from smartphone. It shows the list of available and unavailable sensors in green and red colors respectively. It can collect data from all available sensors simultaneously. We used multi-threading technique to parallelize the operation and separate data collection process from the main thread. It provides more precise sensor data at each timestamp. The developed tool is generic. It can be used to collect data from a specific set of sensors. The frequency can be specified from the settings of the application. The data collection process can be labeled. It offers a stop watch to start and stop the data collection process. The recorded data can be exported as a CSV (comma separated value) file. Beside human activity data collection, it can be used for a wide range of purposes to collect sensor data from built-in smartphone sensors.

### 7.2.4 Novel Light Weight Smartphone based Activity Recognition using Gaussian Mixture Models of Reconstructed Phase Space

Human activity recognition is an important area of research because it can be used in context-aware applications. It also has significant influence in many other research areas and applications including healthcare, assisted living, personal fitness, and entertainment. With the pervasive use of smartphones, which contain numerous sensors, data for modeling human activity is readily available. This study presents a computationally efficient smartphone based human activity recognizer, based on dynamical systems and chaos theory. A reconstructed phase space is formed from the accelerometer sensor data using time-delay embedding. A single accelerometer axis is used to reduce memory and computational complexity. A Gaussian mixture model is learned on the reconstructed phase space. A maximum likelihood classifier uses the Gaussian mixture model to classify ten different human activities and a baseline. One public and one collected dataset were used to validate the proposed approach. Data was collected from 10 subjects. The public dataset contains data from 30 subjects. Out-of-sample experimental results show that the proposed approach is able to recognize human activities from smartphones' one-axis raw accelerometer sensor data. The proposed approach achieved 100% accuracy for individual models across all activities and datasets. The proposed research requires three to seven times less amount of data than existing approaches to classify activities. It also requires three to four times less time to build reconstructed phase space compare to time and frequency domain features.

#### 7.2.5 Application of Simple Full Body Motor Activity Recognition System as A Service

A support system, which will provide information about current activity of the user by hiding all the complex details behind activity recognition, is a time demanding service in HAR applications. We implemented the developed simple activity recognition system in the Android application framework as a service. The applications from the application layer and other services from the application framework can register to get the activity information. It provides an opportunity to a wide range of application areas to leverage activity information.

#### 7.2.6 Recognition of Complex Functional Activity

Human activity recognition has importance in many research areas including healthcare, elderly care, assisted living, and context-aware applications. There has been much work involving simple human activities like walking, sitting, and running. There are only a few studies that considered recognizing complex human activities such as reading a book, watching TV, doing dishes, and cooking. This study presents a novel framework to recognize complex activities. The framework uses the time, location, and simple activity to recognize complex activities. These inputs of the framework have been used to model the observation and the complex activities as the states of a Hidden Markov Model. Then the Viterbi algorithm was used to find the hidden states (complex activities) from the observations (time, location, and simple activity). Data was collected from three subjects for a total of 56 days consisting 51 unique complex activities. Out-of-sample experimental results show that the proposed approach is able to recognize these 51 unique complex activities. The approach achieved an accuracy of above 97% for all the subjects. The proposed approach leverages time, location, and simple activity information to recognize complex activities. It also achieved up to 94% accuracy with just time and simple activity information. We also evaluated the proposed system using a public dataset. It classified a set of 7 complex human activities collected over 28 days with an accuracy of 98.51%.

### 7.3 Broader Impact

Our research work helps to understand the key issues and challenges in the area of human activity recognition. It also describes the different issues related to building localization systems using RSSI value of wireless networks. The localization technique developed here will help building low cost, infrastructure-less mobile systems. The simple human activity recognition system developed here helps in the recognition of the human activities with reduced computational and memory complexity. It also improves the recognition accuracy. The complex human activity recognition provides a bigger picture of daily human life. To the best of our knowledge, this is the first system to recognize complex human activities using time, location, and simple activity. Also, this is the first system to recognize a large number of complex human activities. It will be helpful in many different areas from achieving context-awareness in ubiquitous computing systems to perform functional assessment, cognitive assessment, and measure health outcomes in occupational science and rehabilitation engineering. Besides, the followings are the list of products that has been/can be developed from this dissertation:

- Child tracking or asset tracking device with smartphone application
- System service in smartphone to offer simple human activity recognition
- Simple activity recognition API
- Software application to estimate complex human activity information from time, location, and simple activity information
- System for rehabilitation engineers and occupational therapist to estimate patients activity and perform assessment after surgery.

### 7.4 Future Works

Automated recognition of human activities plays an important role in our everyday life. The length of the activities ranges from seconds to hours. Also, we interact with other objects in the environment while performing these activities. A series of simple activities and changes in time and location forms a more complex activity. The changes in time along with simple activity and location history can be used to investigate complex activity recognition. The interactions with the surrounding objects in the connected home environment may lead to a better understanding of the human activities and their recognition process. The use of sensor signals from a single device to recognize complex activity may not provide us a good activity recognition system. Rather, working in a bottom-up approach, where these simple information can be bundled together along with location history, time changes, input from surrounding devices to get more intelligence about the activity, needs to investigated to recognize different levels of human activities. With the progress in human activity recognition, there are many exciting applications from personal management and context-aware personal assistant to ubiquitous mobile computing system in the connected world.

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# Appendix A

## WRIST-WORN HEART RATE SENSOR TO RECOGNIZE HUMAN ACTIVITIES

We worked on recognizing human activities from wrist-worn heart rate sensor data. The apple watch is equipped with a heart rate sensor to measure heart rate. We collected heart rate data using a wrist-worn apple watch from two subjects. The data were collected for 1 week for three different activities. The activities are walking, sitting, and standing. The watch was worn in three different configurations: loose fit, fit, and tight. These configurations are based on how tight or loose the watch is worn with the wrist. We have used last three holes of the watch belt for each of the configurations. For each configuration, we collected heart data from the apple watch heart rate sensor every 15 to 20 minutes. We collected four heart rate samples every time. We have also collected heart rate data using the Pulse Oximeter and hand reading.

We have analyzed the collected heart rate data to find correlation with the human activities. At first, we have analyzed the apple watch heart rate data. We observed that the heart rate data varies within a short time period. It shows a significant difference even in four samples collected at each iteration where time difference is less than a minute and there was no changes in activities and emotion. We than compared the data collected from apple watch with the data collected using hand reading and Pulse Oximeter. The hand reading and reading from the Pulse Oximeter are consistent and had a little to no difference. On the other hand, the apple watch heart rate sensor data were significantly different from the Pulse Oximeter reading. We have found a mean root mean square error (RMSE) of 21 beats per minute (BPM) for all configurations. The lowest RMSE was 9 BPM for the fit configuration for fourth heart rate reading and the highest RMSE was 33 for the tight configuration for second heart rate reading. In general, there is an mean error of 15 to 20 BPM for all other readings and configurations. Therefore, the unreliability of heart rate data from the apple watch heart rate sensor makes it difficult to recognize human activities.

# APPENDIX B

## SMART SPECTACLE CLIP TO TRAIN AND PREVENT FALL

Elderly people are the fastest growing segment of the population in the world. According to the Administration on Aging (AoA), the older population, 65 years or older people, numbered 46.2 million in 2014. They represent the 14.5% of the US population and by 2060, there will be more than twice their number in 2014 [106]. Falls are the leading cause of accidents in elderly people. It is also the primary cause of serious injuries and accidental deaths. It is more common than strokes [44]. Research has identified the leading risk factors that contribute to falling. The four leading risk factors are vision problems, lower body weakness, difficulty with walking and balance, and home hazards [54]. Most of the falls are caused by a combination of the above risk factors. Changes or modification to these risk factors can help to train and prevent falls.

Healthcare providers (rehabilitation therapist) can help to cut down risk by reducing fall risk factors. Vision problem is an important risk factor. Wearing multifocal glasses while walking leads to falls [56]. Though nowadays many presbyopes use the progressive lenses, conventional bifocal and trifocals. They offer wider lens areas than progressive lenses for reading and using computer. People with progressive lenses use another pair of glasses for other activities such as walking. These different types of lenses can make things seem closer or farther away than they actually are and leads to a fall if they forget to wear the correct glass [64]. In this work, we worked to develop a portable smart spectacle clip to remind the subject when to change glasses. The smart clip recognizes and track the activities. It reminds and warns the user to change the glasses suitable for the activities. The repeated reminders help training the subject to wear right glasses for the activities. Also, the real-time warnings help prevent the falls.

# APPENDIX C

## LINK TO CODE

The code to recognize simple human activities and corresponding C code to implement system service in Android Application Framework is uploaded to the `https://bitbucket.org` under Ubicomp Laboratory account. The link to the repository is:

`https://bitbucket.org/ubicomplaboratory/simple-human-activity-recognition`

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# APPENDIX D

## LINK TO PUBLISHED PAPERS

The papers published from this dissertation is stored in the `https://bitbucket.org` under Ubicomp Laboratory account. The link to the repository is:

`https://bitbucket.org/ubicomplaboratory/papers`

# APPENDIX E

## LIST OF PRODUCTS

The followings are the list of products that has been/can be developed from this dissertation:

- Child tracking or asset tracking device with smartphone application
- System service in smartphone to offer simple human activity recognition
- Simple activity recognition API
- Software application to estimate complex human activity information from time, location, and simple activity information
- System for rehabilitation engineers and occupational therapist to estimate patients activity and perform assessment after surgery.
- Smart spectacle clip to train and prevent fall