Computational Approaches for Remote Monitoring of Symptoms and Activities

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COMPUTATIONAL APPROACHES FOR REMOTE MONITORING OF SYMPTOMS AND ACTIVITIES

by
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ABSTRACT
COMPUTATIONAL APPROACHES FOR REMOTE MONITORING OF SYMPTOMS AND ACTIVITIES

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We now have a unique phenomenon where significant computational power, storage, connectivity, and built-in sensors are carried by many people willingly as part of their life style; two billion people now use smart phones. Unique and innovative solutions using smart phones are motivated by rising health care cost in both the developed and developing worlds. In this work, development of a methodology for building a remote symptom monitoring system for rural people in developing countries has been explored. Design, development, deployment, and evaluation of e-ESAS is described. The system's performance was studied by analyzing feedback from users. A smart phone based prototype activity detection system that can detect basic human activities for monitoring by remote observers was developed and explored in this study. The majority voting fusion technique, along with decision tree learners were used to classify eight activities in a multi-sensor framework. This multimodal approach was examined in details and evaluated for both single and multi-subject cases. Time-delay embedding with expectation-maximization for Gaussian Mixture Model was explored as a way of developing activity detection system using reduced number of sensors, leading to a lower computational cost algorithm.

The systems and algorithms developed in this work focus on means for remote monitoring using smart phones. The smart phone based remote symptom monitoring system called e-ESAS serves as a working tool to monitor essential symptoms of patients with breast cancer by doctors. The activity detection system allows a remote observer to monitor basic human activities. For the activity detection system, the majority voting fusion technique in multi-sensor architecture is evaluated for eight activities in both single and multiple subjects cases. Time-delay embedding with expectation-maximization algorithm for Gaussian Mixture Model was studied using data from multiple single sensor cases.

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Chapter 1

Introduction

Remote monitoring of different parameters is important for many reasons. Information like different symptoms can be crucial for doctors to provide quality treatment to the patients. Accurate information regarding human physical activity and ability to access that information real time remotely has far-reaching significance. Activity information is important to doctors who wants to monitor their patients. This technology can be used for monitoring elderly people who wants to maintain their independence. However, such monitoring systems usually require complex devices and significant involvement from the participants. Complex devices can be expensive whereas intrusive systems greatly discourages the usage in real life. Consequently, we focused on developing monitoring systems using smart phones. Smart phones are ideal candidate for numerous innovation. This is the first device that has significant computational power, storage and communication capability and is conveniently carried out by mass people. Developing a system centered around smart phones will most likely remove the necessity of carrying other extra devices. Even if it is required to use other sensors, it is possible to connect with those sensors using Bluetooth connectivity. As, by now 2 billion people worldwide are using smart phones, we now have a unique phenomenon where significant computational power, storage, connectivity, and built-in sensors are carried by mass people willingly as part of their life style. This unique phenomenon provides a great opportunity in terms of research and innovation. A realistic smart phone based symptom monitoring system or activity monitoring system can help to reduce the cost of health care. Rising cost of health care in developed countries are a serious threat for a sustainable economy. On the other hand, expensive health care prevents the poor from accessing basic health care service.

Inexpensive monitoring system through smart phones has the potential to greatly narrow the gap between rich and poor in terms of access to health care service. It can also help governments by reducing health care cost by reducing hospital visits and admission as some of the hospital services can be provided to patients even when the patients are at home. This dissertation focuses on design, development and deployment of self-reported remote symptom monitoring system as well as development of algorithm for activity detection from analysis of multiple sensor data.

1.1 Dissertation focus

In this dissertation we discuss how we developed a remote symptom monitoring system according Edmonton Symptom Assessment Scale (ESAS) to monitor rural breast cancer patients in Bangladesh. We described our plantar pressure based activity detection system that we built to enable remote monitoring of activities. We also developed a multimodal method for human activity detection and evaluated its performance. Another time-delay embedding approach was developed as a way of finding computationally inexpensive algorithm for activity detection.

1.2 Dissertation organization

Chapter 2 of this dissertation describes the mathematics behind machine learning algorithms that we have used for developing our activity detection system. This chapter also describes the necessary mathematics behind time-delay embedding approach for activity detection. Chapter 3 describes a detailed study of various research on different activity detection systems so far. Chapter 4 describes the methodology we adopted for design, development and deployment of e-ESAS. We also identified the barriers in developing a remote symptom monitoring system for rural developing countries and discussed them in this chapter. In chapter 5, a detail discussion about the design and development of e-ESAS was presented along with evaluation of the system from the deployment of e-ESAS. Chapter 6 describes the multimodal approach for activity detection and the design and development of our prototype system. In this chapter, we worked with single subject and for four activities. In chapter 7, we applied our multimodal approach in multiple subject scenario for eight activities. In chapter 8, we presented our findings from applying time-delay embedding with Gaussian Mixture Model for activity detection.

1.3 Publications

- **Ferdaus Kawsar**, Munirul Haque, Mohammad Adibuzzaman, Sheikh Iqbal Ahamed, Md Uddin. ***e-ESAS: Improving Quality of Life for Breast Cancer Patients in Developing Countries*** in MobileHealth 2012, SC, USA.

- **Ferdaus Kawsar**, Md Kamrul Hasan, Richard Love, Sheikh Iqbal Ahamed. ***A Novel Activity Detection System using Plantar Pressure Sensors and Smartphone*** in COMPSAC 2015, Taichung, Taiwan

- Md Munirul Haque, **Ferdaus Kawsar**, Mohammad Adibuzzaman, Sheikh Iqbal Ahamed, Richard Love, Rumana Dowla, David Roe, Syed Hossain, Reza Selim. ***Findings of e-ESAS: A Mobile Based Symptom Monitoring System for Breast Cancer Patients in Rural Bangladesh*** in CHI 2012, Austin, Texas, USA. (Honorable Mention)

- Md Munirul Haque, **Ferdaus Kawsar**, Mohammad Adibuzzaman,Sheikh Ahamed, Richard Love, Rumana Dowla, David Roe, reza Selim. ***Mobile Based health Care Solution for Breast Cancer Patients*** in M4D 2012, New Delhi, India (Nominated for Best Paper Award).

- Chowdhury Hasan, Mohammad Adibuzzaman, **Ferdaus Kawsar**, Munir Haque, Sheikh Iqbal Ahamed. ***PryGuard: A Secure Distributed Authentication Protocol for Pervasive Computing Environment*** in Modern Approaches in Applied Intelligence,Springer Berlin Heidelberg, 2011.

- Farzana Rahman, Md. Endadul Hoque, **Ferdaus kawsar**, Sheikh Iqbal Ahamed. ***Preserve Your Privacy with PCO: A Privacy Sensitive Architecture for Context Obfuscation for Pervasive E-Community based applications*** in Proceedings of the International Conference on Social Computing (SocialCom10), MN, USA, 2010.

- **Ferdaus Kawsar**, Jahangir A. Majumder, Sheikh Ahamed, William Cheng-Chung Chu. ***Identifying Phases of Gait and Development of Walking Model from Pressure and Accelerometer Data and It's Ramifications in Elderly Walking*** in ICOST, 2013:273-279

- Mohammad Adibuzzaman, Niharika Jain, Nicholas Steinhafel, Munir Haque, **Ferdaus Kawsar**, Sheikh Iqbal Ahamed,Richard Love: ***Towards In Situ Affect Detection in Mobile Devices: A multimodal approach,*** in Research in Adaptive and Convergent Systems(RACS, 2013)(Best Paper)

- Munirul Haque, **Ferdaus Kawsar**, Mohammad Adibuzzaman, Mohammad Miftah Uddin, Sheikh I. Ahamed, Richard Love, Ragib Hasan, Rumana Dowla, Tahmina Ferdousy, Reza Selim: ***Barriers for Breast Cancer (BC) Patients in Rural Bangladesh: Design and Deployment of a Mobile based Solution,*** In Proceedings of the 20th Americas Conference on Information Systems (AMCIS 2014), August 7 10, Savannah, Georgia.

- **Ferdaus Kawsar**, Sheikh Iqbal Ahamed, Richard Love: ***Remote Monitoring Using Smartphone Based Plantar Pressure Sensors: Unimodal and Multimodal Activity Detection,*** (ICOST, 2014, Denvaer, Colorado, USA.)

- **Ferdaus Kawsar**, Sheikh Iqbal Ahamed: ***Smartphone Based Multimodal Activity Detection System Using Plantar Pressure Sensors,*** In SAC 2014, Gyeongju, Korea.

- Munirul Haque, Mohammad Adibuzzaman, Md. Uddin, **Ferdaus Kawsar**, Sheikh I. Ahamed, Richard Love, Rumana Dowla, Reza Selim, Tahmina Ferdousy: ***Findings of Mobile based Palliative Care System: Towards a Generic Framework for Measuring QoL,*** In PervasiveHealth 2014, Oldenburg, Germany (Nominated for Best Paper Award)

- Munirul Haque, **Ferdaus Kawsar**, Mohammad Adibuzzaman, Md Uddin, Sheikh I. Ahamed, Richard Love, Ragib Hasan, Rumana Dowla, Tahmina Ferdousy, Reza Selim: ***e-ESAS: Evolution of a participatory design-based solution for breast cancer (BC) patients in rural Bangladesh,*** Personal and Ubiquitous Computing (2014): 1-19.

Chapter 2

Background

In this chapter, we provide background knowledge of some of the concepts that we have used. We have extensively used decision learning algorithm for activity detection. The primary motivation is twofold. First, decision tree based learners are quite accurate in classification. Second, it is easy implement the learned decision tree. We have also used time-delay embedding with Gaussian Mixture Model. We will discuss these two concepts in this chapter.

2.1 Decision Tree

In decision tree learning, the learned function is represented by a decision tree. Decision tree classify instances by traversing down the tree from the root to some leaf node. Leaf node is where classification of the instances is decided,. Each node in tree conducts a test of some feature on the instance. Each branch descending from that node corresponds to possible values of that feature. An instance is classified by starting at the root node, test attribute specified by this node, and then moving down the branch based on the outcome of the test until it reaches one of the leaves. We will demonstrate this using examples from our experiments. In a simple three activity scenario, we have two features, namely $meanP5$ and $meanP2$. $meanP5$ is defined as the average of 60 consecutive samples of pressure sensor P5 whereas $meanP2$ is the average of 60 consecutive samples of pressure sensor P2.

$meanP5 = \frac{\sum_{n=i}^{i+60} P5(i)}{60}$

Similarly for P2, the equation is:

$meanP2 = \frac{\sum_{n=i}^{i+60} P2(i)}{60}$

In our prototype system, the three activities we worked with were sitting, standing and walking. The tree we generated is shown below.

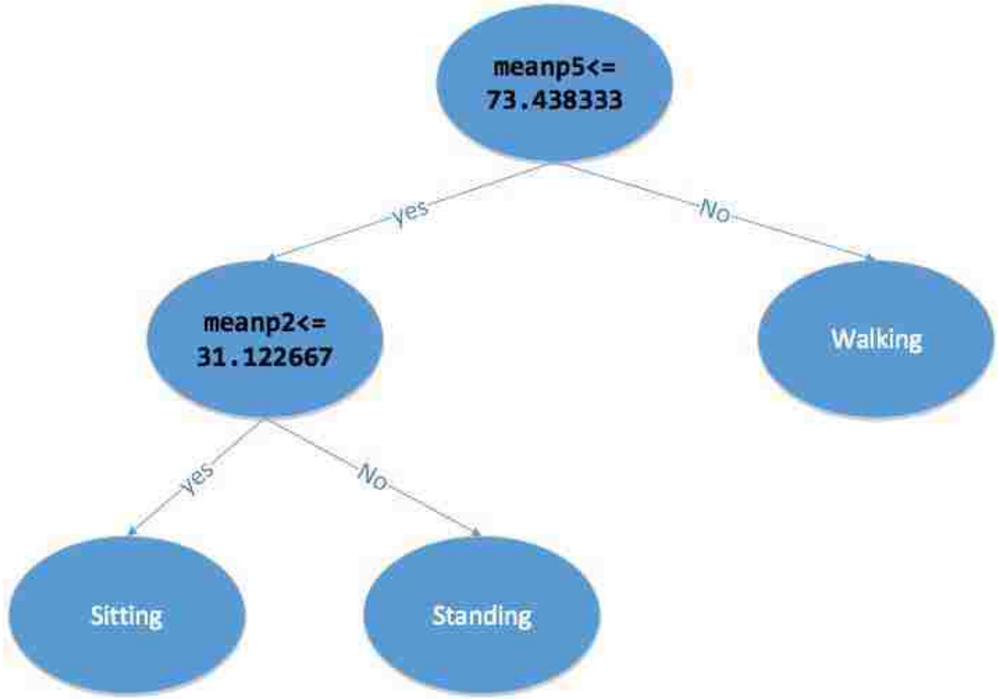


Figure 2.1: Generated decision tree

In general, decision tree represent a disjunction of conjunction of constraint on the feature values. Each path from root node to leaf node is associated with a conjunction and tree itself is a disjunction of these conjunctions. For example, for sitting,

$sitting = meanP5 \leq 73.44 \wedge meanP2 \leq 31.12$

For walking, the expression will be

$walking = \neg(meanP5 \leq 73.44)$

For standing, the expression will be,

$standing = meanP5 \leq 73.44 \wedge \neg(meanP2 \leq 31.12)$

2.1.1 Decision Tree Learning Algorithm

Basic algorithm for learning decision tree is Iterative Dichotomiser 3 (ID3). This is a top-down, greedy search for best possible decision tree. In short, this is how it works. First, to find which attribute should be tested at the root, each attribute or feature is evaluated to determine how well it alone classifies the training examples. Based on this evaluation of all attributes, the best attribute is selected to be the root node. A descended of the root node is created using all possible values of attribute at the root. Training examples are distributed to appropriate descendant node. This process is repeated for each of these descendant nodes using training examples associated with that node.

A statistical property called, *information gain* is defined that measures how well a given attribute separates the training examples. ID3 uses information gain to select among the possible attributes at each step of growing decision tree.

Information gain is closely related to *entropy*. *Entropy* from information theory, we know, is defined for a collection with positive and negative examples of some target concept,

$Entropy = -p_+ log_2 p_+ - p_- log_2 p_-$ where p_+ is the proportion of positive examples and p_- is the proportion of negative examples.

More generally, when the target classification can take m different values, then entropy equation is generalized as $Entropy = \sum_{i=1}^{i=m} -p_i log_2 p_i$

In our case, for a three activity scenario, we have 110 examples of sitting, 111 examples of standing and 111 examples of walking data. As m is 3 , entropy in this case is 1.585. We can interpret *entropy* as the minimum number of bits needed to encode an arbitrary member from the sample set.

Effectiveness of an attribute can be measured using information gain, which is simply the expected reduction in entropy. Mathematically, *Gain(S,A)* for an attribute A for a collection of samples S is defined as,

$Gain(S, A) = Entropy(S) - \sum_{v \in Values(A)} \frac{|S_v|}{|S|} Entropy(S_v)$ where $Values(A)$ is the set of all possible values for attribute A and S_v is the subset of S for which attribute A has value v. *Gain(S,A)* can be interpreted as expected reduction in entropy caused by knowing the value of attribute A. In ID3 approach, Gain for all attributes are estimated and the attribute with highest gain is specified as root node. The training examples are distributed over the descendants of root node according to the attribute values of node at root. Same process is repeated for all the descendant nodes. The attributes at the higher in the tree are excluded. As a result any attribute can occur at most once in any path in the tree. The process continues for each new leaf new node until either of two conditions are met: (1) every attribute has already been included along this path or (2) the training examples associated with leaf node all have the same target attribute value.

2.2 Time-Delay Embedding with Gaussian Mixture Model

Time-delay embedding theorem gives the conditions under which a chaotic dynamical system can be reconstructed from sequence of observations of the state of dynamical system. The reconstruction preserves the properties of dynamical system that do not change under smooth coordinate changes. Taken's theorem [88] provides the conditions under which a smooth attractor can be reconstructed from observations. This theorem essentially provides approaches for reconstructing the essential dynamics of the underlying system using a sequence of observations. The assumption is that the dynamics of the underlying system are significantly different for different activities of a person. In our case, we observed accelerometer data along X and Y axis as well as six pressure sensors from left shoe.

The parameters of time-delay embedding models are learned using a Gaussian Mixture Model. In our experiments, number of mixture models we used are three.

In reality, true dimension of phase space is usually unknown. Based on some trial and error, we used a six dimensional phase space with time lag, $\delta = 5$.

2.2.1 Gaussian Mixture Model

Gaussian mixture models are extension of k-means models. If random variable X is Gaussian, it has the following pdf:

$N(x|\mu, \sigma^2) = p(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{\frac{-(x-\mu)^2}{2\sigma^2}}$ The two parameters are mean, μ and variance, σ^2. $p(x)$ can be conveniently written as $N(x|\mu, \sigma^2)$. If we have independent and identically distributed observations X_1^n from a Gaussian distribution with unknown mean μ, maximum likelihood estimation for μ will be $\frac{1}{N} \sum_i x_i$.

Gaussian mixture model (GMM) is useful for modeling data that comes from one of several groups. The groups may be different from each other. However, data from same group can be modeled using Gaussian distribution.

A superposition of K Gaussian densities can be written as $p(x) = sum_{k=1}^{K} \pi_k N(x|\mu, \sigma^2)$ which is called a mixture of Gaussians. Each Gauassian density is called a component of the mixture and has its own mean, μ_k and variance σ. The parameters π_k is called mixing co-efficients. Also, $sum_{k=1}^{K} \pi_k = 1$ and $0 \leq \pi_k \leq 1$ in order to be valid probabilities.

Expectation-maximization (EM) algorithm is an iterative method for finding maximum likelihood estimates of parameters in Gaussian Mixture environment. Maximum likelihood estimation in Gaussian mixture model is the estimation of π_k, μ and σ of the component of Gaussian mixture.

Chapter 3

Recognizing Human Physical Activity Using Accelerometers: Current Status and Open Issues

Automatic detection of human physical activity is a long sought goal in scientific community. Human posture and activity is an important contextual information and identifying the context is important for context-sensitive applications. On the other hand, quality and quantity of physical activity is an important indicator of energy expenditure. Along with that, physical activity also indicates the health condition of people. Traditional methods to quantify this parameter are subjective and very much dependent on interpretation of the people involved. Consequently, an objective method to quantify physical activity is of much importance to different stakeholders including scientific community. Accelerometers provide an excellent opportunity for identifying and quantifying physical activity. With the evolution of accelerometers and cell phones with accelerometers, new opportunities are being explored. Here we classified all the models detecting physical activity involving accelerometers under different category and summed up their vital information in a comparison table. Finally we talked about some open issues for future directions of research in this area.

3.1 Introduction

The amount of physical activity is closely related to general wellbeing of a person. People, who are ill, have difficulty in performing daily physical activities. Also people who are in good health but avoid adequate physical activity runs the risk of various health problems later in their lives. Considering the importance of Physical Activity (PA), the organization Healthy People 2020 has recognized PA as one of the leading health indicators (LHI). Identifying different human physical activities automatically is very important to a great many group of people. Researchers want to find a cheap and easy alternative to measure energy expenditure. Also research is going on for monitoring older people or people who are ill. Identifying and quantifying human physical activity is also necessary for establishing correlation between activity pattern and future health risk. Human activity is one of the most important context information and context is center to ubiquitous application [78] as ubiquitous applications are expected to provide services in seamless manner.

Two of the techniques to identify and measure physical activity involve questionnaire [76] and videotaping [56] [80]. The first is interpretation dependent and prone to recall bias whereas the later usually requires human to decode. Some questions are lengthy that require up to an hour and sometimes need assistance from a trained observer [86]. With the rapid increase of surveillance camera deployed in public spaces, research is going on automatic detection, categorization and recognition of human activity. But in many cases people feel uncomfortable to be videotaped continuously. Also video camera is installed to fixed places and a person cannot be videotaped every place he/she goes. Sensors like accelerometers have the advantage of being portable and unobtrusive. On the other hand, objective techniques use wearable or body-fixed motion sensors which range from switches, pedometers, accelerometers and gyroscopes [55]. Step counters are the simplest wearable sensors to measure human motion. Though these devices are cheap, they cannot identify other physical activities like lying, sitting or upper body movements. They also cannot reflect intensity of movement and cannot predict energy expenditure accurately [81]. Accelerometers can measure acceleration of objects along different axes. Pedometers count body movement only if a certain threshold is passed. The advantage of using accelerometer for identifying and measuring physical activity is that acceleration is proportional to forces; thus estimates from accelerometers reflect intensity and regularity of movement and thus is more accurate and performs better than pedometers. Data from accelerometer have been successfully captured and analyzed to classify different human postures and activities. These studies vary in number of accelerometers they use and their placements in the body. Some of the studies include other sensors (gyroscope, digital compass [53][38]. Moreover, different studies applied different classification algorithms. These studies also vary in different features that were extracted from raw sensor data. Most of the research addressed activity recognition in laboratory environment [16][53] [78]. A few also successfully recognized physical activities in naturalistic and semi naturalistic environment [90] with encouraging accuracy. The initial accelerometers were wired and transferred data to a PDA or Laptop which hinders the free movements of the subjects.

3.2 Activty Recognition System

3.2.1 General Approach

An activity recognition system broadly consists of the following components. These components are data acquisition, labeling of the data by the user, feature extraction and classification. A data acquisition system consists of different sensors. These systems can vary in number of sensors, types of sensors and placements of sensors. Many parameters can differ in the design of a data acquisition system. Some systems used tri-axial accelerometers and some systems used bi-axial accelerometers. Among other parameters, sampling rate of accelerometers, naturalistic or laboratory settings, placements of the sensors can also vary.

Supervised learning algorithms require training data. Researchers can directly observe and label activity in real-time. Subjects can carry PDA where a digital diary called Experience sampling Method (ESM) is running. Often subjects are reminded periodically to fill a questionnaire to describe the activity he/she was doing.

Different features were extracted in different studies. Mean, standard deviation, energy and correlation were extracted in [17] by Bao et al. Correlation is useful in differentiating walking and running from climbing. Kwapisz et al. [50] extracted the following features from raw data: Average acceleration (for each axis), standard deviation, average absolute difference, average resultant acceleration, time between peaks and binned distribution. The right choice of features depends on the activity that is being recognized. Figure 3.1 is a flow diagram of a generic activity recognition system.

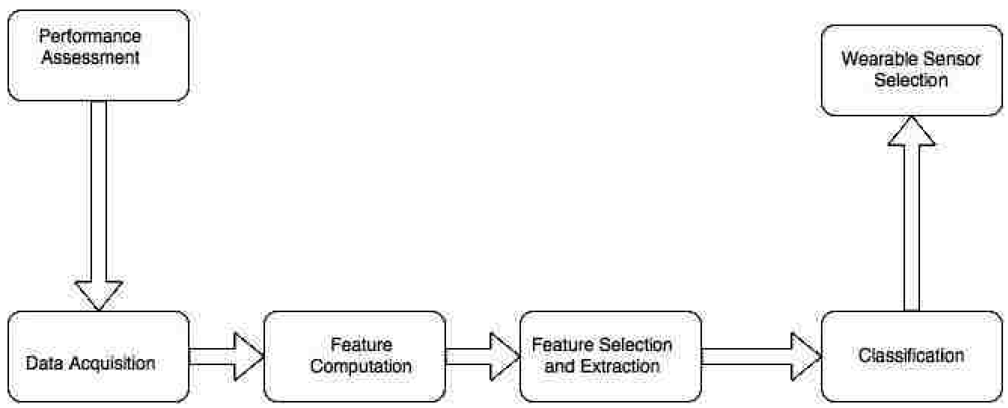


Figure 3.1: Generic Activity recognition System.

3.2.2 Classification Approach

Automatic recognition of physical activity is well-studied topic. Studies and researches so far conducted vary in terms of environment, use of hardware, and also classification algorithm. Environment, where the test has been performed is quite important. Foerster et al. [34] demonstrated 95.8% recognition rates for data collected in the laboratory but recognition rates dropped to 66.7% for data collected outside the laboratory in naturalistic settings. In terms of use of sensors, most researchers adopted multimodal format that incorporates other sensors along with accelerometer. Classification algorithms include k-Nearest Neighbor (kNN) classification [34] [22], Support Vector Machines (SVM) [51] [95], Naive Bayes classifier [39] [59], Gaussian Mixture Model (GMM) [15], and Hidden Markov Model (HMM) [77]. A Bayes classifier is a simple probabilistic classifier based on applying Bayes' theorem with naive independence assumptions. A naive Bayes classifier assumes that the presence of a particular feature of a class is unrelated to the presence of any other feature. Naive Bayes classifier classifies a pattern as an activity according to the probabilities of that signal pattern. Transitions from one activity to another can be described as a Markov chain. After the HMM is trained by training data, it can be used to determine possible activity state transitions. Figure 3.2 depicts the high level view for different approaches of physical activity recognition.

Figure 3.2: Classification of physical activity recognition systems.

3.3 State of the Art

Researchers have tried to identify many activities including brushing, shaving, vacuuming, walking, running, just to name a few. In table 3.1, we sum up different activities that the researchers attempted to detect.

In the following subsections, we categorized and described different approaches. It is difficult to categorize and label research in activity recognition as there is no single criteria for categorization. Moreover, most of the studies about activity recognition go through somewhat similar steps. They all go through data acquisition, preprocessing, segmentation, feature extraction, dimensionality reduction, and classification. As a result, any research in activity recognition falls into multiple categories. We tried to categorize the research works based on their principal

	W	J	S	LD	L	C	CU	CD	St	R	SU	Sp	BT	V	WF	Sh	DV	Ss	EU	ED
Ravi et al[79]	✓						✓	✓	✓	✓	✓		✓	✓						
Lee and Mase [53]	✓		✓						✓											
Randell and Muller [78]	✓		✓				✓	✓	✓	✓										
Kwapisz et al. [50]	✓	✓	✓				✓	✓	✓											
Long et al.[59]	✓	✓				✓				✓		✓								
Krishnan et al. [45]	✓		✓	✓					✓	✓										
Ince et al. [40]													✓		✓	✓				
Subramanya et al. [87]	✓	✓					✓	✓									✓			
Krishnan and Panchanathan [47]	✓		✓	✓		✓	✓		✓	✓										
Uiterwaal et al. [90]			✓		✓				✓									✓		
Yang 2009 [94]	✓		✓			✓			✓	✓							✓			
Choudhury et al. [28]	✓		✓				✓	✓	✓				✓						✓	✓
Maurer et al. [65]	✓		✓				✓	✓	✓	✓										
Lester et al. [54]	✓		✓				✓	✓	✓				✓						✓	✓
Lee et al. [66]	✓		✓		✓				✓	✓										
Karantonis et al. [43]			✓		✓				✓											
Miluzzo et al. [67]	✓		✓						✓	✓										

Table 3.1: Comparison Table Based on Different Physical Activity.
W: Walking, J: Jogging, S: Sitting, LD: Lying Down, L: Lying, C: Cycling, CU: Climbing Upstairs, CD: Climbing Downstairs, St: Standing, R: Running, SU: Sit-ups, Sp: Sports, BT: Brushing Teeth, V: Vacuuming, WF: Washing Face, Sh: Shaving, DV: Driving Vehicle, Ss: Seasaw, EU: Elevator Up, ED: Elevator Down

emphasis.

3.3.1 Comparison of Different Classification Algorithms

Ravi et al. [79] formulated activity recognition as a classification problem. Performance of base-level classifiers (decision tables, decision trees, k-nearest neighbors, SVM, Naive Bayes) and meta-level classifiers (boosting and bagging, plurality voting, stacking) were evaluated and compared. No noise filtering was carried out on the data. Four features, namely mean, standard deviation, energy and correlation were extracted. It was found that energy is the least significant attribute for classification of activities. The overall performance of meta-level classifiers is found to be better. Combining classifiers using Plurality Voting performs as the best classifier for activity recognition from a single accelerometer and consistently outperformed stacking. Accelerometer and Bluetooth transmitter is placed on a hoarder board. Though data transmission is wireless, it is somewhat cumbersome to use. It was found that climbing stairs up and down are hard to tell apart using this system. Brushing was also often confused with standing or vacuuming and is in general hard to recognize. Another drawback of this experiment is that, it was carried on two persons only.

Long, Yin, and Aarts collected accelerometer data from twenty-four users using a single tri-axial accelerometer worn at the users waist without regard for orientation [59]. Data were collected in natural environment, and decision trees (DT) as well as a Bayes classifier were used to recognize activities. Performance of Bayesian classifier with decision tree based approach was evaluated. DT shows good performance but DT classifier has to be completely re-built if the activity set changes or new features are incorporated which indicates low extensibility or poor forward compatibility. Bayesian has the advantage of incorporating additional features. A total of 19 features of 3 categories, namely time domain, frequency domain, and spatial domain were considered. It was observed that standard deviation and intensity of movement during activity is related. Orientation variation, one of the features, shows how severe the posture change can be during activity. Low pass filter was used to filter high-frequency noises.

Standard Deviation may be a good feature to recognize running from others. The drawback is that this study could identify cycling activity only with 50% accuracy. The reason could be that sensor was placed at the waist. Performance of the three classifiers is as follows: DT classifier- 72.8%, NB- 71.5%, NB classifier with PCA- 72.3%. PCA successfully reduced redundancy in features (19 reduced to 5) thus reducing computational complexity.

Users wore five bi-axial accelerometers at right hip, dominant wrist, non-dominant upper arm, dominant ankle, and non-dominant thigh in the experiment done by Bao and Intille [17]. Data were collected from 20 users. Models were created to recognize twenty daily activities using decision tables, instance-based learning, C4.5 (An extension of ID3 algorithm) and Naive Bayes classifiers. Dataset was annotated by subjects themselves. Here 10G accelerometers were used where 12G is the maximum acceleration in human body. The features extracted are: mean energy, frequency domain entropy, and correlation of accelerometer data.

This work [17] investigated the performance of recognition algorithms with multiple(5) wire-free accelerometers. Of all the classifiers, (decision table, instance-based learning, C4.5 decision tree, and Naive Bayes classifiers), decision tree classifier showed best performance with 84% accuracy. Decision trees run fast but are slow to train. This study showed that conjunction of multiple accelerometer data can help to identify some activities. There is a slight performance drop in case of using just these two sensors for the whole activity recognition process. This paper also evaluated the discriminatory power of each accelerometer location by determining recognition accuracy. This was performed through decision tree classifier using leave-one-accelerometer-in protocol. It was found that accelerometer placed in thigh is the most important. If 2 accelerometers are used, then wrist and hip or wrist and thigh are the best places. One important improvement over earlier works is that there was no researcher supervision and subjects were free to move while collecting and annotating their own data. One drawback is the use of bi-axial accelerometers instead of tri-axial accelerometers. For some activities, recognition accuracies were as low as 41%.

3.3.2 Extraction of Features

Krishnan and his colleagues in [45] collected data from three users using two accelerometers and recognized five activities. The accelerometers were placed on the right ankle and on left thigh. The authors carried experiments that demonstrated the importance of multiple accelerometers for recognizing the selected activities. Their work showed that data from a thigh accelerometer were not enough for classifying activities that involve legs such as sitting, lying down, walking, and running. The system was divided into three components:pre-processing, feature extraction, and classification.

The main contribution of the paper is the improvement of standard feature extraction frameworks by using a boosted classifier which produced higher accuracy for real-time activity recognition. Each data segment passes through the feature extraction step. In this step, features are extracted to capture the properties of the raw data. These feature vectors are then sent through the classification stage, where a trained AdaBoost classifier identifies the activity corresponding to the sample. The accuracy was 84.4% for a fast walking subject. The most likely misclassification is between walking and running. Data were transferred to a Pentium computer over Bluetooth. The authors did not explore the high end cell phones and rather used a PC. Also they did not recognize upper body movements. They did not explore use of other sensors such as plantar pressure sensors.

Seven lower body activities are examined by Krishnan and Panchanathan [47] using data collected from ten subjects wearing three accelerometers. This method was tested in supervised and semi-naturalistic settings. Ten Randomly selected subjects’ data from the experiments of Bao and Intille[17] were used. Statistical and spectral features from acceleration data were extracted. Additionally, a new feature that characterizes the variations in the first order derivative of the acceleration signal was proposed. Introduction of this new feature resulted in 3% increase in the classification accuracy. The usual features are mean, variance, correlation between all the axis of all the accelerometers, along with the spectral features like energy and entropy. For activities like walking and running, that has a significant amount of motion, the rate at which the acceleration changes is a characteristic property of that activity. These variations were captured by computing statistical features like mean, variance and correlation between all the axes on the first order derivative of the acceleration data. Performance of different discriminatory classifiers like, adaptive boosting (AdaBoost), support vector machines (SVM) and Regularized Logistic Regression (RLogReg) under three different evaluation scenarios (Subject Independent, Subject Adaptive, and Subject Dependent) were evaluated. The superiority of AdaBoost for subject independent classification was observed. An important drawback of these classifiers is that they do not consider temporal information for continuous recognition. Krishnan and Panchanathan[47] proposed adding temporal information on top of the classifier. By adding temporal information, an improvement of 2.5-3% was observed for both AdaBoost and RLogReg.

Tapia and his colleagues [89] collected data from five tri-axial accelerometers from twenty-one users and used this data to implement a real-time system to automatically recognize thirty gymnasium activities. Incorporating data from a heart monitor in addition to the accelerometer data resulted in a slight increase in performance. For some of the activities (walking, cyclic, and rowing), intensities were also determined along with recognizing the activities. The performance accuracy is 94.6% and 56.3% for subject-dependent and subject-independent training respectively. As heart rate is influenced by other factors such as emotional states, ambient temperature, and fitness level, its usefulness at discriminating intensities is not significant. Features extracted are area under curve (AUC), variance, mean distances between axes, mean, entropy, correlation coefficients, FFT peaks, and energy. The most important features found, in decreasing order of importance, were the area under curve (93.1% accuracy using only this feature), mean distances between axes (92.1%), mean (91.3%), variance (88.7%), FFT peaks (86.1%), and correlation coefficients (74.8%). However, instead of using portable devices like smart phones or PDAs, Tapia et al. [89] in this work used a laptop to receive data wirelessly. The overall setup thus become impractical for remote activity monitoring as it is unrealistic that laptops will be carried by users.

Ince et al. [40] developed a system that can identify some morning bathroom activities like brushing, washing face, and shaving activities. They placed a wireless accelerometer at right wrist. Different time and frequency domain features were extracted and efficiency of the extracted time and frequency domain features were compared. They used FFT and autoregressive modeling for this comparison. When only time domain features were considered, classification accuracy was found to be poor. This work shows that combination of time domain (TD) and frequency domain (BP) features yields better classification performance than using time domain (TD) and autoregressive (AR) features. They used Gaussian Mixture Model (GMM) and finite state machine to classify the extracted features. Accuracies are 93.5%, 92.5%, 95.6% for washing face, shaving and brushing respectively.

Lee and Mase [52] studied two well-established statistical tools PCA and ICA to find features in order to help classifier to perform better. Movements of hip data were collected using two sets of 3-axes accelerometer sensors placed in the hip using a belt. The classifiers used were Multilayer Perceptron (MLP). Three MLPs were trained using back propagation algorithm. Interestingly, it was found that ICA reveals the first step in a walk which is not visible in the original data. It was found that the use of

PCA and ICA in feature generation process improves classification performance. No significant difference was observed between PCA and ICA performances.

Though this paper shows significance of using PCA and ICA for feature generation, they only classified four activities, level walk, down stairs, up stairs, and start/stop points. Here only two accelerometers were used and both of them were placed in the hip. However, it is unclear how the PCa and ICA will influence if other classification algorithms were applied. It is also not evident the influence of applying PCA and ICA on other sensor data, pressure sensors, for example.

3.3.3 Studying and Developing Classification Algorithms

DeVaul and Dunn [31] identified standing, walking, riding the T and riding a bicycle. Two 2-axes accelerometers were placed at right angles resulting in a 4 axes accelerometer (2 redundant axes). Features were generated using Fastest Fourier Transform in the West (FFTW) and Bayesian Information Criterion (BIC) and Expectation Maximization (EM) were used for classification. BIC was first run without FFTW and it chose a five-component model with two clear components: One for walking and one for running. With FFTW, there were eight components that had strong clusters for walking and running too. In both cases, with and without FFTW, walking and running were classified with fine accuracy but this model could not recognize other activities. To solve this problem, Markov models were constructed on top of the Gaussian Mixture Model (GMM) to capture the dynamics of the data. First-order Markov model classifier does good job in classifying 5 activities. It is better than Gaussian class conditional assignments.

A generic classification framework consisting of a hierarchical binary tree for classification of basic daily movements using a tri-axial accelerometer was developed by Mathie et al. [63]. High level distinctions between human movements were applied on the top level of the binary tree and successively more detailed classifications were made in the lower levels of the tree. For example, movements were first divided as activity and rest and then activities were classified as postural transitions, falling, walking, and other movements. The rest could also be classified as lying, sitting, or standing. The advantage of this framework is that it will allow arbitrary movements to be added to the classification without the need to redesign other parts of the classifier. A classifier was developed in six steps: defining requirements, selecting instruments, arranging movements within the tree, developing algorithms, evaluating the classifier and refining the classifier. One drawback of the system is that it was carried out in controlled laboratory environment. Experiment was carried out on 26 subjects.

3.3.4 Multimodal Systems

Lee and Mase [53] tested the feasibility of dead reckoning method to determine a person's location in indoor environment. The focus was to detect walking and counting the steps in a particular direction. Main source of error was in recognizing human activity. To improve activity recognition, the study included a gyroscope and a digital compass. Two sensing modules, placed in pelvic region and thigh, identify sitting, standing and 3 types of walking. Leg module contains accelerometer and angular motion sensor (gyroscope) while the digital compass was worn at belt. The unit motion recognizer identifies one of the five predefined types of unit motion. The location recognizer determines the displacement vector by dead reckoning. Based on some trials, they also found the optimum placement for the sensing modules at hip and thigh.

Subramanya et al. [87] built a model using data from a tri-axial accelerometer, two microphones, phototransistors, temperature and barometric pressure sensors, and GPS. The model can distinguish between a stationary state, walking, jogging, driving a vehicle, climbing up, and down stairs. Their work claims to detect both the location of a person and the activity he is engaged to. Using one sensor device located at only one location of the body, this work applied Dynamic Baysian Network (DBN) to model dependency between different parts of the system.

Choudhury et al. [28] used a multiple sensor device consisting of seven different types of sensors (tri-axial accelerometer, microphone, visible light phototransistor, barometer, visible and IR light sensor, humidity/temperature reader, and digital compass) to recognize activities. Their work, Mobile Sensing Platform (MSP) attempts to develop a trainable learning algorithm. They adopt an iterative development and deployment approach. The lessons learned in earlier deployment are addressed in next deployment. To make the system less intrusive, they placed all the sensors in a single location of the body. Lester and his colleagues in this work [54] showed that placing multiple sensors in same location can offset the information loss of placement of multiple sensors in different body locations. The first effort incorporated Bluetooth connectivity to transfer data to iPaq, but later they switched to wired connection as a quick fix version.

Basic postures, like standing, sitting, lying, seesaw and locomotion were identified in [90] by Uiterwaal. Two sensors are placed perpendicular to each other and one is placed externally. Data is recorded in 10MB memory card continuously for 24 hours. In this setup, processing and analysis of raw accelerometer signals were carried out after data were transferred to a local computer manually. Transmission of data to the recorder happened through wired connection causing free movement difficult. One sensor was placed in the belt, adjacent to the recorder. Other sensor was placed in one of the thighs. An observer observed the video and annotated the class of the activities through an interface. Though data were collected in natural, non-laboratory settings, it was not processed in real time. Also, the wired connection between sensors and recorder was inconvenient for free movement.

Schmidt [83] designed a system that could differentiate between stationary, walking and running activity using a bi-axial accelerometer placed in a tie. Placing an external accelerometer in tie is inconvenient and impractical, specially now that we have accelerometers in cell phones. Moreover, this work only identifies very basic activities and does not address many relevant activities. No data were transmitted as algorithm was implemented in a micro-controller.

‘eWatch’ by Maurer [65] is an activity recognition system which has multiple types of sensors. Experimentation with different locations were carried out to find a suitable location. Following locations were investigated: belt, shirt pocket, trouser pocket, backpack, and necklace. Each ‘eWatch’ consists of a bi-axial accelerometer, microphone, temperature sensor, and a light sensor. Decision trees, k-Nearest Neighbor, Naive Bayes, and Bayes Net classifiers with five-fold cross validation were used for learning. Decision Trees and Naive-Bayes were found to achieve high recognition accuracy with acceptable computational complexity. It was demonstrated that any of the six locations of ‘eWatch’ are good for detecting walking, standing, sitting and running. Ascending and descending the stairs is difficult to distinguish from walking activity in all locations of ‘eWatch’.

A single tri-axial accelerometer, along with an embedded image sensor worn at the user’s waist has been used by Cho [27] to identify nine activities. In the image sensor, features were extracted by using Lukas-Kanade Optical Flow. In the 3-axis accelerometer sensor, correlation between axes and the magnitude of the FFT was used for feature extraction. Also mean and energy features were calculated. Support Vector Machine (SVM) was used for classification of different activities. Experiments showed an overall accuracy rate of 93% in recognizing activities. They observed that human activity recognition performance is improved if they use hybrid of image data and accelerometer data.

Gyorbro [36] used ‘MotionBands’ attached to the dominant wrist, hip and ankle of each subject to distinguish between six different motion patterns in real-time. Each ‘MotionBands’ contained a tri-axial accelerometer, magnetometer and gyroscope. The data collected by MotionBands were transmitted wirelessly to a smart phone carried by the users, enabling unobtrusive data collection. The researchers in this study adopted feed-forward back propagation neural networks. The six activities to be recognized were resting, typing, gesticulating, walking, running and cycling. The average recognition rate was 79.76%.

Mobile phones lack processing power and constant supply of power. Supervised learning is too heavy for even powerful mobile phones. So the system is trained on a desktop workstation using feed-forward neural networks after collecting sensory data. Feed-forward neural networks are powerful at pattern recognition and after training, classification can be performed quickly. After training, neural network can be implemented on a cell phone by setting the parameters of neural network equal to the trained network of the workstation. It means that the learning phase was done offline on a desktop workstation using MATLAB. Training of activities was done using the Neural Network Toolbox in MATLAB. For the neural network, multiple small networks architecture was chosen instead of a large single architecture. One problem with this system was that recognition was somewhat insensitive to the training subjects individual characteristics. If fine tuning on individual data were carried out then greater accuracy could be expected. Due to limitations of Bluetooth technology, at most seven MotionBands can connect at once to a single mobile phone or a computer.

Lester [54] used accelerometer data, along with audio and barometric sensor data, to recognize eight daily activities from a small set of users. The experiments in this study were carried out with some specific goals. Data should be collected only from a single body location and it does not have to be from the same point for every user. The system should be designed in such a manner that it works out across individuals. Personalization should increase recognition abilities; and the system should be effective even with a cost-sensitive subset of the sensors and data features. Lester and his colleagues collected data for 8 different activities from 12 different subjects. They showed that the resultant system has an accuracy rate of approximately 90% while meeting the previously mentioned requirements. The authors were able to demonstrate that their activity recognition system generalizes well. So there is no need to learn body location-specific activity models. They also demonstrated that customization to specific individuals is not required and the system works reliably across new individuals. Another contribution of this work is identification of most discriminative modalities. It was found that three modalities gave the most discriminative information for activities: the audio, barometric pressure, and accelerometer sensors. For classification algorithm, they employed a 2-layer architecture. In the first layer, an ensemble of static classifiers selects the most useful features, and then recognizes a set of basic human movements based on those features. In the second layer, hidden Markov models (HMMs) combines the outputs of the classifiers of the first layer and calculates the most likely activity.

3.3.5 Cell Phone-based Systems

Kwapisz et al. [50] used phone-based accelerometers to perform human physical activity recognition. Labeled accelerometer data were collected from twenty-nine users as they performed daily activities such as walking, jogging, climbing stairs, sitting and standing. Authors used these data as training data to build a predictive model for activity recognition. As users always carry cell phones in their pockets, this work can help to collect information about the habits of millions of users.

They have used accelerometer data from android phone to identify several activities. Android was chosen because the OS is free and open-source, easy to program, and have potential to become dominant market leader in the coming days. This architecture has the advantage of using a device that is conveniently carried by mass people in their pockets. Authors have used the data to extract six features, namely standard deviation, average absolute difference, average resultant acceleration, time between peaks and binned distribution. Now raw time-series accelerometer data must be transformed into examples since standard classification algorithms cannot be directly applied to it. Three classification techniques - decision trees (J48), logistic regression and multilayer neural network from WEKA data mining suite were used. The system is very unobtrusive as the cell phone carried by users work as data collection system. But it does not identify other common activities, bicycling for instance.

Indoor location of a person is estimated in Lee and Mase's [52] work. The system uses a bi-axial accelerometer, a digital compass and an infrared light detector. This work identifies walking and whether the person is walking in level ground, going up or going down. It also counts the number of steps. The strategy adopted by the researchers is hybrid: dead-reckoning for relative measurements and infrared-based beacon method for absolute measurement. Accumulation of error is common in dead-reckoning system and an infrared-based beacon method that detects signals from a transmitter in a fixed place (stairway) helps to correct those errors. By using conventional peak detection algorithm, the system tries to find the peak values at every sampling. If the values of all four peaks follow some specific conditions, step count is incremented. Another feature called cross-correlation function of x(t) and z(t) is used to improve performance. This feature is helpful for discriminating between level and up/down. The classification results show good performance for level and down behaviors but up behavior detection is not satisfactory. One problem with this work is that as the connection to central mobile unit is not wireless.

Yang [94] developed an activity recognition system using the built-in accelerometers in Nokia N95 phone. Although the study achieved relatively high accuracies of prediction, stair climbing was not considered and the system was trained and tested using data from only four users. Decision tree performed best among the four classifiers evaluated. Other classifiers that were evaluated are Naïve Bayes (NB), k-Nearest Neighbor (kNN) and Support Vector Machine (SVM). As phone's position on a human body varies from person to person, its orientation cannot be fixed. Orientation-independent features extraction was also explored in this study.

Miluzzo et al. [67] exploits various sensors (such as a microphone, accelerometer, GPS and camera) that are available on commercial smart phones for activity recognition and mobile social networking applications. They collected accelerometer data from ten users to build an activity recognition model for walking, running, sitting and standing. Their applications 'CenceMe', collects sensor data of individuals using off-the-shelf, sensor-enabled mobile phones, analyzes these data, detects the activities and share these information through social networking applications such as Facebook and MySpace. To make the system scalable, classification task was shared between cell phones and backend servers. They also carried a user study on twenty two people who used CenceMe continuously over a three week period.

Both the Symbian operating system and Java Micro Edition (JME) virtual machine which runs on top of the N95 have been designed to use small amounts of memory and computational resources. Designing and implementing 'CenceMe' application on top of this environment was thus resource-constraining. One of the contributions of the paper is the design of lightweight classifiers, running on mobile phones where classification is split between cell phone and servers. Another contribution is the measurement of the RAM, CPU, and energy performance of the classifiers and the whole 'CenceMe' software suite.

3.3.6 Accelerometers for Detecting Fall, Sleep-time Activity, Postures and Others

Accelerometers have been used to identify many other types of activities including falls, sleep, snoring, gait pattern etc. Here we mention a few of those.

Existing fall detection solutions can be divided into two categories. The characteristic of the first category is that it only analyzes acceleration to detect falls. The second class of solutions uses both acceleration and body orientation information to detect falls.

Mathie et al. [62] used a single, waist-mounted, tri-axial accelerometer to detect falls. Lindemann et al. [57] placed an accelerometer in hearing aid housing for detecting falls. The reasoning of this sensor placement was based on the hypothesis that the individual intends to protect the head against higher acceleration caused by abnormal activities. The system could also detect other daily activities. Lindemann [57] used thresholds for acceleration and velocity for fall detection.

Kangas et al. [42] showed that acceleration measurements from waist and head were more important for fall detection. Their findings show that parameter values calculated at waist had some overlap in ADL and fall, which is contrary to findings of Bourke's [19] work where they were able to determine total sum vector, SV_{TOT}, a threshold value capable of discriminating between falls and ADL with 100$\%$ sensitivity and specificity. Bourke and his colleagues [19] placed two tri-axial accelerometers at the trunk and thigh. They estimated upper and lower thresholds for both the trunk and thigh. Fall was indicated by exceeding any of these four thresholds. Some other activities, like sitting down quickly or jumping also have large vertical acceleration and thus can fool this method.

The followings are description of systems that use both acceleration and body orientation to detect fall. Fall detection system developed by Noury et al. [71] has three sensors: body orientation was measured using a tilt sensor; vertical acceleration was measured using an accelerometer. They used a vibration sensor to monitor body movements. Chen et al. [24] investigated change in body orientation during an impact to monitor falls. Incorporation of body orientation information improves the fall detection accuracy.

Below we discuss some works that was conducted to detect and measure sleep-time activities through the analysis of accelerometer data.

Morillo et al. [69] evaluates the feasibility of using accelerometer in screening sleep apnea which can be an alternative to 'gold standard' such as overnight full-channel polysomnography (PSG). Vibration sounds were acquired from an accelerometer placed on supra-sternal notch of subjects in supine condition. Digital signal processing was used to extract respiratory, cardiac and snoring components. Right now current technology decides if an overnight polysomnography is needed based on an output from oximetry sensors. So the oximetry sensors work as screening device. The objective is to provide a new tool for screening Sleep Apnea-Hypopnea Syndrome (SAHS). The goal is to develop a new tool that decreases false positives during screening. For example, a simple algorithm was used to extract respiratory information from the accelerometer signal. Respiration rate during normal breathing ranges from 6 to 30 breaths/min (0.10.5 Hz). Hence, after removing the DC level, the signals were passed through a 40th-order LP FIR filter with Hamming windowing and a cutoff frequency of 1 Hz in order to remove noise and information out of the band of interest. An algorithm was applied to estimate the breathing rate, using both acceleration signal and airflow information.

Liszka-Hackzell et al. [58] determined sleep time duration from an accelerometer (Actiwatch AW-64) placed on non-dominant arm of 18 patients with chronic back-pain. Pain levels were calculated and correlations were calculated between Actiwatch Sleep Analysis Variables and mean pain level differences. A correlation was found between the difference in nighttime activity levels and the daytime pain variance. They observed that if patients have large variability in their daytime pain levels, they also experience large fluctuations in their nighttime activity. In [64], Mathie and his colleagues diagnosed sleep apnea by detecting respiratory and snoring features using an accelerometer worn at chest.

Gait-related features are best reflected by ankle-attached accelerometers. Park et al. [72], Kuo et al. [48] in their work estimated steps, distance travelled, velocity, and energy expenditure using an ankle-worn accelerometer. Foerster et al.[34], Veltink et al. [91], Lyons et al. [60] in their works attached two accelerometers to the torso and thigh to distinguish standing and sitting postures from static activities.

Najafi et al. [70] studied the characteristics of postural transition (PT) and their correlation with falling risk in elderly people using a new method.

Accelerometers also provide an alternative method to estimate energy expenditure in a free-living environment. Bouten et al. [21] showed that energy expenditure due to physical activity can be predicted from the acceleration integral in anterior-posterior direction of an accelerometer.

3.3.7 Single Accelerometer-based Systems

Randell and Muller [78] focused on minimizing the number of devices needed by using a single accelerometer device. In steady state, the main processor will be switched off and the sensors will remain as the only active parts. Four features were extracted from accelerometer data collected from 2 axes. Several activity data are collected to train for activity recognition. It was found that RMS and integrated values of last 2 seconds were enough for recognizing these activities. THis study focused on identifying the context for a tourist guide application. The tourist guide application is suspended when the user is running; thus reducing irritation by inappropriate and untimely rendering of information. One drawback of the system is that misclassification occurred when people were going upstairs.

3.3.8 Others

Aminian et al. [16] created Physilog, a new activity monitoring system that identifies lying, sitting, standing and locomotion using accelerometers placed at chest and thigh with an error rate of 10.7%. Experiment was carried on 5 normal subjects. Here the extracted features are average and deviation of acceleration signal. This paper claims that parameters like threshold (th), angular threshold, sampling frequency (fs) need to be carefully selected to have good result. Physilog uses two accelerometers and is good for long term monitoring. It is validated against video. Basically it classifies static versus dynamic postures.

Kurata et al. [49] used two tri-axial accelerometers placed across a joint (elbow or knee). This paper measures one axis joint movement (movement along elbow or knee) using a new method developed by the authors. In the first part, a method that measures one axis joint motion is described. Two accelerometers were placed on both sides of the one-axis joint (elbow). Each x-y plane of both sensors is in the same plane. Using rotation matrix, the relation between (a_{x1}, a_{y1}) and (a_{x2}, a_{y2}) can be described by

$$\begin{bmatrix} a_{x1} \\ a_{y1} \end{bmatrix} = \begin{bmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{bmatrix} \begin{bmatrix} a_{x2} \\ a_{y2} \end{bmatrix}$$

Here (a_{x1}, a_{y1}) and (a_{x2}, a_{y2}) are acceleration components of accelerometers placed across the joint and θ is the joint angle. From the above equation, joint angle can be calculated. Joint angle was calculated using two potentiometers and was found consistent with the proposed method. A similar but more complicated equation was derived for three-axis joints (shoulder or hip). The problem is that when acceleration becomes smaller it cannot show joint angle accurately.

In [61], Mannini and Sabatini discussed most common methods to automatically classify human physical activity. They used five tri-axial accelerometers attached to the hip, wrist, arm, ankle and thigh in order to recognize twenty activities from thirteen users. Mannini and Sabatini also presented a state-of-the-art table of features and classifiers for human activity recognition using accelerometer. This work demonstrated that Markov model is effective in classification of human activities.

Lee et al. [66] used a single tri-axial accelerometer attached to the left waist of five users. Five activities- standing, sitting, walking, lying and running were recognized. Accuracy was high (99.5%) and they used fuzzy c-means classification algorithm. Features extracted were mean and standard deviation of acceleration. Some correlation features were also extracted. Acceleration signal was stored on micro

SD-Memory card or transmitted wirelessly using (Zigbee-compatible) 2.4G bandwidth for wireless communication.

Krishnan et al. [46] developed and evaluated algorithms for detecting and recognizing short duration hand movements (lift to mouth, scoop, stir, pour, unscrew cap). Subjects wore wireless tri-axial accelerometers on different parts of the hand and data was simultaneously collected from these accelerometers. Mean, variance, correlation, spectral entropy, and spectral energy were calculated. Three classifiers, AdaBoost, HMM and k-NN were applied on these calculated features. AdaBoost showed best performance, with accuracy of 86% for detecting each of these hand actions. It was also demonstrated that some actions require some amount of subject-specific training.

Yang and Hsu [93] designed a portable microprocessor-based acceleration measuring device that works as real-time physical activity identification system. They developed an algorithm to process tri-axial acceleration signals produced by human movements. Their works not only identify still postures, postural transitions, and dynamic movements, but also it can detect fall. Three still postures (sitting still, standing still and lying still), four postural transitions (sit-to-stand, stand-to-sit, lie-to-sit and sit-to-lie), and two dynamic movements (turning on bed and walking) were detected. Their work achieved high identification accuracy in performance evaluation. One important contribution of this work is its ability to detect activities in real-time. The authors claim that the system can be used for long term physical activity and mobility monitoring in the home environment.

Karantonis et al. [43] presented the implementation of a real-time classification system with embedded intelligence. Data were acquired from a single, tri-axial accelerometer which was attached to waist. The system is able to distinguish between periods of activity and rest. It also has the ability to recognize the postural orientation of the wearer. It also detects events such as walking and falls, and can give an estimation of metabolic energy expenditure. In a laboratory-based trial involving six subjects, an overall accuracy of 90.8% across a series of 12 tasks (283 tests) was observed. There was no error in distinguishing between activity and rest. Recognition of postural orientation, walking, and possible falls were carried out with 94.1%, 83.3%, and 95.6% accuracy respectively. It also can differentiate between different lying postures of left, right, front and back lying. The use of ZigBee for data transmission will serve to maximize battery life. To perform the task in real-time, several constrains had to be addressed. Sitting and standing sometimes may be incorrectly classified. Identification of walking was interesting because the system only stores 1 seconds worth of data which is usually not enough. So if any upright activity is recognized, raw z-axis data is transmitted and buffered. It also provides an indirect measure of energy estimation.

Bouten et al. [20] developed a tri-axial accelerometer using three perpendicular uni-axial accelerometers. They also developed a portable data processing unit and used it for measuring of physical activity. The experiment was carried out in laboratory setting on 13 subjects and Bouten and others demonstrated a close relationship between accelerometer output and energy expenditure as a result of physical activity. One drawback of their work is low sensitivity to sedentary activities. The other drawback is its inability to detect static exercise. The accelerometer was specifically designed considering the amplitude and frequency characteristics of human motions. Trunk was chosen as the appropriate placement of the accelerometer as trunk contains a major part of total body mass and also it moves during most daily activities.

Table 3.2 provides comparison information among commonly used models of physical activity recognition.

3.4 Open Issues

A rich amount of study and research has been carried out and quite a few experimental systems were built for activity recognition. There is significant diversity

Name	Platform	NoA	R	OS	Inside Cell-Phone	NAc	CA	NU	A
Long et al. 2009[59]	No Cell-phone	Tri-axial				5	Naive Bayesian vs Decision tree	24	8̃0%
Schmidt et al. 1999 [83]		Bi-axial(1)							
Bao and Intille 2004 [17]		Bi-axial(5)		N	No, Wireless	20*		20	41-97%
DeVaul and Dunn 2001 [31]		Bi-axial(2)	Y				1st order Markov Model		
Lee and Mase 2001[52]	Notebook Pentium II	Bi-axial(1)			No,wired	3		6	
Kawada et al.2008 [44]								5	
Ravi et al.2005 [79]	HP iPaq, Microsoft Windows	Tri-axial(1)				8*		2	
Lee and Mase 2002 [53]	Linux based PDA	Bi-axial(1)		Y	No,wired	5			
Randell and Muller 2000 [78]	MatsuCom onHand PC	Bi-axial(1)				6*	Neural Network	10	85-90%
Kwapisz et al. 2010 [50]	Android	1		N	Yes	6		29	
Krishnan et al. 2008] [45]	MMA7260Q triple axis accelerometer	Tri-axial(2)	Y			5	AdaBoost	3	95%
Ince et al. 2007]. [40]		Bi-axial				3		7	93.5%
Subramanya et al. 2006] [87]	iPAQ PDA	Tri-axial(1)		Y	No,wired	5			
Krishnan and Panchanathan 2008 [47]	Dataset of [Bao and Intille 2004] was used	3				7	AdaBoost		95.35%
Uiterwaal et al. 1998[90]		2+1	N						
Tapia et al. 2007 [89]		Tri-axial(5)	Y	Y	No, wireless	30	Decision Tree	21	94.6%
Yang 2009 [94]	Nokia N95	Tri-axial(1)			Yes	6		4	
Lee et al. 2009 [66]		Tri-axial(1)	N		No Cell-phone	5	Fuzzy Logic	5	99.5%

Table 3.2: Comparison Table Based on Model.

NoA: Number of Accelerometer, R: Real time, OS: Other Sensors, A: Accuracy, NAc: Number of Activities, CA: Classification Algorithm, NU: Number of User in the approaches they adopted in these studies.

In the earlier systems the focus was on recognizing the activities using accelerometers. Usually these sensors were wired to a PDA. This setting was not practical since the natural movement is hindered by the wired connections. Some studies were carried in laboratory environment and the accuracy obtained by these studies may not be attained in naturalistic environment. The focus of several research projects was too centered on the issue of activity recognition and failed to take the feasibility issue in account. Usability was not a concern for these systems. Therefore some of the studies showed good accuracy in laboratory but fail to be useful in real life naturalistic environment.

Many studies sends data to a PDA or Laptop, not to a cell phone. So the goal of remote monitoring is not materialized by these systems. Some of the later studies use mobile phone but orientation of the mobile phones changes in the pocket over time. Also different persons keep phones in different locations in the body in different orientations. Sometimes people do not keep the phone with themselves, specially when sitting or studying in a desk. This issue is relevant to recent cell phone based activity recognition systems because earlier systems used accelerometers that were tightly attached to specific known body locations. Cell phone-based systems are also constrained by limited computational power. Some methods that can be applied in desktop computers cannot be used in cell phones. For example, FFT was avoided by Yang [94] to save computational cost.

One problem with phone-based system is that transmitting over Bluetooth is power consuming which creates serious strain on battery life. According to [28], Bluetooth connection is not reliable enough. Packet losses and intermittent connection losses were common. Another problem with cell phone based system is that mobile phones are primarily designed for handling phone calls. As a result, resource requests may be denied to third party applications running on the phone.

The problem of automatically identifying a small set of features useful for recognizing a particular set of activities has not been explored completely yet. Such a finding can immensely simplify the classification process. Again so far no work has been done where both phone-accelerometer and extra accelerometer have been used. This could be a promising direction of study to increase accuracy of classification as well as increased usability.

3.5 Future Works And Conclusions

Identification of human physical activities with accelerometers has gained a lot of attention from the research communities for several years. The recent cause of attention is due to the incorporation of accelerometers in the cell phones. During the earlier attempts the focus was on identifying the activities where the usability was not considered with enough importance.

The use of accelerometers for identification of human physical activities is important for several reasons. One important advantage of accelerometers is that they are better than other alternative ways of identifying human activities because they are less obtrusive than them, especially as accelerometers are being incorporated in cell phones and cell phones can collect acceleration data unobtrusively.

We want to find human activities for several reasons. One reason is that the knowledge of human activity gives a very good description of context which can help context-sensitive application to perform better. The information that a person needs or does not need is very much dependent on the activities he/she is engaged to. The second reason is that the quantity and quality of physical activities is important to healthcare personnel, doctors or healthcare policy makers. For example, with widespread obesity worldwide, it is important to find more accurate quantitative relation between the quality and quantity of human activities and obesity. Possible correlation between back pain and human activities or posture can be studied using activity recognition systems. A good objective method for unobtrusively detecting human activities is of utmost importance to doctors and healthcare policy makers as well as context-sensitive application developers.

The future brings in some old and some new challenges as well. It is true that many human activities can be recognized now with good accuracy, still there are some activities that are difficult to recognize. Stair climbing up and down are significant source of error in many activity recognition systems. And again some approaches perform very well in the laboratory setting but fail to perform in real environment with an acceptable accuracy. Human activity is one of the most important context information and identifying contexts is a step towards Weiser's dream of ubiquitous computing.

There is a rich set of ideas that can be explored in the future. Some old challenges are still unresolved and new challenges are emerging as work goes on. One challenge with cell phone based systems is that cell phones can change orientation in pocket due to human movements. It is challenging to interpret the acceleration data when issues like this happen.

Future works can try to answer a lot of questions and explore some challenges. Is it possible to determine intensity of earthquakes from accelerometer of cell phones? How can we exploit acceleration data from millions of cell phones at different geographical locations and extract information? Do activity recognition systems open new doors of violation of privacy?If yes, how do we protect these privacy? If someone carries two cell phones, can we exploit accelerometer data from two phones and improve the accuracy of activity identification? Can we determine walking speed from accelerometer data? Nokia already has made a wellness diary which count steps, calculate distance traveled and energy expenditure. But can we detect pace of running from accelerometer data placed on wrist/wrists?

How the recognition capabilities vary with the inclusion of additional accelerometers with cell phones? Does placing accelerometer on hands while walking or jogging increase accuracy of identifying activity? Can we derive breathing rate from accelerometer data? If we incorporate gyroscope with accelerometer does it increase accuracy of activity recognition? Activities like nodding and other head movements can be explored in future. If we decide to use two accelerometers, what are the optimal locations for the pair of accelerometers? What about three accelerometers? Also identifying age or gender or some disease from gait pattern can be a challenging problem. Investigating how gait pattern changes gradually for a particular disease with time will be interesting topic for the healthcare personnel. These questions only show the richness of opportunities that are still unexplored.

Chapter 4

Remote Symptom Monitoring System: Methodology and Barriers

The goal of this chapter is to discuss the background of our remote symptom monitoring system. We will also discuss our study procedure. Later in this chapter we will describe the barriers we identified and challenges we faced in the development of our e-ESAS.

4.1 Introduction

According to Bangladesh Bureau of Statistics, cancer is the sixth leading cause of death in Bangladesh [13]. Cancer is predicted to be an increasingly important cause for mortality and morbidity in next few decades. According to International Agency for Research on Cancer, cancer-related deaths will jump from 7.5% in 2005 to 13% in 2030 [33]. For males, two leading causes are lung cancer and oral cancer whereas for females, it is breast cancer and cervical cancer. Lung cancer in males and cervical and breast cancer in females constitute 38% of all cancer patients. The Government of Bangladesh devised the 'National Non Communicable Diseases Strategy and Plan of Action' with technical support from WHO in 2007.

While the cancer statistics from Bangladesh looks gloomy, cancer statistics for women in Bangladesh is even gloomier. Cancer has become the number one killer of women in childbearing age in Bangladesh, according to Maternal Mortality Survey in 2010. While looking for causes of death of women in childbearing age [8], this shocking finding was noticed. It showed that cancer accounts for 21 percent of women's deaths between 15 and 49 years of age. Breast cancer statistics from Bangladesh in particular is scary. Sixteen percent of the total cancer affected women in Bangladesh are victims of breast cancer, says a World Health Organization (WHO) study [1]. WHO also ranked Bangladesh 2nd in terms of mortality rate of women in the country from breast cancer [1]. Similar scenarios prevail in other developing countries as 70% of all cancer deaths occurred in low or mid-income countries in 2008.

Although breast cancer is the most common type of cancer among women worldwide, 69% of all deaths occur in developing countries [92]. Unlike western countries where 89% of the women have a survival rate of more than 5 years [73], most breast cancer (BC) patients in Bangladesh die because majority of cases are diagnosed in late stages [10]. These patients need palliative care (treatment process for terminally ill patients through symptom management to improve quality of life (QoL)) which is almost absent in rural Bangladesh.

Even in this scenario, more than 22,000 new BC patients being added each year and 70% of them die due to lack of treatment [12] though it is possible to prevent at least one-third of the deaths through early detection, allocation of adequate resources and effective treatment. Many women in Bangladesh either never seek treatment or arrive at hospitals with late-stage cancer.

Healthcare in a developing country such as Bangladesh is scarce. Too few doctors have to attend too many patients degrading the quality of care in this process.

However, there are some promising statistics from Bangladesh too. As of January 2015, there are 121.86 million cell phone subscription [11] in a country with population 160 million. Even very poor people have access to cell phones. Moreover, cell phone service is extremely cheap due to high population density. As a result there is a great potential to address heath care problems using cell phones.

Our goal was to identify the problems in the treatment of rural women with breast cancer and come up with a sustainable inexpensive solution that will improve the quality of life of patients, doctors and healthcare personnel and thus improve the healthcare infrastructure as a whole. With this goal in mind, we visited Bangladesh in five phases and worked with Amader Gram. Our system helps in the communication between doctors and patients by creating a cell-phone based channel.

4.2 Local Partner Information

We partnered with a local NGO named ‘Amader Gram’ (literally ‘Our Village’) for our pilot study. Amader Gram is an initiative of Bangladesh Friendship Education Society (BFES). In 2006 Amader Gram partnered with International Breast Cancer Research Foundation (IBCRF) to open Amader Gram Breast Care Center (AGBCC). The mission for AGBCC is to reduce morbidity and mortality from breast cancer and other breast diseases. A trained female doctor and medical assistant attend each center, examining and keeping records of patients. From 2006 till 2010, the total number of patients diagnosed with BC is 1405. Over 500 women have been examined as of October, 2007.

4.3 Time Line

We made five field trips between July 2010 and June 2012. The first two field trips focused on identifying the challenges faced by doctors and patients in providing and receiving treatments and how emerging mobile technology can solve these challenges. The deployment of e-ESAS was done in the 3rd field trip. The last 2 field trips focused on collecting feedback data from e-ESAS use and analyzing the collected data. Here we provide a summary of tasks and milestones completed in each of the field trips.

4.3.1 Field Trip 1 (4 Weeks, Jul ’10-Aug ’10)

In our first visit to Bangladesh in summer 2010, we tried to understand the current practice so that we can propose a system which will improve the current system. With this goal in mind, we interviewed people with different roles in the system. We interviewed 39 patients, 12 doctors, and several medical assistants and field workers. We were interested about their level of familiarity with cell phones, especially in case of rural women. We observed patient-doctor interactions in clinical setting, interviewed patients in 2 hospitals and several patients in their homes. We were especially interested in identifying barriers both from the perspectives of patients in obtaining treatment, and of doctors in providing treatment. Instead of targeting all the barriers, the goal was to identify a subset of problems that our proposed system will be able to solve. We asked patients about their education, environment, family, disease, economic condition and knowledge about cell phone use.

4.3.2 Field Trip 2 (3 Weeks, Dec '10-Jan '11)

We showed the 1^{st} version of e-ESAS to 31 BC patients and 10 doctors and collected their feedback.

4.3.3 Field Trip 3 (12 weeks, Jun '11-Aug '11)

We deployed the 2^{nd} version of e-ESAS on 12 Nokia X6 mobiles. 10 of them were given to 10 selected patients and the 2 others were given to doctors. Chronic pain level ≤ 5 on ESAS scale, life expectancy $>$6 months and performance status ≤ 2 on ECOG scale [2] were the main selection criteria. We will call these patients MOs (Mobile Owners). We also interviewed a separate number of other BC patients (registered with AGBCC) during different field trips. We call this patient group as OPs (Other Patients).

4.3.4 Field Trip 4 (12 weeks, Nov '11-Jan '12)

Due to delayed approval from Bangladesh Medical Research Council (BMRC), we started collecting data in Nov '11. Two of the MOs were replaced since they no longer met the selection criteria. In Dec '11, we made 10 house visits to learn the experience of MOs using e-ESAS. We observed a total of 77 patient visits (both MOs and OPs) to evaluate the difference between doctor-MO interaction and that of doctor-OP. We also had focus group sessions with the doctors.

4.3.5 Field Trip 5 (3 weeks, May ’12-Jun ’12)

We had open discussions with the MOs and their family members during this time period. We also had two open discussion sessions with the doctors. We all shared our thoughts and talked about the future of e-ESAS.

4.4 Methodology

We followed a mixture of clinical observation, home interviews, and hospital interviews as our methodology

4.4.1 Study Procedures

In our first trip, we observed 22 doctor-patient interactions during patient visits. We measured the average duration of patient meetings, the steps followed by the doctors, common questions asked by both patients and doctors. One researcher was present during these sessions. The sessions lasted between 6 and 11 minutes. Later we interviewed a total of 39 BC patients. The interviews took place in 3 different scenarios- patients’ homes (5), AGBCC (22) and a hospital (12). One research team member and one doctor or health worker (HW) took part in the interview with each patient separately. The interview session had two parts. In the first part, we measured their familiarity with mobile phones and in the 2nd part we collected demographic information and had an open discussion regarding the socio-cultural barriers they face as BC patients. We also collected information about average time spent in transportation, average waiting time to visit doctors and average number of visits per month. We had two focus group sessions with doctors. One session was with 8 doctors in AGBCC at Khulna and the other was in Dhaka with four doctors.

Clinic Observation

We first observed 22 patient-doctor interactions in AGBCCs (11 in Khulna, 10 in Bagerhat and 1 in Rampal) to get better understanding of the current procedures and practices. We found doctors using a paper based symptom monitoring system named ESAS. We then interviewed each patient following the above mentioned procedure.

Hospital Interviews

We interviewed 9 patients in Dhaka Medical College and Hospital (DMCH) and 3 more in Khulna Medical College and Hospital (KMCH). These patients were admitted in the hospital for either chemotherapy or surgery. The main goal of talking with these patients was to observe how they use mobile phones in advanced stages of the disease.

Home Interviews

Generally patients feel more comfortable to talk and discuss in their home environment. Also, 5 patients failed to show up due to the severity of their diseases. To account for all these facts, we visited the houses of these patients in Khulna.

4.4.2 Participant information

As per requirement analysis we talked with 39 patients, 12 doctors, and 6 HWs in Dhaka, Khulna, and Bagerhat region of Bangladesh. Table 4.1 summarizes the participant distribution.

People—Places	Khulna	Bagerhat	Rampal	Dhaka
Patient	19	10	1	9
Heath Worker	2	2	2	0
Doctors	8	0	0	4

Table 4.1: Participant list

Patients

The patients were quite diverse in terms of level of education, expertise with mobile phones whereas there was similarity in terms of occupation and household income. Their ages ranged from 21 to 45 years. Patients' education varied from illiterate to high school. The average family income of the patients we met is BDT 4500 ($63) per

Features	Category	Percent	Features	Category	Percent
Familiarity (breast cancer)	Yes	7.7	Occupation	Housewife	87
	No	92.3		Employed	13
Education level	Illiterate	34.9	Duration	< 1 year	47.8
	Up to Grade 5	26.1		1-3 years	43.5
	Grade 6 - 10	34.7		>3 years	8.7
	>Grade 10	4.3			
Average family income (per month)	<$42	61	Number of children	0-2	69.5
	$42-$84.5	26.1		3-4	26.1
	>$84.5	12.9		>4	4.4
Experience with mobile	Receive	26.1	Access to mobile	Personal	47.8
	Call, Receive	61		Family	47.8
	Call,Receive,SMS	12.9		Neighbor	4.4

Figure 4.1: Patient information

month. 29 patients were having BC for the first time and 10 for the second time. They were under different types of treatment including radiotherapy, chemotherapy and surgery. 96% of the patients have access to mobile phone. Figure 4.1 provides a high level view of patient information.

Doctors

We had focus group sessions with 8 doctors in AGBCC of Khulna and 4 doctors in DMCH. Four of the doctors have post graduate degrees in their fields and others are resident doctors. Three of the doctors have more than 10 years of experience dealing with BC patients. We primarily asked the following questions:

1. What are the problems you face during diagnosis?
2. Why do patients miss appointments?
3. How frequently the patients come?
4. Average time to assess each patient.
5. How mobile phones can be helpful in your work?

These sessions revealed the following issues:

- Lack of regular information about the patients is the biggest drawback. Also, all the doctors mentioned about the exaggeration of symptom values by patients. Especially pain symptom was often exaggerated. In our clinical observation, we found all 22 patients to report having maximum pain level.
- All the doctors complained that they did not like the manual task of drawing graphs in paper-based ESAS and this consumes major part of the patient visit time. This fact shows the necessity of a tool that can automatically generate longitudinal graph based on patients' symptoms.

4.5 Barriers

From our visits to Bangladesh, interviews with doctors, patients, attendants, medical assistants and field workers, we have identified some barriers in the health care system for the rural women in Bangladesh. Statistics of the country's health care system also gave us some insight. We have grouped the barriers in several categories.

4.5.1 Barriers in Diagnosis

Shyness

Culturally women in rural Bangladesh are very shy. Women feel more uncomfortable to seek help for diseases like breast cancer due to shyness. All the health workers mentioned this issue as one of the barriers in identification of breast cancer patients. Female patients are also sometimes embarrassed to visit male doctors if exposure is needed.

Lack of Familiarity

Though rural people in Bangladesh are well familiar with the term cancer, breast cancer is not so well known to them. In many cases, they take it lightly and fail to pay attention due to lack of understanding of danger. Unless it hurts, people usually do not pay attention and skip visiting doctors. As most breast cancers do not cause pain in the breast, they usually visit doctors at later stage. Out of 39 patients we interviewed, only 3 patients (7.7%) said they had some kind of idea about breast cancer.

4.5.2 Barriers in Obtaining Treatment

Scarcity of Resources

Developing country like Bangladesh lacks the resources required for a good healthcare system. Resources for cancer care are even more limited than the facilities available for other diseases. One reason behind this is that cancer care is very expensive compared to treatment of other diseases. According to a report by ‘National Cancer Control Strategy and Plan of Action 2009-2015’, there are about 500 hospital beds dedicated for cancer patients throughout different hospitals in the country. This number is very small compared to what is needed for a population of 160 million. According to government, there are about 250 doctors for 1.2 million cancer patients. Every year 200000 more cancer patients are added and about 150000 die of cancer related causes [3]. There are only 18 radiotherapy centers in the country where about 300 are required. Only one of them is situated in the rural areas. Only 11 of these are modern Linear Accelerators [4]. The idea of palliative care for relieving the sufferings of patients is almost non-existent in Bangladesh.

Underdeveloped Transport System

Like many other developing countries, Bangladesh suffers from a not-so-well transport system. There are not enough vehicles and roads to support such a large population. Most people use rickshaws to travel short distances and cars are way out of means for majority. In rural area, there is no public transport system. To travel from one city to another, people mostly uses buses, trains or launches which are uncomfortable partly due to bad conditions of the road and partly due to overcrowding. Traveling to and from Dhaka, the capital of the country and moving in the city is a painful ordeal due to its notorious traffic jam. It is very common for people to make multiple change of vehicles to reach clinics. One patient described her experience as:

"I live in a distant village of Rajshahi division. First I took a van to come to the boat stand. Then I crossed the river by boat. Then I shared another van to reach the bus stand. It took 12 hours for the bus to reach Dhaka. Finally I hired a taxi and then a rickshaw to reach here."

4.5.3 Barriers in Continuation of Treatment

Long Term Monitoring

Cancer by nature needs long term monitoring. Even simpler diseases are too much for poor rural patients as they have to make long commute to doctors while being sick. Cancer, which requires long term treatment and care is a great calamity to these patients.

Absence of Palliative Care

In case of terminally ill cancer patients, the treatment is usually palliative in nature where the focus is pain management. In case of Bangladesh, palliative care is almost non-existent, even in urban areas.

Inconsistent Patient Data

Patients some time exaggerate their pain level. Sometimes their information is corrupted by lot of external factors unrelated to diseases. A lot of times doctors have difficulty in interpreting data from subjective, contextual and sometimes contradictory feedback they receive from patients.

Missing Appointments/Irregular Follow ups

Patients in Bangladesh, especially in rural areas, are not very consistent in their subsequent visits to doctors. Reasons are manifold behind this. Traditionally patients visit doctors with a family member or a friend. All the patients we interviewed came with a relative or a friend. Failure to manage a companion can prevent them from visiting doctors. In case of women, they are mostly responsible for household work, like cooking and taking care of children, especially in rural areas. Rural women have to travel a significant distance in case the doctor is in another city and they have to find a substitute for their household works. The long commute to doctors is another deterrent for patients to visit doctors regularly. Financial problem is also very common for not following up with treatment. One patient described her reason as:

"First time I missed the appointment since my husband was out of the town and I failed to manage any other companion. Then my son was having his final examination. There was no one else who can look after him. Then I waited for the crop to be sold so that my husband can save some money for my appointment and medicine."

4.5.4 Structural Issues

Load-shedding

Load-shedding is very common in Bangladesh. In rural areas it is more prevalent. However, there is always enough electricity to charge cell phones as it does not take much electricity to recharge cell phones.

Urban-centric

The whole country is very much centralized. As a result, all the growth and development is centered around Dhaka, the nation's capital. There is shortage of doctors, clinics even in small towns, let alone rural areas. As people in rural areas are poorer, there are not many good doctors in those areas. Especially, oncologists are rare even in Dhaka. As a result people often have to travel to the capital or other big cities through a poor transport system to get treatment.

Lack of Privacy Guidelines

The concept of medical privacy is not very well established. As a result, there is no national privacy framework. In USA, privacy of individually identifiable health information is protected by HIPAA. In the absence of such laws in Bangladesh, health care system developers have difficulty in decoding and implementing privacy concerns of patients.

4.5.5 User Issues

Illiteracy

The rate of education is quite low among poor rural women as is obvious from figure 4.1. Interestingly, out of 12 illiterate patients we interviewed, all but two can count and read numbers. Moreover, all of them said they have close family members in the house who can read and are familiar with mobile applications.

Unfamiliarity with Mobile Technology

Many women, even if they cannot read and write can use cell phones to some extent. They can call and receive receive calls. However, they are unfamiliar with other usage of cell phone, like texting and internet use.

4.6 Observations

4.6.1 Growth of Cell Phone Subscribers

There is a steep growth of cell phone subscribers since 2005 and as of May, 2015, total cell phone subscribers has reached 125.971 million in the country, according to Bangladesh Telecommunication Regulatory Commission [11]. It has actually more than quadrupled since 27.72 million in June, 2007. Unlike other facilities, we observed that cell phones have reached even in rural areas. Almost 96% of patients we interviewed have access to cell phones either by owning a phone personally or having a family member who owns a cell phone.

4.6.2 Cheap Cell Phone Services

Interestingly, cell phone plans are cheaper than lot of developed countries due to intense price competition and high density of population. Also poor families own one cell phone instead of every member in the family. Even a patient, who lives in a mud hut in a remote village of Rampal, a small sub-district of a small southern town, uses a Samsung phone. We found from [5] that 1 MB data cost less than 30 cent and some packages sell 15 MB for 45 cents.

4.6.3 Smart Representation of Data

Medical data are often poorly represented as not enough attention is given to representation of data. Representing data in a smarter way so that trend and pattern is clearly visible will be helpful to doctors.

4.6.4 Lack of Ethnic Cancer Data

According to [6], compared to African-American women, white women are slightly more likely to develop breast cancer, but less likely to die of it in USA. One possible reason is that African American women tend to have more aggressive tumors. There is lack of such ethnic data in Bangladesh. It is true that population is mostly homogeneous in the country but it has a large population and the possibility of any pattern among the population cannot be ignored and thus demands attention from the researchers. Lack of such database prevents the discovery of such demographic pattern.

4.6.5 Pain Management is Important

As cancer progresses, pain management becomes a significant part of treatment. From our sessions with doctor and patients it was evident that pain is a very important symptom as it controls the quality of life of patients significantly. Doctors need regular updated information for improved pain management. The level of pain, trend of pain, current medicine and their doses are some of the parameters that doctors need to be updated of regularly. Doctors have to find the right regimen from the feedback of patients.

4.6.6 Doctors Use ESAS

We found the doctors use a paper-based tool, Edmonton Symptom Assessment System [9], commonly known as ESAS, to record patient data when the patients visit them at AGBCC. This tool was designed to assist in the assessment of ten symptoms common in cancer patients: pain, tiredness, nausea, depression, anxiety, drowsiness, appetite, well-being, shortness of breath and other problems. The symptom values are scored from 0 to 10. Doctors' big concern was lack of availability of symptom data for patients. Patients use ESAS form in figure 4.2 to record their symptom information.

Edmonton Symptom Assessment System: Numerical Scale
Regional Palliative Care Program

Please circle the number that best describes:

No pain	0	1	2	3	4	5	6	7	8	9	10	Worst possible pain
Not tired	0	1	2	3	4	5	6	7	8	9	10	Worst possible tiredness
Not nauseated	0	1	2	3	4	5	6	7	8	9	10	Worst possible nausea
Not depressed	0	1	2	3	4	5	6	7	8	9	10	Worst possible depression
Not anxious	0	1	2	3	4	5	6	7	8	9	10	Worst possible anxiety
Not drowsy	0	1	2	3	4	5	6	7	8	9	10	Worst possible drowsiness
Best appetite	0	1	2	3	4	5	6	7	8	9	10	Worst possible appetite
Best feeling of wellbeing	0	1	2	3	4	5	6	7	8	9	10	Worst possible feeling of wellbeing
No shortness of breath	0	1	2	3	4	5	6	7	8	9	10	Worst possible shortness of breath
Other problem	0	1	2	3	4	5	6	7	8	9	10	

Patient's Name ______________________

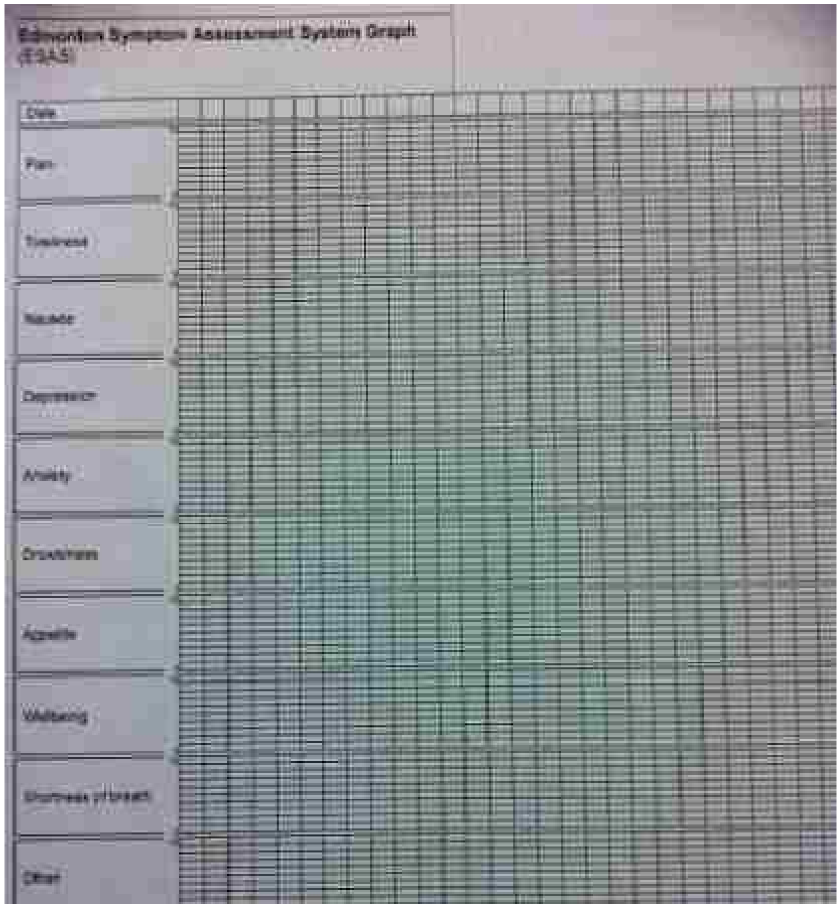
Date ____________ Time ____________

Complete by (check one)
☐ Patient
☐ Caregiver
☐ Caregiver assisted

BODY DIAGRAM ON REVERSE SIDE

Figure 4.2: Unfilled ESAS form

Doctors use form in figure 4.3 to prepare graphs from filled-up ESAS forms of patients.


Edmonton Symptom Assessment System Graph (ESAS)

Date
Pain
Tiredness
Nausea
Depression
Anxiety
Drowsiness
Appetite
Wellbeing
Shortness of breath
Other

Figure 4.3: ESAS graph form

4.6.7 Bias in Data

Sometimes patients exaggerate their pain level to gain attention from doctors. Sometimes symptoms are influenced by patients' long commute to doctors. If we could collect symptoms data in a more natural environment, bias in data could be reduced.

4.6.8 Patient Visit Time

As there is a shortage of doctors, there is a long queue of patients in most hospitals. Doctors are forced to hurry during clinical visits by patients. Often they have to spend crucial time to record symptom information.

4.7 Conclusion

In this chapter, we primarily discussed our adopted methodologies. We also discussed the barriers faced by rural breast cancer patients in different phases of health care system in Bangladesh. Our observations built the foundation of e-ESAS which we developed to address some of the barriers. We will discuss e-ESAS in the next chapter.

4.8 Related Publications

- **Ferdaus Kawsar**, Munirul Haque, Mohammad Adibuzzaman, Sheikh Iqbal Ahamed, Md Uddin: ***e-ESAS: Improving Quality of Life for Breast Cancer Patients in Developing Countries,*** In Proceedings of the 2nd ACM international workshop on Pervasive Wireless Healthcare, pp. 9-14.(ACM, 2012)

- Munirul Haque, **Ferdaus Kawsar**, Mohammad Adibuzzaman, Sheikh I. Ahamed, Richard Love, Rumana Dowla, David Roe, Reza Selim: ***Mobile Based Health Care Solution for Breast Cancer Patients,*** In M4D, New Delhi (2012)

Chapter 5

Design, Development and Evaluation of a Remote Symptom Monitoring System called e-ESAS

5.1 Introduction

For cancer patients, palliative care is very important as quality of life drastically decreases due to pain, tiredness, and depression as a side effect of chemotherapy, radio-therapy, or surgery. Edmonton Symptom Assessment Scale (ESAS) works as a tool for doctors, especially for palliative care specialists to assess symptoms and provide interventions accordingly. Patients usually complete a paper-based ESAS questionnaire when they come to the clinics. This form gives only an instantaneous view of the symptoms to the doctors. Often, patients visit the doctors irregularly and long intervals between visits are quite common. Since patient's symptom levels are recorded only when they visit clinic, doctors have very little data about the patient's symptom history. In addition, loss of previous prescriptions is not very uncommon. We have found 7 patients during our clinical observations who have either forgot to bring or lost their previous prescriptions.

5.2 Related Works

Hayes et al. [37] summarized the detailed overview of the cancer treatment process and possible use of pervasive technology in urban settings. The effectiveness of electronic symptom monitoring has been proven in chronic diseases like asthma [14], diabetes [26] and cancer [32]. All these projects have been deployed in urban settings in the developed world using web based online monitoring systems, which is not feasible for the illiterate in rural areas of a developing country. In rural health care, several projects work as 'decision support system' by implementing a guideline set by WHO or other standard organizations in computer or hand-held devices [30] [75] [68].

Early Diagnosis and Prevention System [75], a computer based healthcare management software, registers patient history. e-IMCI [30] describes a PDA based system for administering the Integrated Management of Childhood Illness (IMCI) protocol. A large number of projects are used for ‘data collection/survey’ including AED SATELLIFE [7] in Mozambique and Uganda and HIV/AIDS program in Angola [25]. Our project has two fundamental differences with these projects. Firstly, instead of trained professionals (health workers (HW) or doctors), patients or attendants (who normally stay with the patients) are filling the symptom information by themselves. Secondly, patients are doing this from home and sending data by using the data network of mobile carriers. In all the aforementioned projects, either the patient has to come to the health center or HWs need to go to remote houses of the patients to collect such information. Several projects like WiLDNet [74], iPath [18] fall under ‘telemedicine’ category aiming to connect physicians with patients residing in rural areas. But the prerequisite of network infrastructure capable of performing real time media connections in a cheaper way makes these solutions infeasible for rural scenarios of Bangladesh.

5.3 Design and Development of e-ESAS

From the clinical observations, it was obvious that it is not feasible for doctors to complete the paper-based ESAS considering the timing restriction due to high patient load. Also, a better tool is needed to obtain patient data on a regular basis. Therefore, we developed a mobile based ESAS named e-ESAS for Nokia X6.

5.3.1 Architecture

The system consists of two parts: A server and a client. The architecture of e-ESAS is shown in figure 5.1. The client has two modules: patient’s module and doctor’s module. Same client software is installed for both modules. So, the same phone can be used by both doctors and patients.

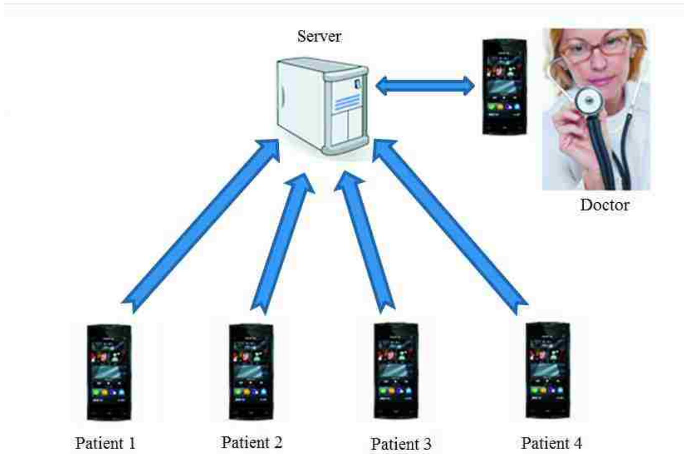


Figure 5.1: e-ESAS architecture

5.3.2 Technologies

On the server side, we used Apache Tomcat 6.0.26 as the server and MYSQL as the database. We created 5 tables in the database; ‘patient’, ‘doctor’, ‘record’, ‘medicine_record ’ and ‘videolog ’. The ‘patient’ table stores patient information. We added a new field in the table for IMEI number as we moved to IMEI-based authentication. The ‘doctor’ table contains doctor information. The ‘record’ table stores all records of 13 symptoms (integer number), their date and patient id in 15 fields. The ‘medicine_record’ table stores prescription, patient ID, doctor ID and time. A new table called ‘videolog’ was added to keep track of frequency of video viewing by patients. It logs ‘video_ID’, patient name and timestamp. Another client was PHP based client website. Ajax with PHP was used for developing the website. For Web Service, JSP and SOAP were used. The application was developed for Nokia X6 phones. We used s60 5th edition SDK v1.0 emulator for developing the system. The data is transmitted over the internet using the data plan of cell phone operators or Wi-Fi service. When a command is executed as a client, a web service is called in from the sever which executes their respective operations on the data in the database,such as insertion, deletion, or updates in the database.

5.3.3 Patients' Module

In our first prototype, the patient module had 10 sliding bars all in the same page, one for each of the ten symptoms of ESAS. After feedback from doctors, we added 3 more sliding bars for 3 more questions. These 3 questions are: the minimum, maximum, and average pain in the last 24 hours. We have put a button with the Bengali label for each symptom and a sliding bar following each button which can be set for any values between 0 and 10. If the button is pressed, it will play a voice instruction in a local Bengali dialect. When the user presses the 'submit' button, located at the bottom, it will send all of the sliding bar values set by the patient to the database server as a string. Patients can also view their prescriptions.

Internaitonal Mobile Equipment Identity(IMEI)-based Login

In the first version, the patients had to log in using traditional usernames and passwords as shown in figure 5.2(a). We changed the authentication process, and now the IMEI number is used for automatic authentication, as the IMEI number of each patient's mobile phone is already in the database. Though we provided a one letter name and password, patients were not enthusiastic about password-based authentication. As one patient said, *"I like the sliding bar part but I really dont like to enter text at the beginning (login). I actually wait for my son to do that."* But the user login is necessary to relate the submitted data with a specific user. To serve both the purposes, we introduced IMEI based login as shown in figure 5.2(b). Here, when the patient enters the e-ESAS application, the system collects the IMEI number using Nokia API and matches the corresponding patient ID from the server. All 10 MOs and their attendants expressed their preference for IMEI based login. Five of the MOs also said that they have started submitting data by themselves without the help of attendants as a result of this change.

H

Figure 5.2: (a) Username-Password based Login. (b) IMEI based Login

Removal of Scrolling

Based on feedback from patients, we also modified the interface in our second version so that 13 sliding bars for 13 questions are distributed over 6 pages. Each of the first 5 pages have 2 sliding bars whereas the last page has 3 sliding bars for 3 questions. In the first version, all the sliding bars were on the same page. The idea was to ensure minimum amount of time for data submission. However, this design proved to be error prone since the users were repeatedly touching the wrong sliding bars, which were placed to close to each other. Based on these findings, we later placed 2 sliding bars per page which ensured enough room in the screen for the patients as shown in figure 5.3(b). We also increased font size and the gap between two sliding bars. This new design got rid of the scrolling bar on the side which was a source of confusion and errors as the patients unintentionally changed previously set values of symptoms while scrolling up and down.

Figure 5.3: Two versions of e-ESAS: (a) All sliding bars in one page. (b) Two sliding bars in each page.

Automation of ESAS Symptom Submission

Instead of using cumbersome, time-consuming paper-based ESAS as in figure 5.4(a), patients can use e-ESAS as in figure 5.4(b). After successful submission of symptom data, the system provides a notification.

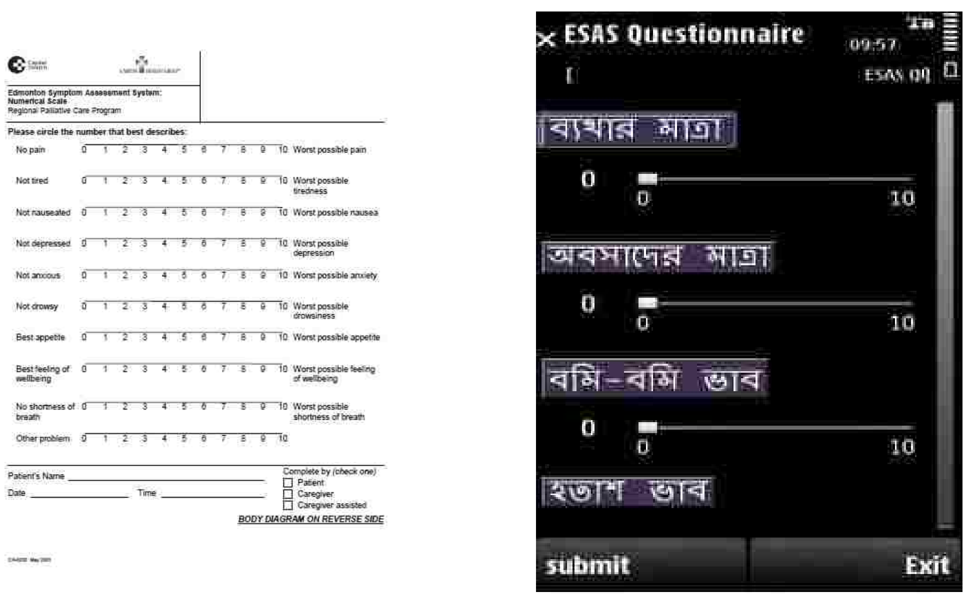


Figure 5.4: Two versions of e-ESAS: (a) Original paper version. (b) e-ESAS.

View Prescription

Patients can view their prescriptions. They can choose to view all of their previous prescriptions as shown in figure 5.5(a) or they can choose to view only their last prescription.

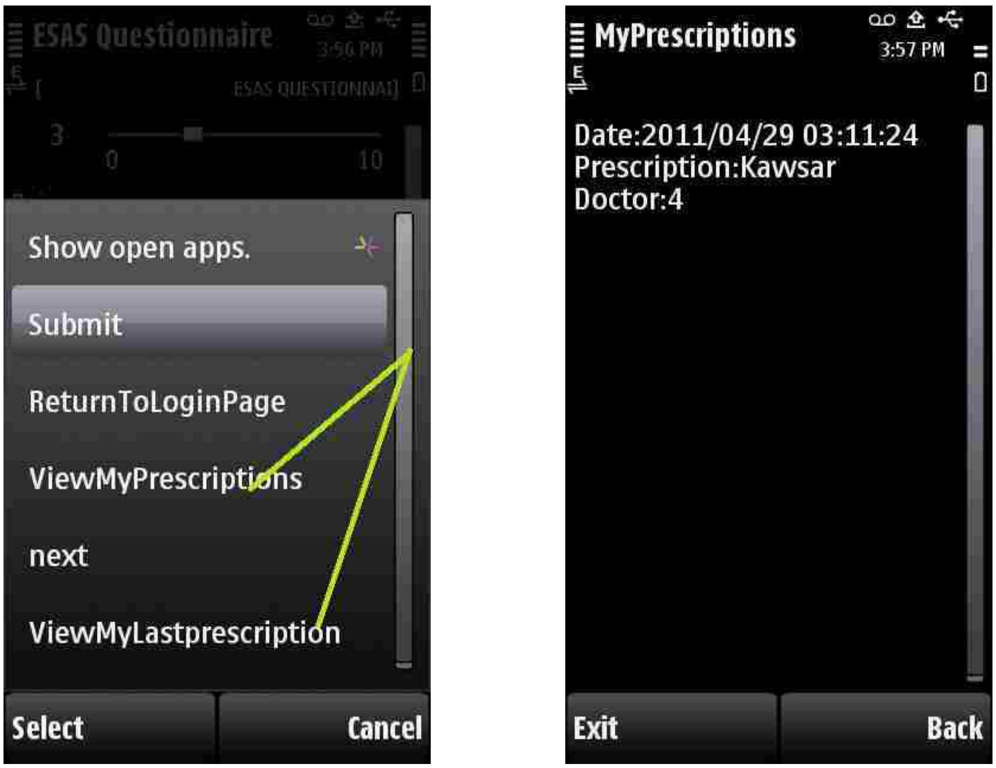


Figure 5.5: (a) Patient options. (b) Patient can view his prescription.

5.3.4 Doctors' Module

The doctors module has the following features:

- Longitudinal graph: Doctors can choose a patient and one or more symptoms to see the values of those symptoms over a selected period of time. He\she can do it either from cell phone or from the web app.
- Prescription: Doctors can check their previous prescriptions of a patient or add a new prescription.

- Alert Generation: An alert will be generated for doctors based on predefined conditions. For example, an alert might be generated if the pain level is more than 6 for 3 consecutive days.

Options

When a user logs in as a doctor, a page with a list of all their patients appears. Figure 5.6(a) shows screen shot of a list of the patients. Doctors can select a patient by selecting the text by finger. After selecting the patient, a doctor has several options as shown in figure 5.6(b). She can view all previous prescriptions, create a new prescription, and view patient symptom data in graphic form or in simple text form. These actions can also be performed from a website.

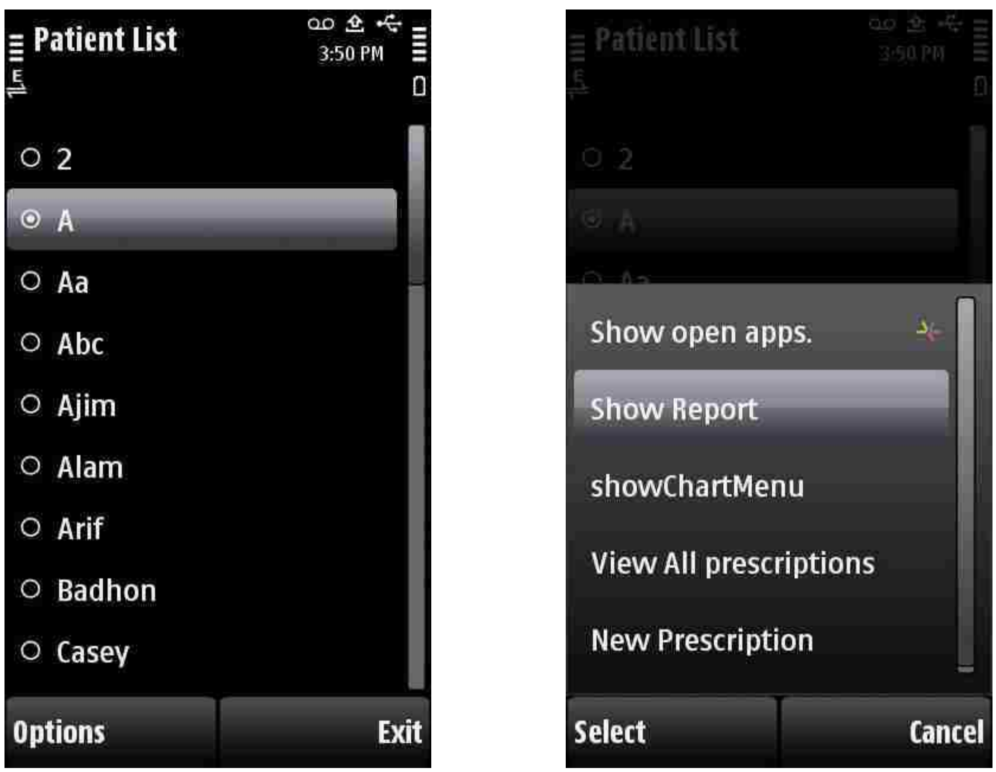


Figure 5.6: (a) Patient list. (b) Doctor's choices.

Selecting Date

If a doctor selects to view the graphs of a patient, a page appears and is prompted for a start date and end date as shown in figure 5.7(a). The doctors have to type dates in the cell phone. After selecting the *'options'* menu in the 'date page', a doctor can select several operations from the menu bar (shown in figure 5.7(b)). There are menu items for each of the symptoms and the doctors can view the graph by selecting the symptom of interest. In our first version, we had 10 menu items for 10 symptoms which we increased to 13 items as 3 more pain questions were added.

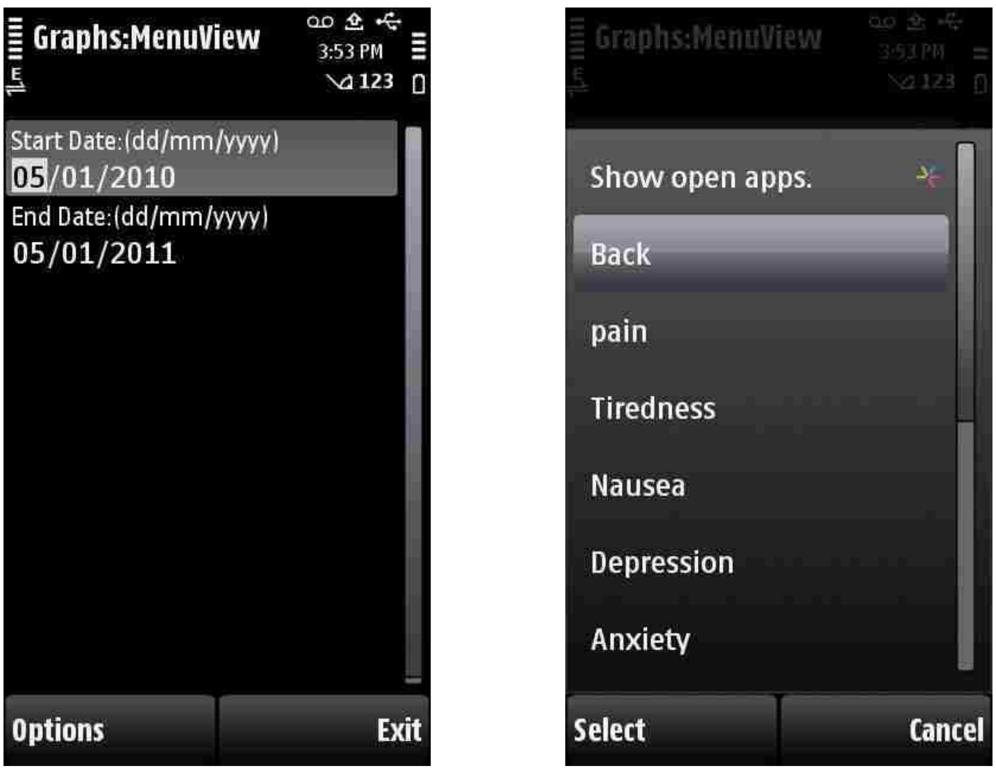


Figure 5.7: (a) Doctor provide dates. (b) Doctor chooses symptom.

Doctor Views Graphs

The label below the graph explains what the graph is displaying, along with the time range and the patient name. Another change we made in the doctor's module is the segmentation of the graph. Instead of squeezing all the data points in a single page, at most 7 data were shown in each page as shown in figure 5.8(b). If more data points are there, the doctor can view them using the *'Next'* and *'Previous'* button. In our first version, we tried to accommodate all data points in a single graph. A large number of data points would not fit in the small screen of a cell phone, as in figure 5.8(a).

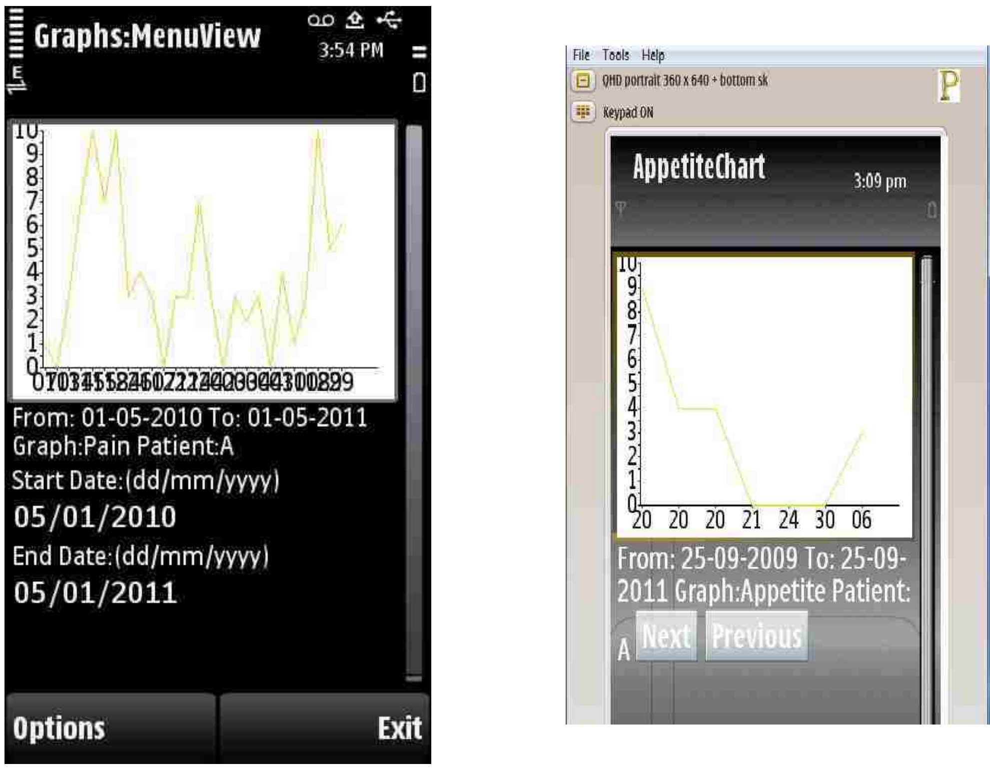


Figure 5.8: (a) Illegible due to too much data points. (b) Doctor views graph for Appetite Symptom.

Doctors have the option to access the same patient data from both cell phones or from a website. Figure 5.9 is graph of 3 symptoms viewed from web app.

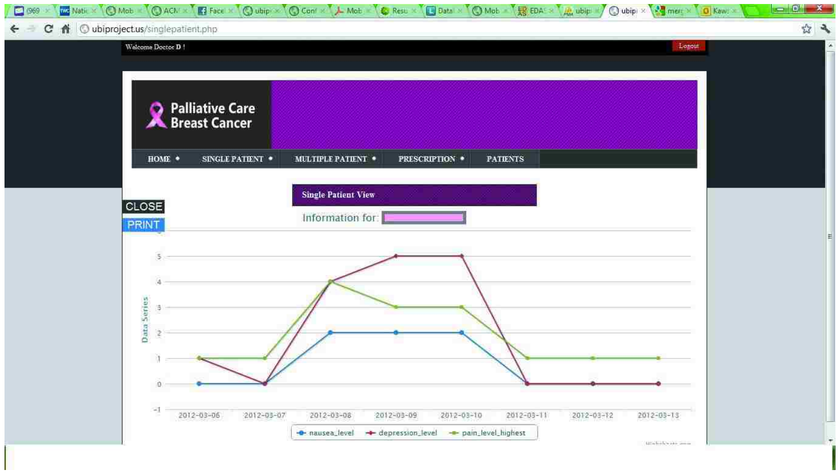


Figure 5.9: Doctor viewing 3 symptoms of a patient in a single graph

Prescriptions

Doctors can view all previous prescriptions for a particular patient shown in figure 5.10(a). He can create a new prescription too as shown in figure 5.10(b). If a new prescription is written, it will be stored in server with previous prescriptions.

Figure 5.10: (a) Doctor views all prescriptions (b) Doctor creates new prescription.

5.4 Evaluation

We deployed e-ESAS in 12 Nokia X6 phones. Two of them will be used by doctors in different locations of AGBCC. The rest will be used by 10 BC patients. Patients were selected based on the following criteria:

- Chronic pain score on ESAS 0-10 scale reported to be less than or equal to 5.
- Life expectancy, greater than 6 months.
- Normal mental status.
- Performance status 0, 1, or 2 based on ECOG scale [2]
- Able to understand and cooperate with study protocol.
- Patient has two people living with her (attendant).
- Patient lives less than one hour commuting distance from either AGBCC or DMCH.

5.4.1 Designing to Reduce Error Rates

We asked the patients to set some values in their ESAS questionnaire. We found that when the patients scroll down to set values of later symptoms, they unintentionally changed previously set values. Also, sometimes they unintentionally touched the exit button and closed the application. As can be seen from table 5.1, the patients made 1.2 errors on average in completing the form. We changed the UI, and instead of all 10 questions in one page, we made 5 pages, each with 2 questions, removing any need to scroll down. We also added one page for 3 new questions related to pain. We also increased the font size and increased the gap between two sliding bars. In our 4th visit, we asked patients to fill out the ESAS form and *only 1 patient made a single mistake*. We also removed the exit button from each page and placed it as a menu item in a menu on the last page. This prevented accidental closing of the application.

	Number of Errors			
Version	0	1	2	3
First	9	16	11	3
Second	16	**1**	0	0

Table 5.1: Error comparisons of two versions of e-ESAS

5.4.2 Faster Use by Attendants

After one month of deployment of the system in November, 2011, we performed the following steps for 10 MOs and their attendants.

- Each patient is given 13 random numbers from 0 to 10 and asked to set these values using the sliding bars of e-ESAS sequentially.
- Record the time required by the patient to set the values.
- Count the number of errors (the values set by the patient that are different than the given values are considered errors).

Figure 5.11 shows the timing requirement for MOs and attendants.

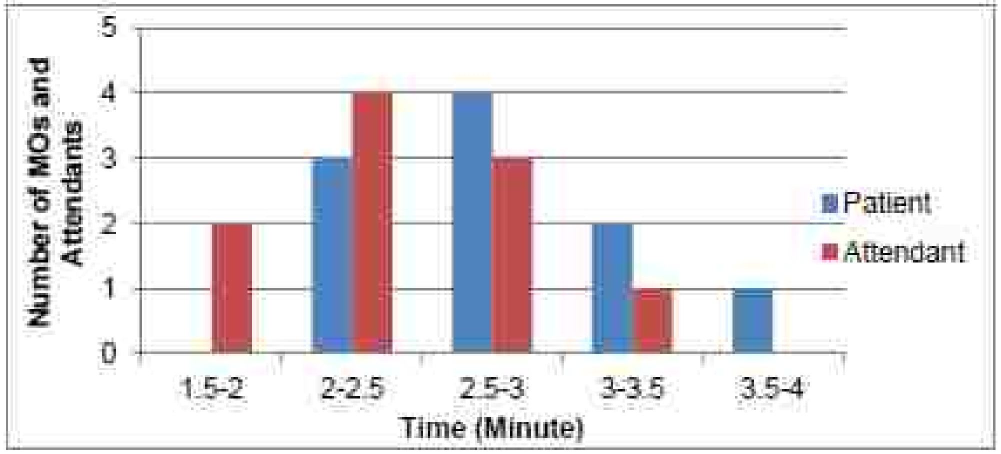


Figure 5.11: Timing requirement histogram

The average time required by attendants is 2.4 minutes which is slightly less than that of the patients (2.8 minutes). This is expected since, in most cases, attendants were younger than the patients and more familiar with mobile phones. One of the patients made 1 error and none of the attendants made any errors. This indicates the simplicity and easy-to-use nature of e-ESAS.

However, we observed there is a slight increase in the timing requirement for the 2nd version of e-ESAS (2.8 minutes) compared to 1st version (2.66 minutes) of e-ESAS. The increase in timing requirement is due to two reasons; First, the number of questions has increased from 10 to 13, and a small amount of time is required to move to the next page (five page changes in total). Table 5.2 summarizes the timing requirement to enter data in two versions.

	Time in minutes				
Version	1.5-2.0	2.0-2.5	2.5-3.0	3-3.5	>3.5
First	3	10	17	9	0
Second	0	3	4	2	1

Table 5.2: Time comparisons of two versions of e-ESAS

5.4.3 Enhanced Flexibility

One advantage of e-ESAS is its flexibility. Doctors can view graphs at anytime and from any place. They can view patient information from their taxi while stuck in traffic, from a train, bus, or rickshaw. Patients can also record symptom data at anytime or from any place. Cell phones have the advantage that people carry them all the time. So, no extra device is needed.

5.4.4 Better Representation

Doctors can view the trend of pain and other symptoms as data is represented graphically, which makes it easy to recognize any patterns if there are any. Based on feedback from doctors, we introduced an option to view data of one symptom (pain or nausea etc.) of multiple patients on a single graph in the web app. This allows doctors to compare how an intervention is working on different patients. An example is shown in figure 5.12.

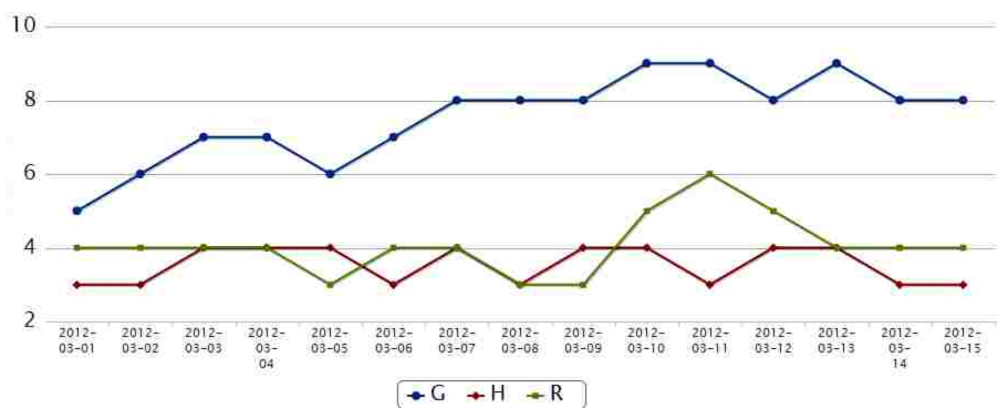


Figure 5.12: Graph of patient G, H and R for the Symptom Pain

Also, multiple symptoms (pain, tiredness and nausea, for example) of one patient can be viewed in a single graph. Viewing this information in graphic form makes it easier to make critical observations. An example is shown in figure 5.13.

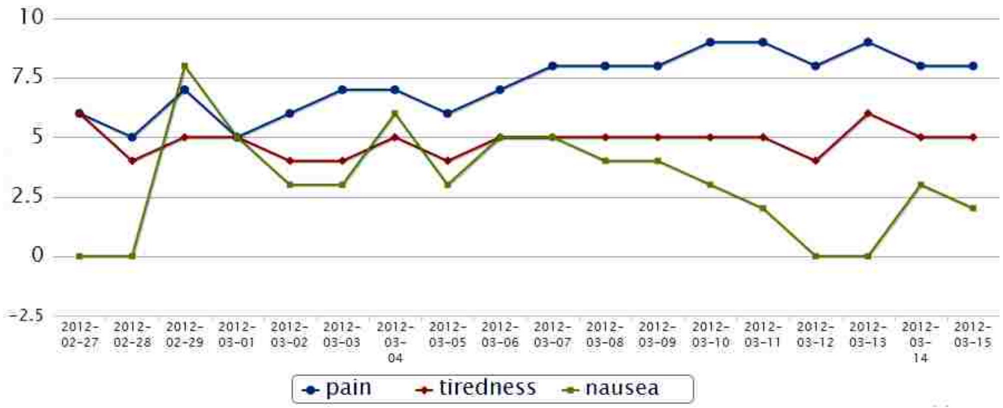


Figure 5.13: Graph of patient X for the symptoms Pain, Tiredness and Nausea against selected time period

5.4.5 Improved Data Quality

Data quality is improved by its validity, regularity, and frequency.

- Validity
  - Doctors can view data instantaneously so that the information is fresh and relevant.
  - There is no possibility of forgetting to record date, time, and patient name as the system automatically records this information, which is a possibility in a paper-based system.
  - The symptoms are recorded in the clinic where they are biased by several factors. It can be the case that the patient exaggerates severity of some symptoms to attract more attention from doctors. Or they might mention higher tiredness levels as a result of traveling a long distance and waiting in the queue at the clinic. The e-ESAS captures the true data as data are recorded in a 'natural' setting and not influenced by external factors.
- Regularity

  - Patients submit their symptoms regularly as it is much easier and as they become an active participant in their treatment.

- Quantity

  - Our e-ESAS improves quality of data as data are captured more frequently.

In case patients forget to bring previous prescriptions, doctors can view all previous prescriptions through e-ESAS from their cell phones or website and still remain informed. Also in paper-based systems, converting data to a smart representation requires human effort and thus have the risk of errors. For e-ESAS, this is not the case. We argue that e-ESAS thus improves the quality of data.

5.4.6 Better Assessment

Better assessment of any chronic disease (e.g., cancer, diabetes, blood pressure) requires information about the crucial symptoms over a period of time. Doctors in rural contexts are highly constrained in assessing the progress and criticality of the BC patients due to extremely limited availability of data. Doctors' diagnosis of the disease symptoms and possible prescriptions were reliant on obscure information of the patients who typically come after long delays, frequently without their previous prescriptions. But now doctors can see the symptom curves for any MOs over any defined period of time. They can also compare a specific symptom of multiple MOs for analysis. Doctors are now able to diagnose patients in a better way due to the availability of a longitudinal history of symptom values created through e-ESAS. For example, D1 said

"These 2 patients (MO1 and MO8) were under my supervision since the beginning and they have almost identical disease condition. They were under same type of medication and their reported pain scores were also similar (figure 5.14). But all on a sudden I found the MO8 is experiencing much higher pain values compared to MO1. Then I talked with her and changed her medication with no effect. Then I

compared their pain symptom graph over around 20 days time (as shown in Figure 7). As you can see pain level of MO1 has decreased after X (some date) where as that of MO8 has increased. Later I found that both these patients were scheduled for chemotherapy around that date. MO8 missed her chemo due to family reasons. Later I talked with the doctors in Khulna Medical College Hospital for her chemotherapy."

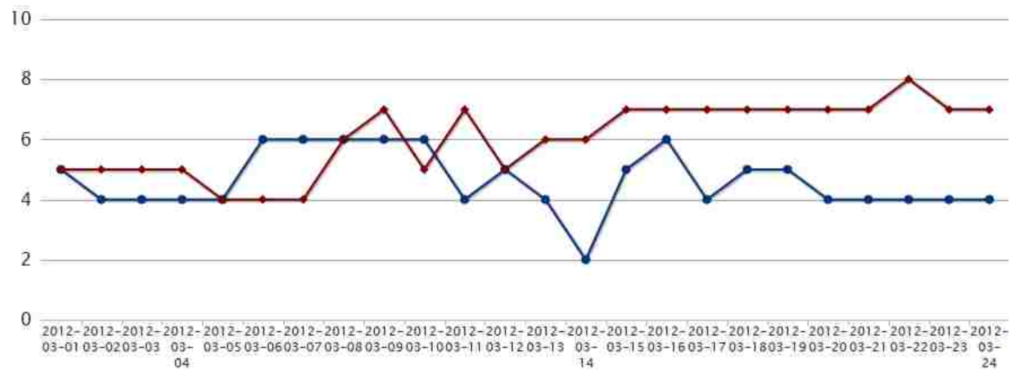


Figure 5.14: Comparison of pain graph for Patient 1 and 8

5.4.7 Reduction in Missed Appointments

We were interested to see the effect of the deployment of e-ESAS on the issue of missing appointments. We analyzed the data in two time frames; Dec '10- May '11 (before the deployment of e-ESAS) and Nov '11-Dec '11. We will call these periods time frame 1 (TF1) and time frame 2 (TF2) respectively. We also divided the cancer patients into 2 groups: MOs and the rest. This is because the MOs, having received the mobiles, are naturally expected to be more punctual in their appointments. We show the missing appointments statistics of each of the MOs for TF1 in figure 5.15. These 10 MOs were scheduled for a total of 107 appointments over the six month period, making an average of 1.78 appointments per patient per month. They missed a total of 40 appointments, thus the average percentage of missed appointments became 37.4%. According to the records of AGBCC, *only 2 MOs* missed one of their appointments each in TF2.

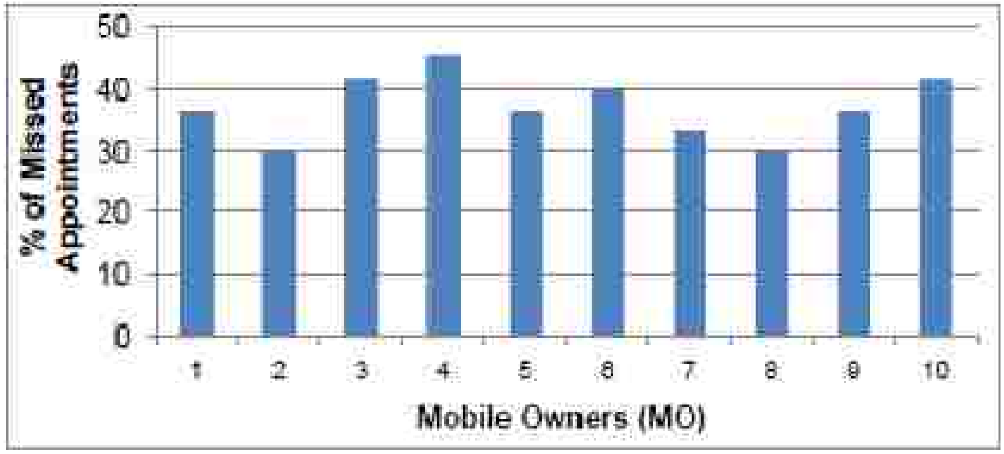


Figure 5.15: Missing appointment data for MOs in before deployment

When we analyze the appointment history of the other BC patients for TF1 and TF2, we observe that the average percentage of missed appointments are 48.8 in TF1 and 39.8 in TF2 as shown by yellow and red solid lines in figure 5.16. There was a 9% drop in missed appointments, even for patients, who were not given e-ESAS cell phones. This is likely due to the positive environment created by the deployment of e-ESAS.

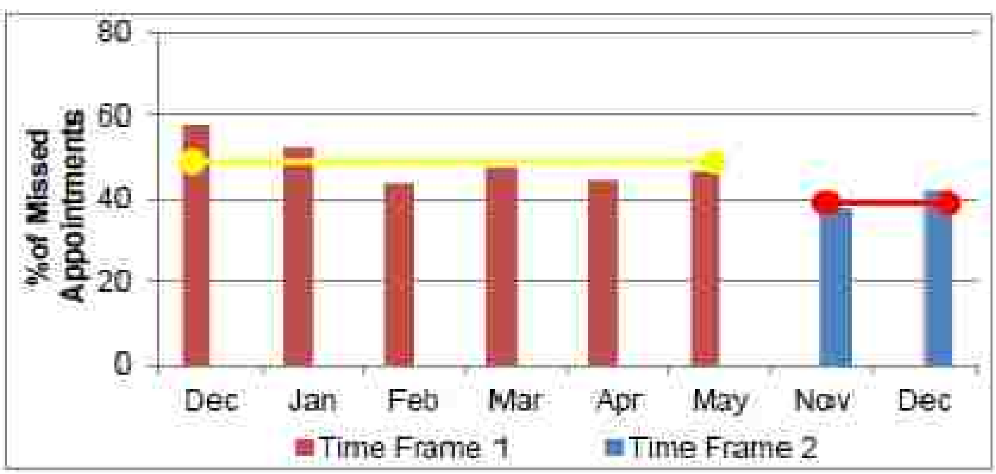


Figure 5.16: Comparison of percentage of missed appointments for BC patients in TF1 and TF2.

5.4.8 Reduction in Number of Appointments

Normally, doctors ask the BC patients to meet weekly or biweekly based on their current health status. But in the case of MOs, doctors asked them to come monthly. They were also encouraged to come if they feel any problems in between. As a result of this, the number of appointments assigned for MOs has been reduced automatically. According to figure 5.17, the average number of appointments for each patient per month has been reduced to 1.25 in TF2 compared to that of 1.78 in TF1.

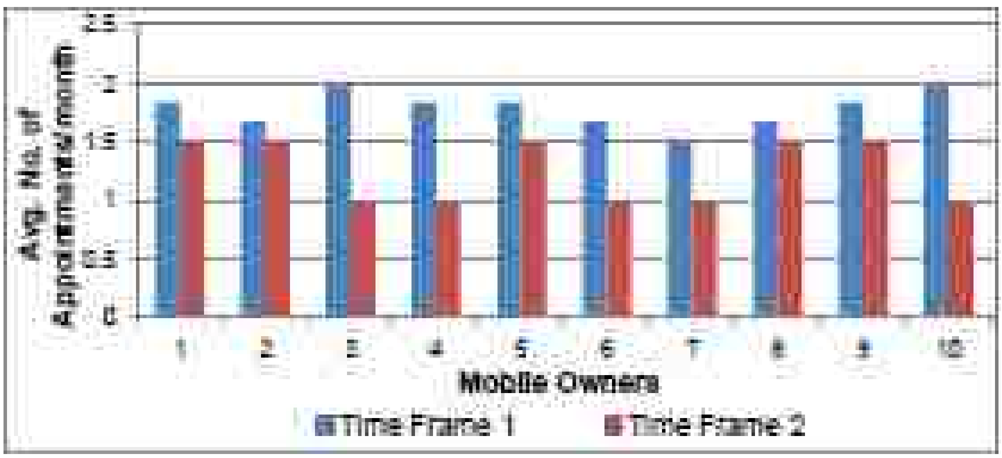


Figure 5.17: Comparison graph of average number of appointments in TF1 and TF2.

5.4.9 Reduction in Visit Time

The effectiveness of doctors can be increased by reducing the visit time required by each patient without compromising the level of care. During TF2 we recorded the duration of clinic visits of MOs and other BC patients through clinic observation. MOs made 12 and 13 appointments in Nov ’11 and Dec ’11 respectively and whereas other BC patients made 51 and 48 appointments respectively. Along with all MO visits we recorded, the timing of 23 and 29 visits of other BC patients were recorded for Nov ’11 and Dec ’11 respectively. The average timing requirement of MOs and other BC patients in TF2 is shown in figure 5.18. The figures are based on averaging the time recorded during those visits. To avoid bias, doctors were not notified about the timing issue.

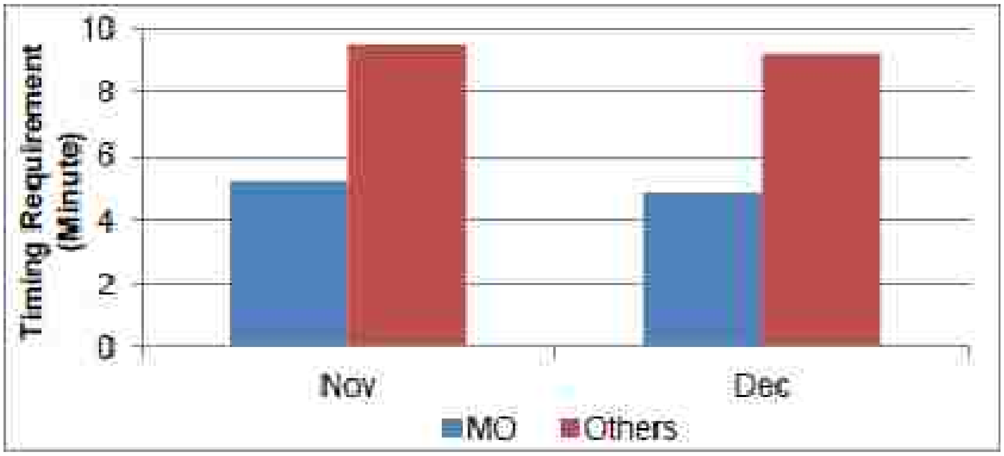


Figure 5.18: Average timing requirements of MOs and others during TF2.

5.4.10 Satisfaction

In order to find the level of satisfaction of the users about e-ESAS, we asked the MOs and 5 doctors to rate their corresponding e-ESAS module against 5 criteria (easiness to use, easiness to learn, interactivity, helpfulness and overall satisfaction) on a scale of 0 to 10. Figure 5.19 shows the average results. Both patients and doctors find the system very satisfactory in terms of ‘helpfulness’. Being more educated and familiar with mobile phones, doctors found e-ESAS more usable than the MOs in terms of the rest of the features.

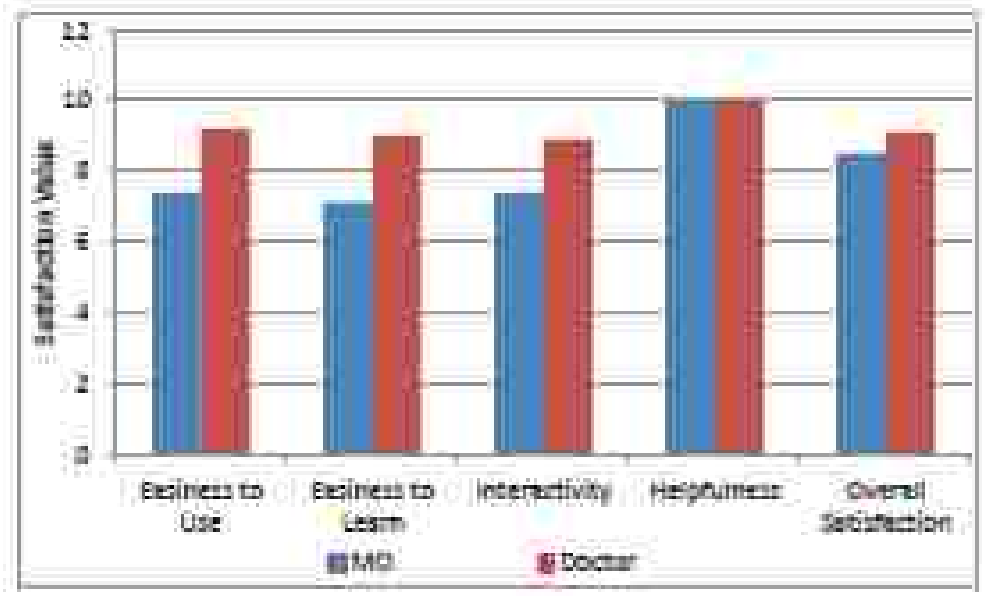


Figure 5.19: Usability results of e-ESAS.

5.5 Conclusion

In this chapter, we presenedt the analysis, design, development, and deployment of e-ESAS. At its present state, the system would be especially helpful to palliative doctors in the management of pain and other symptoms. Patients in a developing country, where there is shortage of palliative doctors, will be immensely helped by accessing services from remote doctors.

One of our design principles was that the system be a viable one. Instead of developing a sophisticated system with good performance, which requires expertise from the users or is expensive, we focused on a simple inexpensive system. As our end users were poor women with breast cancer in rural areas who have some experience with cell phones, we expected that incorporating our system in the cell phone would keep it simpler, instead of introducing a complete new device and training.

Discrimination between health services received by rich and poor can be narrowed to some extent by e-ESAS. In an urban-centric country like Bangladesh, the e-ESAS should remove the notion of distance to some extent and narrow the gap between urban and rural areas.

5.6 Related Publications

- Munirul Haque, **Ferdaus Kawsar**, Mohammad Adibuzzaman, Md Uddin, Sheikh I. Ahamed, Richard Love, Ragib Hasan, Rumana Dowla, Tahmina Ferdousy, Reza Selim: ***e-ESAS: Evolution of a participatory design-based solution for breast cancer (BC) patients in rural Bangladesh,*** Personal and Ubiquitous Computing (2014): 1-19.

- Munirul Haque, **Ferdaus Kawsar**, Mohammad Adibuzzaman, Sheikh I. Ahamed, Richard Love, Rumana Dowla, David Roe, Syed Hossain, Reza Selim: ***Findings of e-ESAS: A Mobile Based Symptom Monitoring System for Breast Cancer Patients in Rural Bangladesh,*** In CHI 2012, Austin, Texas.(Honorable Mention)

- Munirul Haque, **Ferdaus Kawsar**, Mohammad Adibuzzaman, Mohammad Miftah Uddin, Sheikh I. Ahamed, Richard Love, Ragib Hasan, Rumana Dowla, Tahmina Ferdousy, Reza Selim: ***Barriers for Breast Cancer (BC) Patients in Rural Bangladesh: Design and Deployment of a Mobile based Solution,*** In Proceedings of the 20th Americas Conference on Information Systems (AMCIS 2014), August 7-10, Savannah, Georgia.

- Munirul Haque, Mohammad Adibuzzaman, Md. Uddin, **Ferdaus Kawsar**, Sheikh I. Ahamed, Richard Love, Rumana Dowla, Reza Selim, Tahmina Ferdousy: ***Findings of Mobile based Palliative Care System: Towards a Generic Framework for Measuring QoL,*** In PervasiveHealth 2014, Oldenburg, Germany (Nominated for Best Paper Award)

Chapter 6

Smartphone Based Multimodal Activity Detection System Using Plantar Pressure Sensors Placed On Shoes

6.1 Introduction

Physical activity (PA) is defined as bodily movement produced by skeletal muscles that results in energy expenditure [23]. Measurement of physical activity has been studied by researchers to investigate the relationship between human movements and health status [41]. Lack of physical activity is known to be associated with diabetes mellitus, cardiovascular diseases and obesity. Low-level physical activity is a major symptom of illness and indicates functional impairment [85]. Various subjective and objective tools have been developed to assess physical activity. Subjective tools like diaries, surveys and questionnaires suffer from recall bias and thus are inaccurate. A good amount of effort has been put forth to develop an accurate objective tool to measure physical activity automatically.

Automatic detection and measurement of physical activity has applications in context-sensitive systems. For example, they can be used in interruption management systems. Physical activity is one of the most important contexts [78] and identifying the correct activity is thus core to such systems. Such automatic detection of physical activity is also needed by doctors who need to monitor the activity of patients remotely. It has an application in the monitoring of elderly people who want to maintain their independence as well as people who need to measure their physical activity. Researchers in exercise science also want to find a cheap and easy alternative to measure energy expenditure. On the other hand, identifying and quantifying human physical activity is necessary for establishing correlation between activity patterns and future health risk.

The automatic physical activity detection systems mostly use accelerometer data collected from accelerometers placed on different locations on the body [17] [28] [34]. For example, Bao [17] used 5 accelerometers and placed them in five different locations of the body. Some of the systems use other sensor data along with accelerometer data [28], however such systems suffer from some limitations. First, many of these studies primarily focused on the task of activity detection and ignored usability resulting in an obtrusive system. For example, Chowdhury and her colleagues [28], for example used a wired version making the system unobtrusive. Second, some of the systems [34] perform well in a controlled laboratory environment but not so well in a naturalistic environment.

In this paper, we came up with a wireless system that requires few extra devices and was designed to accommodate human phone behavior patterns. For a system to be user-friendly and unobtrusive, we argue that first it should be wireless. The presence of wires makes any system obtrusive and unsuitable to be worn in a natural setting. The user should not be required to wear any extra devices. Smart phones are typically already carried by the users and they come with built-in accelerometers and other sensors making smart phone based systems inherently unobtrusive. Smart phones are thus the natural choice for an unobtrusive activity detection system. However, the problem with a smart phone based system is that it is based on the assumption that the smart phone will be carried by the users (usually in the pocket). Such assumptions are not necessarily realistic as we have observed that people often put their phones on their desk while working in the office. Furthermore, women often carry their phones in their purses. Thus, in spite of a smart phone based system being unobtrusive, people's behavior patterns limit the applicability of such systems. For any such system to be useful, the phone carrying behavior patterns of people must be considered. In this chapter, we present and discuss our novel activity detection system. As our system uses accelerometer and gyroscope data from smart phones and pressure data from pressure sensors placed in shoes, users will not be required to carry or wear any new devices they are not already carrying or wearing. Our contributions:

- We have proposed a novel architecture for the unobtrusive detection of human physical activity using accelerometer and gyroscope data from smart phones as well as pressure data from shoes.
- Our architecture was designed to make the system unobtrusive and robust against various human behavior patterns.
- We developed a prototype of the activity detection system using smart phones and plantar pressure sensors based on our proposed architecture.
- We identified the various issues that came up while developing the system alongside the caveats and their origins and possible solutions.
- We analyzed data from four activities and developed an algorithm based on our analysis. Later we tested how our algorithm performs and achieved very good accuracy for the activities in the data analysis stage. Several modifications of the algorithm and the evaluation of their performances were also discussed.

6.2 Related Works

6.2.1 Smartphone based activity recognition system

Phone-based accelerometers were used to perform human physical activity recognition by Kwapisz and her colleagues [50]. Labeled accelerometer data from Android phones were collected from twenty-nine users as they performed daily activities such as walking, jogging, climbing stairs, sitting and standing. Authors used these data as training data to build a predictive model for activity recognition. After extracting six features from the data, classification techniques such as decision trees, logistic regression, and multi-layer neural network were used for classification. Though the architecture has the advantage of using a device that is conveniently carried by people in their pockets, it fails to capture activities when the phone is not in the pocket. In [94], Yang developed an activity recognition system using the built-in accelerometers in the Nokia N95 phone. His work used orientation-independent features, such as vertical and horizontal components in acceleration as well as magnitude of acceleration to recognize daily motion activities. The decision tree performed best among the four classifiers (Naïve Bayes (NB), k-Nearest Neighbor (kNN) and Support Vector Machine (SVM)) he evaluated. Miluzzo and his colleagues developed CenceMe [67], using off-the-shelf, sensor-enabled mobile phones (Nokia N95) and exploited various sensors (such as a microphone, accelerometer, GPS and camera) that are available for activity recognition. They made it scalable by distributing the classification task between cell phones and back-end servers and recognized walking, running, sitting and standing activity.

In all of the above cases, the solution is phone based and the assumption is that the phone will be carried by the users all the time in their pockets. This is not a very realistic assumption as we found in our survey and observations forcing us to rethink such approaches.

6.2.2 Multimodal activity recognition system

Lee and Mase tested the feasibility of the dead reckoning method to determine a persons location in an indoor environment in [53]. The idea was to detect walking and count the steps in a particular direction to determine indoor location. Data from a gyroscope and a digital compass was used along with an accelerometer to detect sitting, standing and 3 types of walking. Two extra sensing modules, placed in the pelvic region and thigh. Multiple sensors in different locations of the body make the system somewhat intrusive. Subramanya and his colleagues [87] built a model using data from a tri-axial accelerometer, two microphones, phototransistors, temperature and barometric pressure sensors, and GPS. The model can distinguish between a stationary state, walking, jogging, driving a vehicle, and climbing up and down stairs.

Their work claims to detect both the location of a person and the activity he is engaged in. In this case, an extra sensor board needs to be worn by the users as well.

Choudhury [28] used multiple sensor devices consisting of seven different types of sensors (tri-axial accelerometer, microphone, visible light phototransistor, barometer, visible and IR light sensor, humidity/temperature reader, and digital compass) to recognize activities. They placed all the sensors in a single location on the body to make it less intrusive. In reality, the wired connection of the sensor module with iPaq and the very use of the extra sensor device make it somewhat intrusive. Uiterwaal [90] used two sensors placed in the belt and thigh to detect standing, sitting, lying, seesawing and locomotion. Data transmission to a recorder was possible through a wired connection. Wired connections and the use of multiple extra devices make the system very obtrusive. In [65], Maurer used 'eWatch' which was worn in six different locations to find the most suitable position for activity recognition. Each 'eWatch' has a bi-axial accelerometer, microphone, temperature sensor and a light sensor. This 'eWatch' needs to be worn by the users and detected activity cannot be communicated. Cho [27] used a single tri-axial accelerometer, along with an embedded image sensor worn at the users waist to identify nine activities. Support Vector Machine (SVM) was used for classification of different activities based on features like mean, energy expenditure and FFT.

In [36], Gyorbro used 'MotionBands' attached to the dominant wrist, hip and ankle of each subject to distinguish between six different motion patterns in real-time. Each 'MotionBand' contained a tri-axial accelerometer, magnetometer, and gyroscope. The data collected by MotionBands were transmitted wirelessly to a smart phone carried by the user, thus enabling unobtrusive collection of data. The six activities recognized were resting, typing, gesticulating, walking, running and cycling. The average recognition rate was 79.76%. Though some unobtrusiveness is achieved, multiple Motionbands need to be worn by users along with carrying the smart phone.

In [54], Lester and his colleagues used accelerometer data, along with audio and barometric sensor data, to recognize eight daily activities from a small set of users. They collected data for 8 different activities from 12 different subjects. The subjects had to wear three multi-modal sensor board (MSBs) resulting in an obtrusive system.

6.3 Motivation

Here we illustrate the motivation behind our system using some plausible cases.

6.3.1 Case 1

Ryan is a software engineer and he is always close to his phone. The way he carries his phone primarily depends on the activity he is engaged in. Approximately 30-40% time the phone is in his shirt pocket, 30-40% time it is in his pocket, 0-20% time it is in his hand.

6.3.2 Case 2

Erin is an undergraduate student at a university in the USA. She spends lot of time in the library. While in the library, she places her phone on the table. She also uses her phone to send approximately 200 text messages a week. When she is walking, she puts the phone in her back pocket and listens to music.

6.3.3 Case 3

Linda is a woman in her 40s. She will either carry her phone in her bag/purse or in her hand and almost never carries her phone in her pocket.

We have observed that phone carrying habits vary a lot depending on gender, country, culture, the type of activity he or she is engaged in as well as some other factors. Cui and his colleagues studied the phone carrying behavior of people in 11 cities in Europe, America, Africa, the Middle East, India and East Asia extensively and showed in their paper [29] that generally women used bags (61% of women versus

10% of men) and men use pant pockets as the primary way to carry a phone. A significant percentage of men (∼14%) use belt cases to carry phones whereas the percentage of women using belt cases is insignificant. They also found that phone carrying behavior also depends on culture. For example 80% women in Helsinki carry phones in their handbags while only 50% do so in Delhi. This is consistent with the small survey we conducted among five graduate students. Only one of them keeps his phone in his pocket 90% of the time. For others, it is less than 50%. Other popular locations are the shirt pocket, hand, bag and the desk. We also observed undergraduate students in a library setting and found differences in behavior between men and women. All 13 women put their phones on the table while 8 of the 14 men put their phones on the table.

Under these circumstances, we argue that any smart phone based system that detects different activities based on the assumption that the phone will be carried by users in their pockets will not be a pragmatic solution.

6.4 System Architecture

We propose an architecture where pressure sensors will be placed on the shoes and these pressure data will be transmitted over Bluetooth to a smart phone carried by the user. Now it does not matter where the phone is being carried as long as the phone is within the Bluetooth range of the shoes. As Bluetooth has a range of 5-30 meters and the distance from a person to his phone is almost always within this range, this proposed architecture can almost always collect pressure data from shoes. We propose a plantar pressure sensor system that interfaces with cell phones for activity detection. Our system works in two phases: i) learning phase and ii) activity recognition phase. In the learning phase, after the sensor data is collected and processed, the data is analyzed to develop an algorithm. In the activity recognition phase, the algorithm is implemented and the incoming sensor data is used by the algorithm to detect activities.

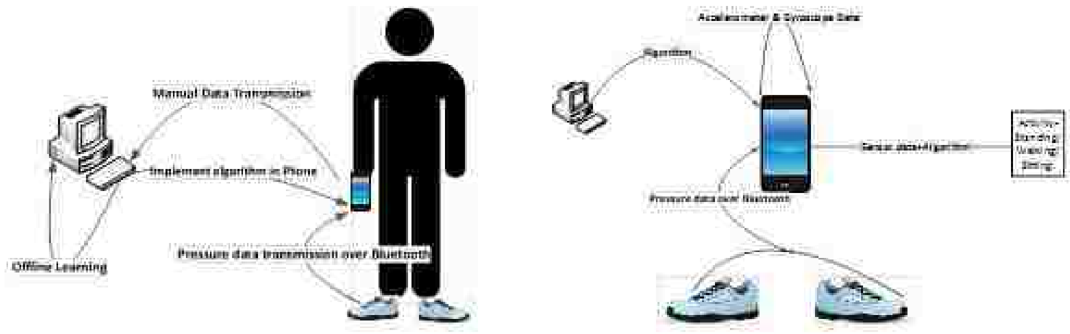


Figure 6.1: a) System architecture for learning stage and b) system architecture for activity recognition stage.

This novel architecture is our contribution 1 (C1), which ensures unobtrusiveness for the users. Our system has two principal components: i) data collection system and ii) activity recognition system.

6.4.1 Data Collection System

The Data Collection (DC) System is responsible for collecting sensor data. In our case, we are collecting pressure data from pressure sensors placed on the sole of both shoes, accelerometer data from the cell phone and gyroscope data from the cell phone. The data collection system collects data from these four sensor systems and stores them in four files in three different folders. We used DC in two stages. First, the data collection system is used to collect the data and the collected data was later used to learn a classification algorithm offline. Second, the learned algorithm detects activities from the incoming sensor data collected by the DC system during the activity recognition phase.

6.4.2 Activity Recognition System

The activity recognition system mainly consists of the implementation of the algorithm learned in the learning phase. After data analysis, an algorithm is developed. When this algorithm is implemented, it continuously takes sensor data as input. The algorithm detects the activities during each time segment as streams of sensor data are fed to the algorithm and the algorithm outputs the activity. In our case, a decision tree was learned after the learning phase and the decision tree was implemented as the activity recognition system.

6.5 Prototype System Description

Based on the proposed architecture, we developed a prototype of the activity recognition system. To reduce complexity, we only intended to detect three activities: sitting, standing and walking. Instead of using data from all sensor systems, we only used pressure data from the left shoe. Development of the system consisted of four stages: data collection, data processing, algorithm continuously and recognition system implementation.

6.5.1 Plantar pressure Sensor System

We decided to use an in-shoe plantar pressure sensor system based on a fabric sensor array as in figure 6.2.

Figure 6.2: Pressure sensor system.

This system was developed by Lin Shu et al. [84]. It has 8 pressure sensors in each shoe. There is also a Bluetooth interface to transfer the pressure data to an Android phone.

6.5.2 Data Collection

We used the system for collecting pressure sensor data. Though we collected data from both shoes, we used data from only the left shoe. We collected data for walking, sitting and standing. After the connection between the phone and shoe was established, we performed the activities for 3 minutes. The subject disconnected the connection by pressing the disconnect button when he finished the activity. While the data was being collected, the phone was in the user's hand. The collected data has 8 columns for data from 8 pressure sensors along with a time stamp.

6.5.3 Data Processing

We removed noise data throughout our dataset in the beginning and in the end to reduce any possibility of data corruption. In figure 6.3, the raw data from the left shoe is shown for both walking and sitting. There are about 37 samples of data for

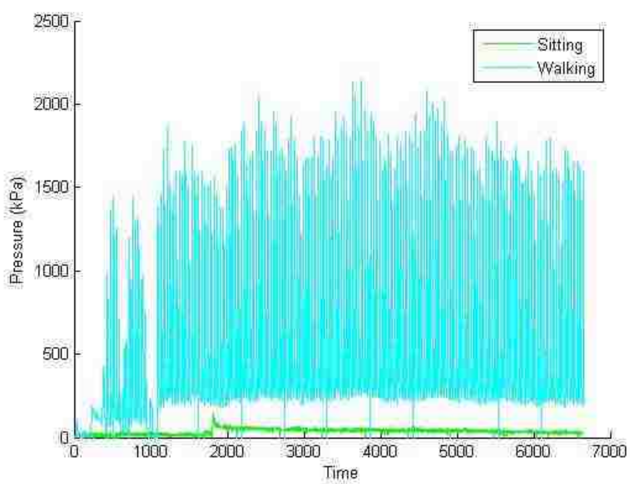


Figure 6.3: Data from second pressure sensor (P2) in the left shoe: walking and sitting.

each second (sampling rate 37Hz). We created a summary file where each row is a summary of 160 samples of raw data and then we used Matlab to generate the summary file for each of the three activities. Each summary file contains 40 columns of data as we estimated mean, median, mode, standard deviation and summation of 160 samples for each of the 8 pressure sensors in the left shoe. After this, we merged these three summary files and added another column at the end to indicate the activity class (sitting, standing or walking).

6.5.4 Learning and Activity Recognition

We applied a decision tree based machine learning algorithm to generate a decision tree classifier. This classifier algorithm (figure 6.4) was able to classify correctly with 98.83% accuracy in a 10-fold cross validation setting. This means that it showed 98.83% accuracy for the same data from which the classifier was generated. After we implemented this generated tree in our recognition system, we found it took a long time to detect the activity. According to our previous calculation, 160 samples should take 4.3 seconds at 37Hz sampling rate. To address this issue we reduced sample size to 60 from 160. This was done following the same process except that now the sample size was 60. As a result, the accuracy remained the same but it took less time to detect the activities than the prototype Activity Detection System. For a 60-sample system, the following algorithm (figure 6.4) was generated:

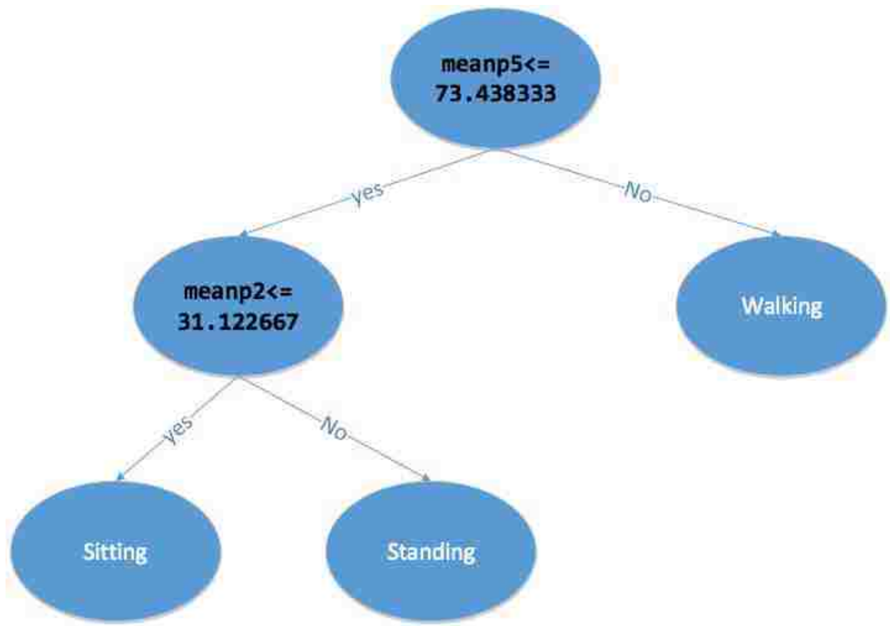


Figure 6.4: Decision tree for three activities.

Here $meanP5$ is the average of 60 consecutive samples from pressure sensor 5 from the left shoe. Similarly, $meanP2$ is the average of 60 readings from pressure sensor 2 from left shoe. We implemented a modified version of the algorithm (figure 6.5) based on trial and error. Whenever new data comes, the oldest data from queue is removed and features are calculated again. Thus a queue (first-in-first-out) data structure is used to ensure that features are calculated from the most recent 60 samples. Then the algorithm is used to derive the activity.

6.5.5 Caveats and Discussion

We developed this prototype activity recognition system as a first version of the more complex future activity recognition system. The design and development of this prototype system is our contribution 3 (C3) which elicits some of the issues that came up during the development of the system.

Delay in settling to the right activity

The activity recognition system we built can correctly detect sitting, standing and walking. But, for some transitions, it cannot immediately follow the activity. For example, for transitioning from sitting to standing, detection is immediate, while transitioning from standing to walking can take several seconds. This issue is more pronounced for transition from a high acceleration activity to a low acceleration activity. Theoretically, it should not be more than two seconds as we are dealing with 60 samples at a 37Hz sampling rate.A detailed investigation of our data stream reveal couple of reasons. Obviously sample size has a major role. We know this because the delay was much larger for a sample size of 160. The question is, ”How small we can make the sample size without compromising the accuracy?” This is one issue that we will investigate in the future. The second reason is that our decision tree is fairly simple. We derived our decision tree from considering only discrete activities like sitting, standing or walking. However, transition activities like sit-to-stand or walk-to-stand have different patterns of data. As the data for transition between activities were not considered during training our model, the model fails to capture these transitory scenarios. The problem is that transition between activities takes so little time that it is difficult to annotate data for transitory activities.

Empirically derived threshold values

We modified the generated algorithm (figure 6.4) and obtained the algorithm in figure 6.5 empirically. Though the structure remained same, the threshold values were estimated empirically through trial and error. The original generated algorithm of figure 6.4 works well when the subject is performing an activity for sometime. However, when there is a transition from one activity to another, the dynamics is not captured well. As a result, the time it takes to settle to sitting activity from standing activity is significant. To address this, we observed the values of $meanP2$ while performing transition activities. We found that if we changed the threshold for $meanP2$ from generated value 31.12 to 56.05, the time to settle from transition decreases significantly. The following algorithm (figure 6.5) was finally obtained:

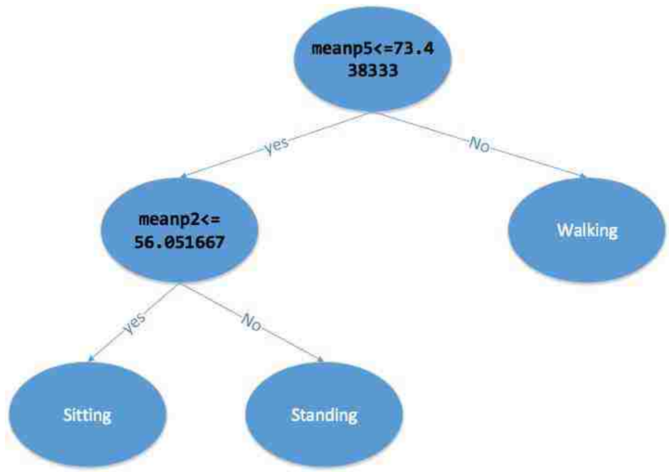


Figure 6.5: Modified decision tree.

Battery drainage

We found that Bluetooth connections are expensive in terms of battery use. We propose several suggestions to address this issue. First, instead of maintaining a connection all the time over Bluetooth, the connection should be intermittent and for a percentage of time duration. Also, these periods of connectedness can be uniformly distributed and the final estimation of activity can be extrapolated. This will be a tradeoff between power consumption and accuracy of estimate of physical activity.

6.6 Remote Monitoring

After activity is detected, our system sends the information to a remote server. A decision about activity is made in every 2 seconds. However, activity information is not sent to server every two seconds. Instead, we developed a local database using SQLite which stores activity record instantaneously every two seconds. A process continuously runs in the background. The background process prepares a summary for every minute's data from SQLite and sends the summary to remote server. The background process also erases the data from SQLite after it has sent the summary to server. This structure prevents the necessity to send activity data instantaneously and thus save precious battery power of smart phones. Right now, we are updating the server in every one minute. We can change it to other convenient intervals. However, if we increase the time to 30 minutes, the remote monitoring person may have to access 30 minute old data. The best strategy probably is to set this interval according to need of particular situation. Figure 6.6 shows a screen shot from our remote monitoring system. A user can login to view the summary of activities by date. After date column, first column is sitting time, followed by standing time and walking time in seconds.

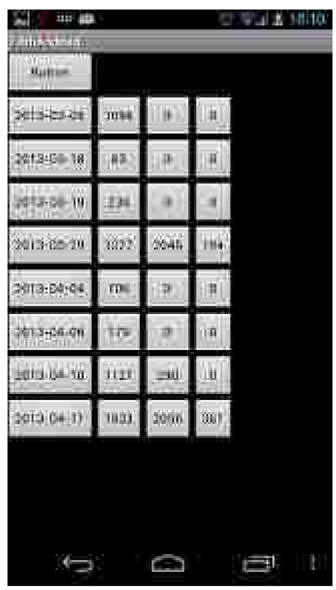


Figure 6.6: Remote activity monitoring screen.

6.7 The Multimodal Approach

In the multimodal approach, we combined four classifiers obtained from analyzing data from *gyroscope*, *accelerometer*, *right* and *left shoe*. Each classifier was obtained following data collection, processing and learning. Four classifiers were combined and in the recognition phase, the combined classifier was used to detect activity.

6.7.1 Data Collection

We collected data for four different activities: standing, sitting, walking and running. As we need to synchronize data from all four systems (gyroscope data collection system, accelerometer data collection system, left shoe data collection system, right shoe data collection system), we needed the timestamp. For each activity, we collected data three times (3 minutes each time).

6.7.2 System Description

We wrote two services on the android platform: *TestService* and *GyroService*. *TestService*, when started will collect data from the accelerometer in the cell phone and stores it in the SD card. Similarly, *GyroService* when started will collect data from the gyroscope of the cell phone and store it in a file. *DataReceiverService* in the same way collects pressure data from the left and right shoes. These services run in the background on the android and after we start our application, the three Services continue to run in the background to collect data from the accelerometer, gyroscope, left shoe pressure sensors and right shoe pressure sensors. In all cases, the time stamp is also recorded along with the data.

A sample row of data is shown in table 6.1. The first number is the timestamp. For example, the data in table 6.1 was recorded at 1:41:42.5 p.m. P1 to P8 are pressure data are in kilo Pascal (kPa).

Time	P1	P2	P3	P4	P5	P6	P7	P8
1:41:42.5 p.m.	25.3	11.9	0	5.1	13.5	22.9	14.2	7

Table 6.1: Sample data collected from left shoe during sitting activity.

When we press the *connect device 1* menu item, *TestService* and *GyroService* are started. Also another service is started which collects data from the left shoe. When we press the *connect device 2* menu item, data from the right shoe is being collected. This means data from the right shoe is being collected from a later starting time. We also observed this in our data noticing the later timestamp in the data from the right shoe. Later during the preprocessing stage, we used this timestamp for synchronization so that data from all four sources starts and end at the same time. However, there are two issues that need to be mentioned:

First, while collecting data earlier for our prototype system, we only used pressure data from left shoe. Pressure data was transmitted over Bluetooth to the smart phone. As we were not collecting data from cell phones, the location of the phone was not important. But this time we are collecting data simultaneously from the left shoe, the right shoe, the phone's accelerometer and the phone's gyroscope during different activities. As we start the app from the phone and then put the phone in the pocket, there is some data in the beginning which does not reflect our target activity.

Second, while the phone is in the pocket and we are performing different activities, due to movement and stirring, the *disconnect* button may accidentally be pressed. Whenever the *disconnect* button is pressed, an alert sound is made before stopping the connection. This was done to ensure to receive a notification if the disconnect button is accidentally pressed when the phone is in the pocket. In case of accidental disconnection, we discarded that reading and collected data again.

6.7.3 Data Processing

Data preprocessing is very similar to what we did while developing our prototype. The additional step that we did here is some preprocessing to ensure the synchronization of data from four different sources. To synchronize, we clipped off the initial data. For example, if data from left shoe starts from 41:42.5s and data from right shoe starts from 51:29.3s then all rows in the left data where the time is less than 51:29.3s is removed. We did the same for gyroscope data and accelerometer data assuming data from the right shoe starts at a later time. After this is done, all data starts from the same time. We also clip off data at the end to ensure that all data ends at the same time. Then we wrote a Matlab code to visualize the data in graphical form. This is to check if there is any initial noise.

Figure 6.7 shows a graph of four activities superimposed on each other to show a comparative view. This graph is for acceleration data from the Y axis collected from the phone in the pocket. Similar graphs can be drawn from all 8 pressure sensors from left shoe, 8 pressure sensors from right shoe, 3 axes of accelerometers and 3 axes of gyroscope. Figure 6.8 shows pressure data from P1 of left shoe after pre-processing.

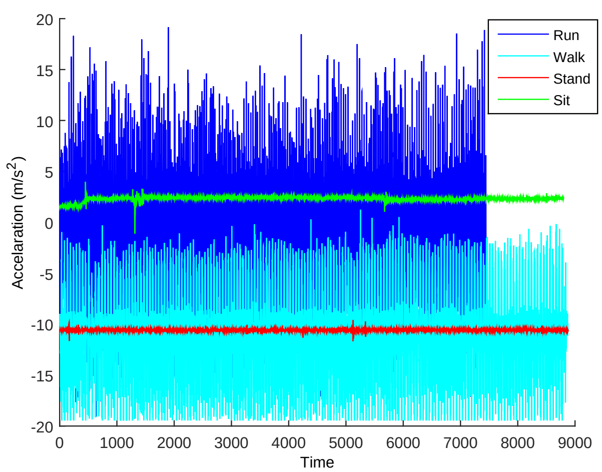


Figure 6.7: Y-axis acceleration data from phone for running, walking, standing and sitting.

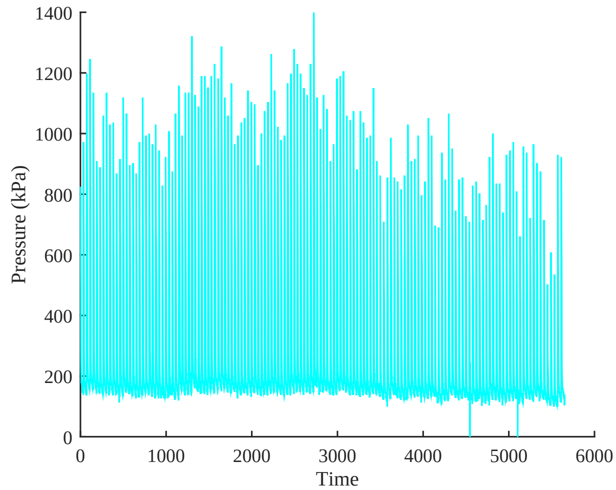


Figure 6.8: After preprocessing, walking data of pressure sensor 1 from left shoe.

After the synchronization part is done and after we have removed the noisy part of the data, we are ready to retrieve the summary of data. In our case, we only used the mean and standard deviation as a feature of the sample data. From our first experiment, we found that a sample size of 60 from the left or right shoe works pretty well for our purposes. We had to find the time equivalent of 60 samples from shoes with accelerometer data and gyroscope data. For the accelerometer, it is about 80 samples and for gyroscope data it is about 167 samples. This of course is due to a different sampling rate of accelerometer, gyroscope and shoes. Data from both shoes has the same sampling frequency while the sampling frequency of the accelerometer and gyroscope are different. Each 60 samples of pressure data from shoes (or each 80 samples in case of accelerometer data or each 167 samples in case of gyroscope data) were converted to summary data from the time series data. The gyroscope had the highest sampling rate where sampling frequency for left and right shoe was lowest. But our sample size was calculated so that they always reflect the same time duration for each of these four sensors.

After creating the summary files, we are almost ready to apply the machine learning algorithms. We compile our data so that in each file we have the summary data for running, sitting, standing and walking. There are four such files for each of the four kinds of data: left shoe data, right shoe data, gyroscope data and accelerometer data. The next step is to make a single file for each of the four sensor systems with an additional column indicating the activity. Sample rows from such files are shown in table 6.2. For example, the first row in table 6.2 is derived by estimating the mean and standard deviation of 60 samples of acceleration while running. Other rows were similarly derived from the acceleration data while sitting, standing and walking respectively. Of course, the original file has a lot more than just one row for each activity (426 rows in total).

mean(X)	**std(X)**	**mean(Y)**	**std(Y)**	**mean(Z)**	**std(Z)**	**mean(Res)**	**std(Res)**	**Activity**
-10.1356	8.2814	-1.2303	4.7405	0.4934	6.9485	14.2984	6.2752	running
-7.6059	0.1863	2.4499	0.3183	6.1035	0.1939	10.0620	0.1828	sitting
-0.9902	0.2050	-10.5848	0.1583	-0.8619	0.1934	10.6697	0.1495	standing
-0.1999	3.0774	-10.0015	4.5001	-0.077	4.4461	11.1049	5.1232	walking

Table 6.2: Four sample rows of summary accelerometer data.

$mean(X)$ is the average of 60 sample of acceleration along X-axis.

$std(X)$ is the variance of 60 sample of acceleration along X-axis.

$mean(Y)$ is the average of 60 sample of acceleration along Y-axis.

$std(Y)$ is the variance of 60 sample of acceleration along Y-axis.

$mean(Z)$ is the average of 60 sample of acceleration along Z-axis.

$std(Z)$ is the variance of 60 sample of acceleration along Z-axis.

Resultant (Res) is obtained by the following equation.

$Resultant, R = \sqrt{{a_x}^2 + {a_y}^2 + {a_z}^2}$

6.7.4 Learning

Then, we applied decision tree algorithms to each file compiled to find a classifier. In each case, the decision tree algorithms gave us a classifier. Now we have four classifiers for each of four kinds of data (pressure data from the left shoe, pressure data from the right shoe, accelerometer data from the phone in the pocket and gyroscope data from the phone in the pocket) from four sensor systems. The classifiers are mentioned below. Each of these classifiers is actually a decision tree.

1) Classifier 1

This classifier classifies based on the accelerometer data. The accuracy is 99.5305%.

2) Classifier 2

This classifier classifies based on the gyroscope data. The accuracy is 94.3662%.

3) Classifier 3

This classifier classifies based on the pressure data from the left shoe. The accuracy is 99.061%.

4) Classifier 4

This classifier classifies based on the pressure data from the right shoe. The accuracy is 98.8263%.

One thing that needs to be emphasized is that these classifiers were developed by applying the decision tree on summary data similar to rows in table 6.2, not the actual time series data. Because of our synchronization work, it was ensured that each nth row in the summary file for acceleration represent a time period which is the same time period in the nth row of summary file for gyroscope, nth row of summary file for the left shoe, and nth row of summary file for the right shoe.

6.7.5 Combined Algorithm for Activity Recognition

In this setting, we developed the following algorithm which basically is a fusion of four classifiers. In short, this is how it works: Classifier 1 takes accelerometer data as input and outputs an activity. In the same way, classifier 2, 3, and 4 takes gyroscope data, pressure data from left shoe and pressure data from right respectively. All four classifiers output activity based on the decision tree they have learned previously in the learning phase. After each classifier gives an activity as output, the algorithm decides the final activity based on the majority vote. This is known as majority voting algorithm. It is displayed in figure 6.9.

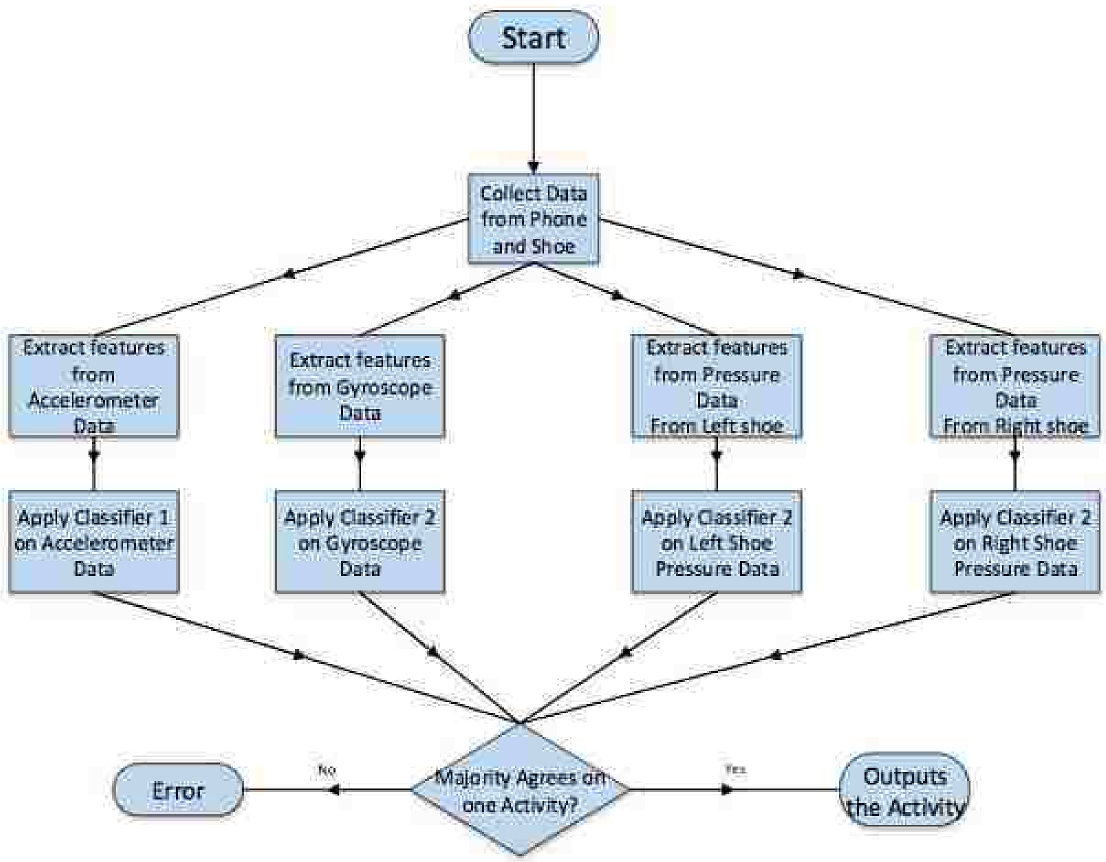


Figure 6.9: Fusion of four sensor systems using majority voting.

6.7.6 Activity Recognition and Evaluation

In this particular setting we have 4 files each consisting of 426 rows of summary data. Each of these rows was created using a summary of 60 samples of pressure data (or 80 samples of accelerometer data from phone or 167 samples of gyroscope data from phone). Four separate classifiers were learnt (decision tree in our case) based on four separate datasets in the *learning phase*. Now in the *recognition* *phase*, for a given input, each decision tree decides an activity using the corresponding classifier. Final activity is decided based on what the majority of classifiers have decided. In the case of a tie, we consider it an error and failure to classify. We implemented the following algorithm to evaluate performance.

Algorithm 1 Majority Voting

procedure ALGORITHM 1
    for R=1: NumberOfRows **do**
        Apply classifier 1 on the data of row R from $accelerometer\_summary\_file$
        Store the decided activity in $decision\_acc$
        Apply classifier 2 on the data of row R from $gyroscope\_summary\_file$
        Store the decided activity in $decision\_gyro$
        Apply classifier 3 on the data of row R from $left\_summary\_file$
        Store the decided activity in $decision\_left$
        Apply classifier 4 on the data of row R from $right\_summary\_file$
        Store the decided activity in $decision\_right$
        $Final\_activity \leftarrow majority\_vote(decision\_acc, decision\_gyro,$
                        $decision\_left, decision\_right)$

The $Majority\_vote$ function finds the activity that has the highest vote. Rows from $accelerometer\_summary\_file, gyroscope\_summary\_file,$ $left\_summary\_file, right\_summary\_file$ are passed through the algorithm.

Here we discuss the evaluation of this algorithm. We implemented each classifier in Matlab. Our results show that though each classifier individually shows errors, their combination using $MajorityVoting$ results in a zero error system. For example, row 94 is classified as sitting by classifier 1, while classifier 2 classifies it to be walking, classifier 3 and 4 both classifies it to be running. So the final activity will be decided as running (voted by majority classifiers). Any tie among decisions of classifiers will be assumed to be an error. The following table summarizes different combination of sensor systems and corresponding number of errors (misclassification).

Structure	Number Of Errors
Fusion of 4 sensor systems	
Classifier 1,2,3,4	0
Fusion of 3 sensor systems	
Classifier 1,2,3	1
Classifier 1,2,4	1
Classifier 1,3,4	0
Classifier 2,3,4	0
Fusion of 2 sensor systems	
Classifier 1,2	9
Classifier 1,3	1
Classifier 1,4	3
Classifier 2,3	9
Classifier 2,4	12
Classifier 3,4	3

Table 6.3: Number of Errors against number of classification system

As we can see, algorithm 1 uses data from all four sensor system and using this algorithm for our data, there was zero error. Average number of errors in general decreases with the incorporation of more and more sensor system as can be seen in figure 6.10.

6.8 Discussion

In table 6.3, we want to emphasize the row where we showed classifier 3 and 4 together made 3 errors. Classifier 3 and 4 were learned based on pressure data collected from the left shoe and the right shoe. These two classifiers also take pressure

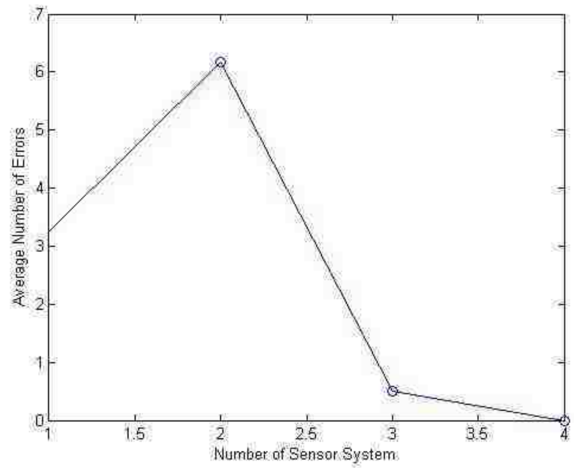


Figure 6.10: Number of Sensor system Vs Average number of Errors.

data as input during the recognition time. This means that classification based on only shoe data is possible with reasonable accuracy. As a result it is possible to detect activities in scenarios where people take their phone out of their pocket, assuming they still are keeping their shoes on. The advantage is that though people tend to use their phones in various ways, the phone is almost always within the Bluetooth range of them hence in range of their shoes. This shows that our architecture ensures robustness against various human behavior patterns validating our contribution 2 (C2). We identified some caveats (C4) during the development of our prototype and proposed some solutions to address them. Our proposed combined algorithm and its evaluation is contribution 5 (C5). To show that our architecture works, we synchronized data from all four sensor systems. In reality, we do not need to synchronize all these data.

6.9 Conclusions

We showed that a decision made from the data of multiple sensors is more accurate than decisions made from data of a single sensor system. In the next chapter, we expand this idea to experiment with four more activities. For now, we worked with 60 samples of pressure data and their time-equivalent accelerometer and gyroscope data.

6.10 Related Publications

- **Ferdaus Kawsar**, Sheikh Iqbal Ahamed, Richard Love: ***Remote Monitoring Using Smartphone Based Plantar Pressure Sensors: Unimodal and Multimodal Activity Detection,*** (ICOST, 2014)
- **Ferdaus Kawsar**, Sheikh Iqbal Ahamed: ***Smartphone Based Multimodal Activity Detection System Using Plantar Pressure Sensors,*** In SAC 2014, Gyeongju, Korea.

Chapter 7

Activity Detection Using Multimodal Approach in Cross Subject Setting for More Activities

7.1 Introduction

In the previous chapter, we developed a multimodal approach for activity detection where we used majority voting fusion to determine the final activity. In this chapter, we expand this approach for multiple subjects and for more activities. In the last chapter, we worked with four activities: sitting, standing, walking and running. In this chapter, we have expanded our framework to include four more activities: cycling, driving, climbing stairs down and up. We also collected data for one more subject. However, for subject 2 we have data for 6 activities.

Our discussion in this chapter includes following topics.

- In the last chapter, we showed how our multimodal approach works for four activities. Here, we will show that our multimodal approach works very well even when we incorporate 8 activities.
- In previous chapter, we included 1 subject only. In this chapter, we discuss how our approach performs when we include multiple subjects.

7.2 Single Subject Multiple Activities

For our experiments, we used decision tree classifier.

7.2.1 Accelerometer

Using only accelerometer data, the decision tree gives an 98.01% accuracy for a single subject 8 activities scenario. The tree we generated has 11 leaves and 21 nodes. The confusion matrix is shown below.

a	**b**	**c**	**d**	**e**	**f**	**g**	**h**	**←Classified as**
119	**1**	0	0	**1**	0	0	0	| a=cycling
0	132	0	0	0	0	0	0	| b=driving
0	0	120	0	0	0	0	**1**	| c=running
1	0	0	119	0	0	0	0	| d=sitting
0	0	0	0	68	**2**	0	**4**	| e=stair Down
0	0	2	0	**4**	76	0	0	| f=stair Up
0	0	0	0	0	**1**	129	0	| g=standing
0	0	0	0	1	0	0	123	| h=walking

Table 7.1: Confusion matrix for activity detection based on *accelerometer* data.

From the confusion matrix in table 7.1, it seems that stair Up is sometimes misclassified as stair Down whereas descending down stairs is sometimes misclassified as walking.

7.2.2 Gyroscope

Using only gyroscope data, the decision tree gives an 89.61% accuracy. The tree we generated has 30 leaves and 59 nodes rendering it almost impractical to implement it. A classifier generated from gyroscope data also introduces more errors as evident from the confusion matrix in table 7.2. The confusion matrix is shown below.

a	b	c	d	e	f	g	h	←Classified as
114	**4**	0	0	**2**	0	**1**	0	| a=cycling
5	106	0	**7**	0	0	**15**	0	| b=driving
0	0	121	0	0	0	0	0	| c=running
0	**9**	0	105	0	0	**6**	0	| d=sitting
1	0	0	0	72	0	0	**1**	| e=stair Down
1	0	0	0	**2**	78	0	**1**	| f=stair Up
0	**20**	0	**18**	0	0	92	0	| g=standing
0	0	**1**	0	0	0	0	123	| h=walking

Table 7.2: Confusion matrix for activity detection based on *gyroscope* data.

7.2.3 Pressure data from left shoe

Using only pressure data from left shoe, the decision tree gives an 99.12% accuracy. The tree we generated has 9 leaves and 17 nodes rendering it easy to implement it. The confusion matrix is shown below.

a	**b**	**c**	**d**	**e**	**f**	**g**	**h**	**←Classified as**
122	0	0	0	0	0	0	**1**	| a=cycling
0	134	0	0	0	0	0	0	| b=driving
0	0	121	0	**1**	0	0	0	| c=running
0	0	0	120	0	0	**1**	0	| d=sitting
0	0	**1**	0	72	0	0	**1**	| e=stair Down
0	0	**1**	0	0	82	0	0	| f=stair Up
0	0	0	0	0	0	131	0	| g=standing
0	0	**2**	0	0	0	0	121	| h=walking

Table 7.3: Confusion matrix for activity detection based on pressure data from *left* shoe.

7.2.4 Pressure data from right shoe

Using only pressure data from right shoe, the decision tree gives an 99.12% accuracy. The tree we generated has 8 leaves and 15 nodes rendering it easy to implement it. The confusion matrix is shown below.

a	**b**	**c**	**d**	**e**	**f**	**g**	**h**	**←Classified as**
122	0	0	0	1	0	0	0	| a=cycling
0	132	0	0	0	0	0	0	| b=driving
0	0	121	0	0	0	0	0	| c=running
0	0	0	121	0	0	0	0	| d=sitting
0	0	0	0	73	0	0	1	| e=stair Down
0	1	0	0	0	80	0	1	| f=stair Up
0	0	0	0	0	0	132	0	| g=standing
0	1	0	0	1	2	0	119	| h=walking

Table 7.4: Confusion matrix for activity detection based on pressure data from *right* shoe.

7.2.5 Multimodal Approach

In the multimodal approach, for each type of sensor data, we create a classifier. As we have four sensors, and hence four types of data, we have four classifiers. We applied each of these classifiers to their corresponding data to get actual and predicted class for each time segment. What it means is that for each time segment, we have accelerometer data, gyroscope data , pressure data from left shoe and pressure data from right shoe. We apply the corresponding decision tree classifier to each time segment who either correctly or incorrectly classify that instance of time segment. Thus for each segment, we have four classification decisions and by using majority voting fusion, the final decision about classification is made. There were 0 errors out of 903 time segments using this multimodal approach. This, off course, is the case when training and testing is performed on one subject's data. We demonstrate this with some sample rows in table 7.5.

For example, row 3 in table 7.5 explains the case for time segment 22.

	Accelerometer			Gyroscope			Left Shoe Data			Right Shoe Data			
inst#	**actual**	**predicted**	**error**	**actual**	**predicted**	**error**	**actual**	**predicted**	**error**	**actual**	**predicted**	**error**	**Decision**
7	drive	drive		drive	drive		drive	drive		drive	stand	+	drive
10	drive	drive		drive	cycle	+	drive	drive		drive	drive		drive
22	cycle	cycle		cycle	stair Dow	+	cycle	cycle		cycle	cycle		cycle
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
32	walk	walk		walk	run	+	walk	walk		walk	walk		walk
45	sit	sit		sit	stand	+	sit	sit		sit	sit		sit
116	cycle	drive	+	cycle	cycle		cycle	cycle		cycle	cycle		cycle
305	walk	walk		walk	walk		walk	stair Down	+	walk	walk		walk
576	walk	walk		walk	walk		walk	walk		walk	stair Up	+	walk

Table 7.5: Error labels by different sensor systems.

Classification from accelerator data correctly classifies the time segment 22 as cycling. However, the classifier from gyroscope data wrongly classifies this time segment as descending down stairs. The classifier from left shoe data and the classifier from right shoe data also correctly classify this time segment 22 as cycling data. In summary, three out of four classifiers classify time segment 22 correctly. According to the majority voting fusion that we adopted, the final decision (last column in table 7.5) will be cycling (correct classification).

Interestingly, our multimodal approach works as well as combining all features from all sensor systems. We combined all features from all four sensor systems creating a system of 368 features and applied decision tree algorithm. We achieved 100% accuracy. The tree was quite simple too, with 8 leaves and 15 nodes. As the accuracy is 100%, we are not providing any confusion matrix.

7.3 Multiple Subjects

We collected data for another subject for all eight activities. However, due to a technical problem, data for running and cycling activities were corrupted for subject 2. We selected our subject based on shoe size. We ensured that both subjects have the same shoe size. From previous experience, we know that our pressure data is not useful when different subjects have a different shoe size. Here we test the performances of our system across different subjects.

In all the following cases, we considered six activities, and we applied the decision tree learning algorithm.

Acceleration: Subject 1 trained using subject 1's data achieves 97.73% accuracy when tested on the data from same subject. However, when tested on subject 2's data, the accuracy drops to 84.08%. Following is the confusion matrix when subject 2's data is tested on the decision tree developed from subject 1's data only.

a	**b**	**c**	**d**	**e**	**f**	←**Classified as**
168	0	0	0	0	0	| a=driving
0	84	0	0	0	0	| b=sitting
0	0	17	**4**	**5**	**17**	| c=stair Down
0	0	**2**	44	**2**	0	| d=stair Up
0	5	0	0	82	0	| e=standing
0	0	**29**	**18**	0	38	| f=walking

Table 7.6: Confusion matrix for testing on subject 2's data based on *accelerometer* data from subject 1.

Gyroscope: Subject 1 trained using subject 1's gyroscope data achieves 98.94% accuracy when tested on the data from the same subject. However, when tested on subject 2's data, the accuracy drops to 54.37%. Following is the confusion matrix when subject 2's gyroscope data is tested on the decision tree developed from subject 1's gyroscope data only.

a	b	c	d	e	f	←Classified as
112	**13**	0	0	**43**	0	| a=driving
4	67	0	0	**13**	0	| b=sitting
10	0	11	**12**	0	**10**	| c=stair Down
3	0	**18**	24	0	**3**	| d=stair Up
13	**11**	0	0	63	0	| e=standing
0	0	**41**	**41**	0	3	| f=walking

Table 7.7: Confusion matrix for testing on subject 2's data based on *gyroscope* data from subject 1.

Left Shoe Data: Subject 1 trained using subject 1's pressure data from left shoe achieves 99.85% accuracy when tested on the data from the same subject. However, when tested on subject 2's data, the accuracy drops to 42.72%. Following is the confusion matrix when subject 2's data is tested on the decision tree developed from subject 1's data only.

a	b	c	d	e	f	←Classified as
94	0	0	**14**	**58**	0	| a=driving
0	70	0	0	0	**14**	| b=sitting
0	0	10	**33**	0	0	| c=stair Down
0	0	**2**	46	0	0	| d=stair Up
0	**74**	0	0	0	**14**	| e=standing
0	0	**80**	**6**	0	0	| f=walking

Table 7.8: Confusion matrix for testing on subject 2's left shoe data based on *left shoe* data from subject 1.

Right Shoe Data: Subject 1 trained using subject 1's pressure data from right shoe achieves 100% accuracy when tested on the data from the same subject. However, when tested on subject 2's data, the accuracy drops to 0.77%. Right shoe is heavily used during driving activity. The asymmetric use of left shoe and right shoe during driving probably explains so many misclassifications in cross-subject setting. Following is the confusion matrix when subject 2's data is tested on the decision tree developed from subject 1's data only.

a	b	c	d	e	f	←Classified as
0	0	0	**168**	0	0	| a=driving
0	0	**63**	**22**	0	0	| b=sitting
0	**18**	0	0	**25**	0	| c=stair Down
0	**48**	0	0	0	0	| d=stair Up
0	0	0	**88**	0	0	| e=standing
3	0	**8**	**71**	0	4	| f=walking

Table 7.9: Confusion matrix for testing on subject 2's right shoe data based on the decision tree from *right shoe* data from subject 1.

We go through a similar process for subject 2's data. We develop our model using subject 2's data for training and test it on subject 1's data.

Acceleration: Subject 2 trained using subject 2's data achieves 100% accuracy when tested on the data from the same subject. However, when tested on subject 1's data, the accuracy drops to 57.25%.

Gyroscope: Subject 2 trained using subject 2's gyroscope data achieves 98.84% accuracy when tested on the data from the same subject. However, when tested on subject 1's data, the accuracy drops to 60.18%.

Left Shoe Data: Subject 2 trained using subject 2's pressure data from left shoe achieves 100% accuracy when tested on the data from the same subject. However, when tested on subject 1's data, the accuracy drops to 21.47%.

Right Shoe Data: Subject 2 trained using subject 2's pressure data from right shoe achieves 99.8% accuracy when tested on the data from the same subject. However, when tested on subject 1's data, the accuracy drops to 38.25%.

We also evaluated the performance of classifiers in a mixed subject setting. Instead of using just one subject's data, we used mixture of both subjects' data for training our decision tree model. Later, we used each subject's data as test data and evaluated the performance of these classifiers developed from using a mixture of both subjects' data as training data.

Acceleration Data: We used mixture of both subjects' acceleration data to develop a decision tree classifier. On the mixed data, the accuracy is 99.74%. We achieved an accuracy of 99.69% when the decision tree was applied to the acceleration data of subject 1. We achieved an accuracy of 99.8% when the decision tree was applied to the acceleration data of subject 2.

Gyroscope Data: We used a mixture of both subjects' gyroscope data to develop a decision tree classifier. On the mixed data, the accuracy is 98.47%. We achieved an accuracy of 98.18% when the decision tree was applied to the gyroscope data of subject 1. We achieved an accuracy of 98.83% when the decision tree was applied to the gyroscope data of subject 2.

Left Shoe Data: We used a mixture of both subjects' pressure data from left shoe to develop a decision tree classifier. On the mixed data, the accuracy is 99.57%. We achieved an accuracy of 99.39% when the decision tree was applied to the left shoe data of subject 1. We achieved an accuracy of 99.8% when the decision tree was applied to the left shoe data of subject 2.

Right Shoe Data: We used a mixture of both subjects' pressure data from right shoe to develop a decision tree classifier. On the mixed data, the accuracy is 99.57%.

We achieved an accuracy of 99.54% when the decision tree was applied to the right shoe data of subject 1. We achieved an accuracy of 99.6% when the decision tree was applied to the right shoe data of subject 2.

7.3.1 Multimodal Approach in Cross-Subject Setting

In the multimodal approach, for each type of data, we create a classifier. However, in cross-subject setting, we create our classifiers by using mixture of data from both subjects as training data. We iterate the same process for all four types of data, namely, accelerometer, gyroscope, left shoe and right shoe. For each time segment, we have accelerometer data, gyroscope data, pressure data from left shoe and pressure data from right shoe.We apply the corresponding decision tree classifier to each type of data on a given time segment to either correctly or incorrectly classify that instance of time segment. However, using majority voting fusion, we observed 0 errors out of 1174 time segments. Table 7.10 demonstrates our multimodal approach in a mixed-subject setting using some sample rows.

	Accelerometer			**Gyroscope**			**Left Shoe Data**			**Right Shoe Data**			
inst#	**actual**	**predicted**	**error**	**actual**	**predicted**	**error**	**actual**	**predicted**	**error**	**actual**	**predicted**	**error**	**Decision**
56	drive	drive		drive	stand	+	drive	drive		drive	drive		drive
144	sit	sit		sit	drive	+	sit	sit		sit	sit		sit
289	stair Dow	stair Up	+	stair Dow	stair Dow		stair Dow	stair Dow		stair Dow	stair Dow		stair Dow
411	stand	stand		stand	drive	+	stand	stand		stand	stand		stand
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
426	stand	stand		stand	drive	+	stand	stand		stand	stand		stand
439	stand	stand		stand	stand		stand	sit	+	stand	stand		stand
706	drive	drive		drive	sit	+	drive	drive		drive	drive		drive
1009	stand	stand		stand	sit	+	stand	stand		stand	stand		stand

Table 7.10: Error labels by different sensor systems in Mixed Subject Setting.

For example, in the last row in the table (instance 1009), the classifier developed from accelerometer data from both subjects' data correctly classifies the time segment as *standing*. In the same way, the classifier generated from pressure sensor data (of both subjects) from left shoe correctly classifies the time segment. The same is true for the classifier generated from pressure sensor data (of both subjects) from right shoe. However, the classifier generated from gyroscope data (of both subjects) incorrectly classifies the time segment as *sitting*. As we used majority voting fusion technique, the final classification decision is correct *(standing)* in spite of misclassification from gyroscope based classifier.

7.3.2 Summary

The majority voting fusion technique works quite well in our multiple sensor system as is evident from our experiments. This is true for single subject setting as well as multiple subject setting. Majority voting fusion technique has some advantages.

Accuracy: Accuracy is quite good as is evident from our experiments. Even if there are errors from the decision of one sensor, the combined decision using all four sensor often corrects the error and thus improves the overall accuracy of fusion.

Robustness: Even if one of the sensor systems is not working, our multimodal approach can still work quite well using other sensor systems. For example, if the data from right shoe is not available due to connection loss, the majority voting fusion with other three sensors can still work quite accurately.

Usable: In an ideal scenario, the phone should be in the pocket since we trained our models assuming that the phone would be in the pocket. However, even if the phone is not in the pocket, accuracy will be still good based on the classification decision from left shoe and right shoe data. In a real life scenario, it is not uncommon for people to not carry their phone in their pockets. In the majority voting fusion technique, such natural human behavior can be accommodated without losing significant accuracy. However, more work is needed to accommodate such scenarios.

7.3.3 Conclusion

In this chapter, we presented our findings from experiments with eight activities; whereas earlier, we presented our findings from four activities. We also presented our findings involving more than one subject. We found drastic drop of accuracy when we tried to detect activities using a model trained on another subject. However, accuracy improves dramatically when both subjects' data is used for training to develop the model.

7.4 Related Publications

- **Ferdaus Kawsar** and Sheikh Iqbal Ahamed. ***Activity Detection System Using Majority Voting Fusion in A Heterogeneous Sensor Platform for Multiple Subject Setting*** in preparation.

Chapter 8

Activity Detection Using Time-Delay Embedding with Gaussian Mixture Model

8.1 Introduction

The theoretical basis for this time series classification comes from the work of Takens [88] and Sauer et al. [82]. Their work shows that a time series of observation samples from a system can be used to reconstruct a space topologically equivalent to original system. It is very easy to reconstruct such reconstructive phase space. Time-delay embeddings attempt to reconstruct the state and dynamics of an unknown dynamical from observations of that system taken over time [35]. Formulating time series algorithm using multi-dimensional phase space is different than algorithms developed using time or frequency domain features.

If a time series $x = x_n$, where $n = 1 \ldots N$, a reconstructive phase space (RPS) matrix of dimension d and time lag τ is given by its row vectors:

$x_n = [x_{n-(d-1)\tau} \ldots\ldots x_{(n-\tau)} x_n]$

Determining the dimension, d, of reconstructive phase space (i.e. how many measurements have to be considered) and determining τ (at what time the measurements should be taken) is a key problem. A row vector is a point in RPS. To be topologically equivalent, d must be greater than twice the box cutting dimension. In our case, d is unknown. However, in our case we experimented with $d = 2$ and $d = 3$ and will present our findings for these two cases.

Following is a plot of a time series for pressure data for pressure sensor 1 (PS1) from left shoe.

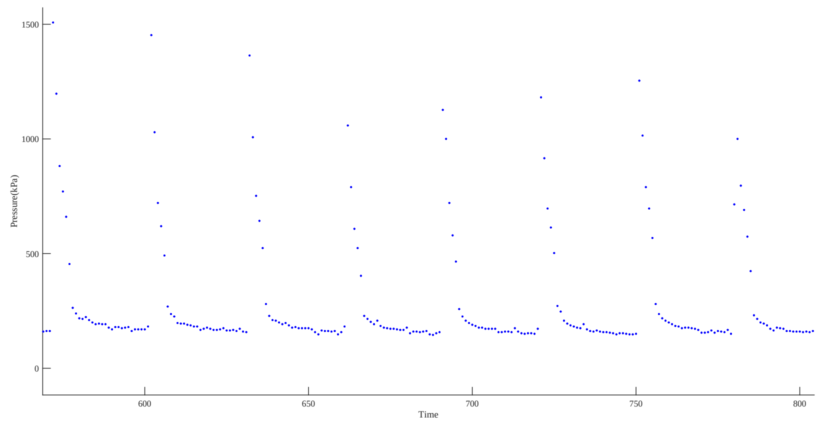


Figure 8.1: Data from PS1 for left shoe for running.

A definite structure is visible from following phaseplot in 2 dimension where time lag is 5.

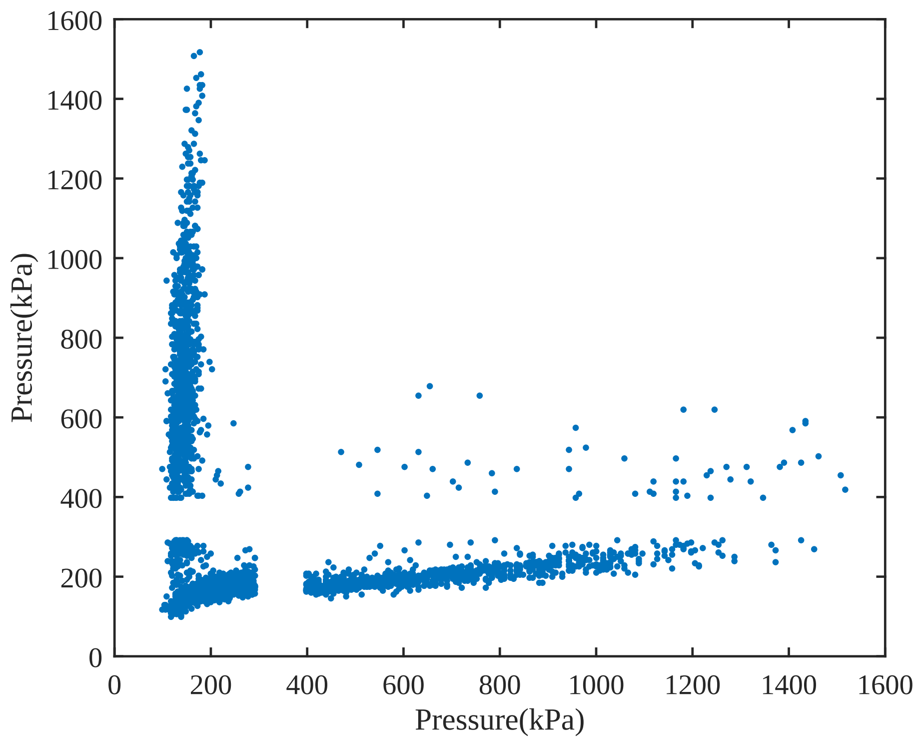


Figure 8.2: PhasePlot in 2 dimension with time lag 5 for running data from pressure sensor 1 of left shoe.

Structure is also obvious from following figure where we made a phase plot in 3 dimension for time lag 5 and 10.

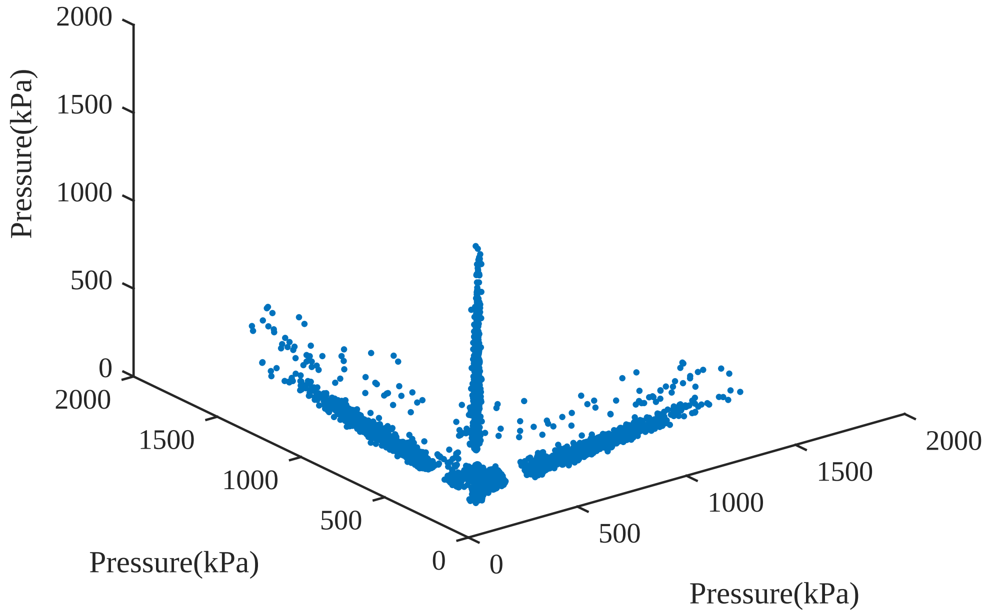


Figure 8.3: PhasePlot in 3 dimension with time lag 5 and 10 for running data from pressure sensor 1 of left shoe.

8.2 Our Approach

First we demonstrate our experiment in the case of 2 activities only: running and sitting. We used Gaussian Mixture Model (GMM) with Expectation Maximization(EM) algorithm for classification of embedding features. We build two models for both running and sitting from pressure sensor data, P1 of left shoe. We used 5 mixtures for GMM. When tested, sitting data for sitting model showed higher probability; same was true for running data for running model. That means GMM with time delay embedding can accurately distinguish these two activities of sitting and running.

We define LP_{mn} as the log probability of applying data of n activity on the model of activity m. We also define following symbols for 8 activities:

R for running

s for sitting

W for walking

St for standing

Sd for stair down

Su for Stair up

C for cycling and

D for Driving

The following table shows the log probability for just 1 pressure sensor data, P1 from left shoe.

Case	**Log Probability**
Testing running data against running model (LP_{RR})	$-3.0050 \times 10^{+04}$
Testing sitting data against sitting model (LP_{ss})	$-1.7031 \times 10^{+04}$
Testing sitting data against running model (LP_{Rs})	$-4.2674 \times 10^{+04}$
Testing running data against sitting model (LP_{sR})	$-1.1068 \times 10^{+06}$

Table 8.1: Log probabilities for siting and running activity for P1 from left shoe.

From the above table we see that $LP_{RR}>LP_{sR}$. We also find that $LP_{ss}>LP_{Rs}$. The significance of this numbers is that we can distinguish running and sitting using just 1 pressure sensor P1's data. After a running model is developed from running data and sitting model is made from sitting data, applying running and sitting data on these models show that the probability of running data coming from running model is higher than it coming from sitting model.

In the following table, we expand to include standing activity making it a three activity scenario.

Case	Log Probability
Testing running data against running model (LP_{R_R})	$-5.2250 \times 10^{+04}$
Testing sitting data against sitting model (LP_{s_s})	$-3.3829 \times 10^{+04}$
Testing standing data against standing model (LP_{St_St})	$-4.025 \times 10^{+04}$
Testing sitting data against running model (LP_{R_s})	$-1.3754 \times 10^{+05}$
Testing running data against sitting model (LP_{s_R})	$-1.6040 \times 10^{+06}$
Testing standing data against sitting model (LP_{s_St})	$-8.1173 \times 10^{+04}$
Testing sitting data against standing model (LP_{St_s})	$-4.0219 \times 10^{+04}$
Testing standing data against running model (LP_{R_St})	$-1.2025 \times 10^{+05}$
Testing running data against standing model (LP_{St_R})	$-1.1099 \times 10^{+06}$

Table 8.2: Log probabilities for siting, running and standing activity for P1 from left shoe.

Since (LP_{R_R}) >(LP_{s_R}) and (LP_{R_R}) >(LP_{St_R}), running activity can be correctly classified.

Since (LP_{s_s}) >(LP_{R_s} and (LP_{s_s}) >(LP_{St_s}), sitting activity can be correctly classified.

Since (LP_{St_St}) >(LP_{s_St}) and (LP_{St_St}) >(LP_{R_St}), standing activity is correctly classified.

We also carried out similar analysis for four activity system and found out that this approach can correctly classify activities in four activity setting. In our case, these four activities are: sitting, standing, walking and running.

8.3 Findings and Evaluation

Based on our preliminary experiments, we expanded our system to 8 activity system. These 8 activities are: cycling, running, climbing stairs down, climbing stairs up, walking, sitting and driving.

For each activity, we worked with 3000 samples and we divided the samples in 20 windows making each window with 150 samples. We applied GMM with EM for training. Here we are working with data of single subject. Parameters are as follows:

Number of Gaussian Mixture: 5

Time Lag, $\tau = 5$

dimension, d =6

Time Lag, τ and dimension, d were empirically obtained. We adopted a grid search approach and observed the values of tau and d for which activity detection accuracy is best. The following table shows a confusion matrix derived from applying our approach on accelearation along X-axis. We use the following symbols in the tables: C for cycling, R for running, Sd for downstairs, Su for Upstairs, St for standing, W for walking, Si for sitting and D for driving. Miss-classifications are shown in red. Out of $8 \times 20 = 160$ time segments, 11 time segments are misclassified (93.13% accuracy).

W1	W2	W3	W4	W5	W6	W7	W8	W9	W10	W11	W12	W13	W14	W15	W16	W17	W18	W19	W20	Actual
C	C	C	C	C	C	C	C	C	C	C	C	C	C	C	C	C	C	C	C	**C**
R	R	R	R	R	R	R	R	R	R	R	R	R	R	R	R	R	R	R	R	**R**
Sd	Sd	Sd	Sd	Sd	Sd	Sd	Sd	Sd	Sd	Sd	Sd	Su	Sd	Sd	Sd	Sd	Sd	Su	Su	**Sd**
Su	Su	Su	Su	Su	Su	Su	Su	Su	Su	Su	Su	Su	Su	Su	Su	Su	Su	Su	Su	**Su**
St	St	St	St	St	St	St	St	St	St	St	St	St	St	St	St	St	St	St	St	**St**
W	W	W	W	W	W	W	W	W	W	W	W	W	W	Sd	Sd	Sd	Sd	Sd	Sd	**W**
Si	Si	Si	Si	Si	Si	Si	Si	Si	Si	Si	Si	Si	Si	Si	Si	Si	Si	Si	Si	**Si**
D	D	D	D	D	D	D	D	D	D	D	D	D	D	C	C	D	D	D	D	**D**

Table 8.3: Confusion matrix using GMM based on accelerometer data along *X-axis*.

A much better accuracy is achieved by using accelerometer along Y-axis as obvious from the following table (table 8.4)

W1	W2	W3	W4	W5	W6	W7	W8	W9	W10	W11	W12	W13	W14	W15	W16	W17	W18	W19	W20	Actual
C	C	C	C	C	C	C	C	C	C	C	C	C	C	C	C	C	C	C	C	**C**
R	R	R	R	R	R	R	R	R	R	R	R	R	R	R	R	R	R	R	R	**R**
Sd	Sd	Sd	Sd	Sd	Sd	Sd	Sd	Sd	Sd	Sd	Sd	Sd	Sd	Sd	Sd	Sd	Sd	Sd	Sd	**Sd**
Su	Su	Su	Su	Su	Su	Su	Su	Su	Su	Su	Su	Su	Su	Su	Su	Su	Su	Su	Su	**Su**
St	St	St	St	St	St	St	St	St	St	St	St	St	St	St	St	St	St	St	St	**St**
W	W	W	W	W	W	W	W	W	W	W	W	W	W	W	W	W	W	W	W	**W**
Si	Si	Si	Si	Si	Si	Si	Si	Si	Si	Si	Si	Si	Si	Si	Si	Si	Si	Si	Si	**Si**
D	D	D	D	D	D	D	D	D	D	D	D	D	D	D	D	D	D	D	D	**D**

Table 8.4: Confusion matrix using GMM based on accelerometer data along *Y-axis*.

We generated similar confusion matrix based on data from P1, P2, P3, P4, P5, P7. In each case, there are $20 \times 8 = 160$ classifications. For P1, there are 41 miss-classifications. Similarly, for P2, 31; for P3, 9; for P4, 29; for P5, 9; and for P7, there were 12 miss-classifications. As an example of performance of pressure sensors, we show the confusion matrix of P3.

W1	W2	W3	W4	W5	W6	W7	W8	W9	W10	W11	W12	W13	W14	W15	W16	W17	W18	W19	W20	Actual
C	C	C	St	C	Si	C	C	C	C	C	C	C	D	C	C	C	C	C	C	**C**
R	R	R	R	R	R	R	R	R	R	R	R	R	R	R	R	R	R	R	R	**R**
Sd	Sd	Sd	Sd	Sd	Sd	Sd	Sd	Sd	Sd	Sd	Sd	Sd	Sd	Sd	Sd	Sd	Sd	Sd	Sd	**Sd**
Su	Su	Su	Su	Su	Su	Su	Su	Su	Su	Su	Su	Su	Su	Su	Su	Su	Su	Su	Su	**Su**
St	St	St	St	Si	St	St	St	St	St	St	St	St	St	St	St	St	St	St	St	**St**
W	W	W	W	W	W	W	W	W	W	W	W	W	W	W	W	W	W	W	W	**W**
St	St	St	Si	Si	Si	Si	Si	Si	Si	Si	Si	Si	Si	Si	Si	Si	Si	Si	Si	**Si**
D	D	D	D	D	D	D	D	D	D	D	D	C	D	D	D	D	D	D	C	**D**

Table 8.5: Confusion matrix using GMM based on pressure sensor data *P3* of left shoe.

8.4 Conclusion

Most promising aspect about time-delay embedding with GMM is that significantly good accuracy is obtained just from analysis of small number of sensor data. We have not applied this approach on gyroscope data, neither did we apply on pressure data from right shoe. We are now working to develop a fusion of this approach. For example, we can generate decisions from P1, P2 and P3 sensor and obtain the final decision from fusion of multiple sensor for any time segment. Even with one sensor, we have significant accuracy.

Consequently, it will be possible to reduce computational complexity if we use small number of sensors. As a result, a more energy-saving system can be reality. Such systems can reduce energy cost in two ways. First, as fewer sensor data will be transmitted over Bluetooth, energy can be saved by reducing energy for Bluetooth transmission. Second, as there is less data and consequently, less computation, reduced energy will be needed for computation. Memory and computational saving is significant as it is most likely that activity detection applications will run on resource-constraint smart phones. Most activity system demands real-time detection of accuracy. Reduction in computational cost implies extended battery life. Computational power and battery life, both are scarce resource in cell phones and an algorithm that protects these resources are obviously preferable.

8.5 Related Publications

- **Ferdaus Kawsar**, Md. Kamrul Hasan, Richard Love, Sheikh I Ahamed: ***A Novel Activity Detection System using Plantar Pressure Sensors and Smartphon,*** in Compsac (Taichung, Taiwan)(2015).

Chapter 9

Conclusion

9.1 Summary

Dramatic increase in computational power and memory in smart phones have created opportunities for innovative solutions. We have developed e-ESAS, a remote symptom monitoring system. We built a prototype activity detection system that can detect three activities and send a summary of these activities regularly to a remote server, which can be accessed by anyone who wants to monitor. This prototype system can detect sitting, standing and walking. We have developed multi-modal activity detection algorithm and evaluated it's performance in single and multi-subject environment. A time-delay embedding with GMM approach we developed and applied reduce the requirement of number of sensors reducing the requirement of computational power and memory.

9.2 Contributions

The contribution of this research work is algorithm development, system design and development, and identifying and solving various usability issues. The contributions are briefly as follows:

- Developed a methodology for building remote symptom monitoring system for rural women in developing countries. We also diagnosed the barriers and cataloged crucial observations in the development of smart phone based system in developing countries.

- Designed, developed and deployed e-ESAS, a smart phone based remote symptom monitoring system and identify and resolve the challenges in the endeavor. We also evaluated the system's performance by studying feedback from users after deployment.

- Built a prototype activity detection system that can detect basic activities for monitoring by remote users.
- Developed a unique majority voting fusion algorithm to classify activities in a multi-sensor framework. We evaluated the algorithm in 'single-subject-4-activity', 'single-subject-8-activity' and 'multiple-subject-6-activity' scenario.
- Developed a computationally inexpensive process using time-delay embedding with Gaussian Mixture Model classification for activity recognition.

9.2.1 Survey of Activity Detection Systems

We have conducted a comprehensive study on research work on activity detection systems. We primarily focused on accelerometer based activity detection systems. A significant amount of research have been carried out so far and the interest has gone up with the widespread use smart phones. However, many challenges still remain to be addressed. Though a number of commercial products have recently hit the market, an unobtrusive system that accurately detects good number of human activities is still proving challenging .

9.2.2 e-ESAS: Remote Symptom Monitoring System

We have designed, developed, deployed and evaluated a smart phone based remote symptom monitoring system. We also have identified the challenges associated with building smart phone based systems for rural developing countries. The methodology we adopted can be translated to the development of similar systems in other developing countries. We have scaled our pilot study of ten patients to more than 1100 patients in three different countries for a cross-sectional study. It proves that such mobile based symptom monitoring system can be applied in realistic scenarios. Lessons learned from our experience can be valuable in monitoring other chronic diseases.

9.2.3 Activity Detection

In case of activity detection system, we have developed a prototype system that can detect sitting, standing and walking. The system can also transmit these information remotely to a remote server which can be accessed by a doctor. We developed a multimodal algorithm and evaluated its performance in single and multiple subject setting. Our time-delay embedding with GMM can be useful in reduction of computational cost, which is important in a resource-constraint smart phone.

9.3 Broader Impact

Smart phone based remote monitoring of human parameters have the potential to create far-reaching impact. Successful development of such systems can significantly change the way we access healthcare services. Health care cost is becoming unsustainable in developed world and tools that can reduce cost is extremely significant. We believe e-ESAS has the potential to positively impact health care system. We have already redeveloped e-ESAS in Android platform and deployed it to collect various information along with ESAS symptoms for a cross-sectional study. Symptom data as well as image data has been collected from Bangladesh, Nepal and North Dakota, USA from more than 1100 patients. Another e-ESAS like systems can simplify accesses to healthcare services for both patients and doctors, another far-reaching byproduct is the collection of large amount of health data. These data can be analyzed for research and critical observations can be made which might not be possible in the absence of such system.

Activity detection in real-time is also crucial. In context-sensitive applications, remote monitoring of patients or elderly people, or for simply to track user's level of physical exercise, such systems are invaluable.

Recently, there is a significant rise in effort to measure health parameters in portable devices driven by mainly mass use smart phones. If enough parameters can be detected or computed, it may significantly reduce the need for travel. Thus a paradigm shift may be possible through these efforts.

9.4 Future Works

There is much opportunities for research to advance knowledge in activity detection. For example, in our research we have repeatedly observed that performances of algorithms deteriorate when multiple subjects are involved. One way to address this challenge is to develop a way to learn activities for each person. In that case, in phone learning will be needed to accommodate personalized calibration. We plan to investigate ways to develop in-phone learning techniques. Another way is to develop an algorithm robust enough to work across subjects. Our multimodal approach shows promising results in later approach. In our experiment, we exclusively used decision tree classifier. We plan to investigate SVM, HMM, GMM, Naïve Bayes to find the best classifier for multiple subject environment. Our experiment with time-delay embedding shows exciting outcome. In the future, we plan to incorporate multimodal fusion approach with time-delay embedding to improve accuracy further.

BIBLIOGRAPHY

[1] http://archive.thedailystar.net/newDesign/news-details.php?nid=156930. [Online; accessed 07-August-2015].

[2] http://www.npcrc.org/files/news/ECOG_performance_status.pdf. [Online; accessed 22-July-2015].

[3] http://english.ohmynews.com/articleview/article_view.asp?menu=c10400&no=335342&rel_no=1. [Online; accessed 23-July-2015].

[4] http://newsroom.varian.com/index.php?s=31868&item=103314. [Online; accessed 23-July-2015].

[5] http://www.grameenphone.com/personal/internet-3g-2g/internet/packages. [Online; accessed 23-July-2015].

[6] http://www.breastcancer.org/symptoms/understand_bc/statistics. [Online; accessed 23-July-2015].

[7] http://healthmarketinnovations.org/about. [Online; accessed 25-July-2015].

[8] Bangladesh maternal mortality and health care survey. *National Institute of Population Research and Training (NIPORT), MEASURE Evaluation, and icddr,b. 2012. year=2010*.

[9] Edmonton symptom assessment system (esas). http://www.npcrc.org/files/news/edmonton_symptom_assessment_scale.pdf. [Online; accessed 22-July-2015].

[10] http://en.people.cn/90001/90782/6521649.html.

[11] http://www.btrc.gov.bd/telco/mobile.

[12] http://www.who.int/cancer/detection/breastcancer/en/index1.html.

[13] Bangladesh bureau of statistics. (2008).ministry of planning. *Statistical Yearbook of Bangladesh*, 2007.

[14] W. G. Adams, A. L. Fuhlbrigge, C. W. Miller, C. G. Panek, Y. Gi, K. C. Loane, N. E. Madden, A. M. Plunkett, and R. H. Friedman. Tlc-asthma: an integrated information system for patient-centered monitoring, case management, and point-of-care decision support. In *AMIA Annual Symposium Proceedings*, volume 2003, page 1. American Medical Informatics Association, 2003.

[15] F. R. Allen, E. Ambikairajah, N. H. Lovell, and B. G. Celler. Classification of a known sequence of motions and postures from accelerometry data using adapted gaussian mixture models. *Physiological Measurement*, 27(10):935, 2006.

[16] K. Aminian, P. Robert, E. Buchser, B. Rutschmann, D. Hayoz, and M. Depairon. Physical activity monitoring based on accelerometry: validation and comparison with video observation. *Medical & biological engineering & computing*, 37(3):304–308, 1999.

[17] L. Bao and S. S. Intille. Activity recognition from user-annotated acceleration data. In *Pervasive computing*, pages 1–17. Springer, 2004.

[18] L. Bos et al. ipath-a telemedicine platform to support health providers in low resource settings. *Medical and Care Compunetics 2*, 114:11, 2005.

[19] A. Bourke, J. Obrien, and G. Lyons. Evaluation of a threshold-based tri-axial accelerometer fall detection algorithm. *Gait & posture*, 26(2):194–199, 2007.

[20] C. V. Bouten, K. Koekkoek, M. Verduin, R. Kodde, and J. D. Janssen. A triaxial accelerometer and portable data processing unit for the assessment of daily physical activity. *Biomedical Engineering, IEEE Transactions on*, 44(3):136–147, 1997.

[21] C. V. Bouten, K. R. Westerterp, M. Verduin, and J. JANSSEN. Assessment of energy expenditure for physical activity using a triax— ai. *Age (yr)*, 23(1.8):21–27, 1994.

[22] H. B. Bussmann, P. J. Reuvekamp, P. H. Veltink, W. L. Martens, and H. J. Stam. Validity and reliability of measurements obtained with an activity monitor in people with and without a transtibial amputation. *Physical therapy*, 78(9):989–998, 1998.

[23] C. J. Caspersen, K. E. Powell, and G. M. Christenson. Physical activity, exercise, and physical fitness: definitions and distinctions for health-related research. *Public health reports*, 100(2):126, 1985.

[24] J. Chen, K. Kwong, D. Chang, J. Luk, and R. Bajcsy. Wearable sensors for reliable fall detection. In *Engineering in Medicine and Biology Society, 2005. IEEE-EMBS 2005. 27th Annual International Conference of the*, pages 3551–3554. IEEE, 2006.

[25] K. G. Cheng, F. Ernesto, and K. N. Truong. Participant and interviewer attitudes toward handheld computers in the context of hiv/aids programs in sub-saharan africa. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, pages 763–766. ACM, 2008.

[26] J. C. Cherry, T. P. Moffatt, C. Rodriguez, and K. Dryden. Diabetes disease management program for an indigent population empowered by telemedicine technology. *Diabetes technology & therapeutics*, 4(6):783–791, 2002.

[27] Y. Cho, Y. Nam, Y.-J. Choi, and W.-D. Cho. Smartbuckle: human activity recognition using a 3-axis accelerometer and a wearable camera. In *Proceedings of the 2nd International Workshop on Systems and Networking Support for Health Care and Assisted Living Environments*, page 7. ACM, 2008.

[28] T. Choudhury, G. Borriello, S. Consolvo, D. Haehnel, B. Harrison, B. Hemingway, J. Hightower, P. Klasnja, K. Koscher, A. LaMarca, et al. The mobile sensing platform: An embedded system for capturing and recognizing human activities. *IEEE Pervasive Computing*, 7(2):32–41, 2008.

[29] Y. Cui, J. Chipchase, and F. Ichikawa. A cross culture study on phone carrying and physical personalization. In *Usability and Internationalization. HCI and Culture*, pages 483–492. Springer, 2007.

[30] B. DeRenzi, N. Lesh, T. Parikh, C. Sims, W. Maokla, M. Chemba, Y. Hamisi, M. Mitchell, G. Borriello, et al. E-imci: Improving pediatric health care in low-income countries. In *Proceedings of the SIGCHI conference on human factors in computing systems*, pages 753–762. ACM, 2008.

[31] R. W. DeVaul and S. Dunn. Real-time motion classification for wearable computing applications. *2001 Project Paper*, 2001.

[32] L. L. DuBenske, M.-Y. Chih, S. Dinauer, D. H. Gustafson, and J. F. Cleary. Development and implementation of a clinician reporting system for advanced stage cancer: initial lessons learned. *Journal of the American Medical Informatics Association*, 15(5):679–686, 2008.

[33] J. Ferlay, H. Shin, F. Bray, D. Forman, C. Mathers, and D. Parkin. Cancer incidence and mortality worldwide. lyon: International agency for research on cancer; 2010.

[34] F. Foerster, M. Smeja, and J. Fahrenberg. Detection of posture and motion by accelerometry: a validation study in ambulatory monitoring. *Computers in Human Behavior*, 15(5):571–583, 1999.

[35] J. Frank, S. Mannor, and D. Precup. Activity and gait recognition with time-delay embeddings. In *AAAI*. Citeseer, 2010.

[36] N. Győrbíró, Á. Fábián, and G. Hományi. An activity recognition system for mobile phones. *Mobile Networks and Applications*, 14(1):82–91, 2009.

[37] G. R. Hayes, G. D. Abowd, J. S. Davis, M. L. Blount, M. Ebling, and E. D. Mynatt. Opportunities for pervasive computing in chronic cancer care. In *Pervasive Computing*, pages 262–279. Springer, 2008.

[38] T. Huynh and B. Schiele. Analyzing features for activity recognition. In *Proceedings of the 2005 joint conference on Smart objects and ambient intelligence: innovative context-aware services: usages and technologies*, pages 159–163. ACM, 2005.

[39] T. Huỳnh and B. Schiele. Towards less supervision in activity recognition from wearable sensors. In *Wearable Computers, 2006 10th IEEE International Symposium on*, pages 3–10. IEEE, 2006.

[40] N. F. Ince, C.-H. Min, and A. H. Tewfik. A feature combination approach for the detection of early morning bathroom activities with wireless sensors. In *Proceedings of the 1st ACM SIGMOBILE international workshop on Systems and networking support for healthcare and assisted living environments*, pages 61–63. ACM, 2007.

[41] I. Janssen and A. G. LeBlanc. Review systematic review of the health benefits of physical activity and fitness in school-aged children and youth. *International Journal of Behavioral Nutrition and Physical Activity*, 7(40):1–16, 2010.

[42] M. Kangas, A. Konttila, I. Winblad, and T. Jamsa. Determination of simple thresholds for accelerometry-based parameters for fall detection. In *Engineering in Medicine and Biology Society, 2007. EMBS 2007. 29th Annual International Conference of the IEEE*, pages 1367–1370. IEEE, 2007.

[43] D. M. Karantonis, M. R. Narayanan, M. Mathie, N. H. Lovell, and B. G. Celler. Implementation of a real-time human movement classifier using a triaxial accelerometer for ambulatory monitoring. *Information Technology in Biomedicine, IEEE Transactions on*, 10(1):156–167, 2006.

[44] T. Kawada, T. Shimizu, A. Fujii, Y. Kuratomi, S. Suto, T. Kanai, A. Nishime, K. Sato, and Y. Otsuka. Activity and sleeping time monitored by an accelerometer in rotating shift workers. *Work (Reading, Mass.)*, 30(2):157–160, 2007.

[45] N. C. Krishnan, D. Colbry, C. Juillard, and S. Panchanathan. Real time human activity recognition using tri-axial accelerometers. In *Sensors, signals and information processing workshop*, 2008.

[46] N. C. Krishnan, C. Juillard, D. Colbry, and S. Panchanathan. Recognition of hand movements using wearable accelerometers. *Journal of Ambient Intelligence and Smart Environments*, 1(2):143–155, 2009.

[47] N. C. Krishnan and S. Panchanathan. Analysis of low resolution accelerometer data for continuous human activity recognition. In *Acoustics, Speech and Signal Processing, 2008. ICASSP 2008. IEEE International Conference on*, pages 3337–3340. IEEE, 2008.

[48] Y.-L. Kuo, K. M. Culhane, P. Thomason, O. Tirosh, and R. Baker. Measuring distance walked and step count in children with cerebral palsy: an evaluation of two portable activity monitors. *Gait & posture*, 29(2):304–310, 2009.

[49] S. Kurata, M. Makikawa, H. Kobayashi, A. Takahashi, and R. Tokue. Joint motion monitoring by accelerometers set at both near sides around the joint. In

Engineering in Medicine and Biology Society, 1998. Proceedings of the 20th Annual International Conference of the IEEE, volume 4, pages 1936–1939. IEEE, 1998.

[50] J. R. Kwapisz, G. M. Weiss, and S. A. Moore. Activity recognition using cell phone accelerometers. *ACM SigKDD Explorations Newsletter*, 12(2):74–82, 2011.

[51] H.-y. Lau, K.-y. Tong, and H. Zhu. Support vector machine for classification of walking conditions of persons after stroke with dropped foot. *Human movement science*, 28(4):504–514, 2009.

[52] S.-W. Lee and K. Mase. Recognition of walking behaviors for pedestrian navigation. In *Control Applications, 2001.(CCA'01). Proceedings of the 2001 IEEE International Conference on*, pages 1152–1155. IEEE, 2001.

[53] S.-W. Lee and K. Mase. Activity and location recognition using wearable sensors. *IEEE pervasive computing*, 1(3):24–32, 2002.

[54] J. Lester, T. Choudhury, and G. Borriello. A practical approach to recognizing physical activities. In *Pervasive Computing*, pages 1–16. Springer, 2006.

[55] Q. Li, J. Stankovic, M. Hanson, A. T. Barth, J. Lach, G. Zhou, et al. Accurate, fast fall detection using gyroscopes and accelerometer-derived posture information. In *Wearable and Implantable Body Sensor Networks, 2009. BSN 2009. Sixth International Workshop on*, pages 138–143. IEEE, 2009.

[56] W. Lin, M. T. Sun, R. Poovandran, and Z. Zhang. Human activity recognition for video surveillance. In *Circuits and Systems, 2008. ISCAS 2008. IEEE International Symposium on*, pages 2737–2740. IEEE, 2008.

[57] U. Lindemann, A. Hock, M. Stuber, W. Keck, and C. Becker. Evaluation of a fall detector based on accelerometers: A pilot study. *Medical and Biological Engineering and Computing*, 43(5):548–551, 2005.

[58] J. J. Liszka-Hackzell and D. P. Martin. Analysis of nighttime activity and daytime pain in patients with chronic back pain using a self-organizing map neural network. *Journal of clinical monitoring and computing*, 19(6):411–414, 2005.

[59] X. Long, B. Yin, and R. M. Aarts. Single-accelerometer-based daily physical activity classification. In *Engineering in Medicine and Biology Society, 2009. EMBC 2009. Annual International Conference of the IEEE*, pages 6107–6110. IEEE, 2009.

[60] G. Lyons, K. Culhane, D. Hilton, P. Grace, and D. Lyons. A description of an accelerometer-based mobility monitoring technique. *Medical engineering & physics*, 27(6):497–504, 2005.

[61] A. Mannini and A. M. Sabatini. Machine learning methods for classifying human physical activity from on-body accelerometers. *Sensors*, 10(2):1154–1175, 2010.

[62] M. Mathie, J. Basilakis, and B. Celler. A system for monitoring posture and physical activity using accelerometers. In *Engineering in Medicine and Biology Society, 2001. Proceedings of the 23rd annual international conference of the IEEE*, volume 4, pages 3654–3657. IEEE, 2001.

[63] M. Mathie, B. G. Celler, N. H. Lovell, and A. Coster. Classification of basic daily movements using a triaxial accelerometer. *Medical and Biological Engineering and Computing*, 42(5):679–687, 2004.

[64] M. J. Mathie, A. C. Coster, N. H. Lovell, and B. G. Celler. Accelerometry: providing an integrated, practical method for long-term, ambulatory monitoring of human movement. *Physiological measurement*, 25(2):R1, 2004.

[65] U. Maurer, A. Smailagic, D. P. Siewiorek, and M. Deisher. Activity recognition and monitoring using multiple sensors on different body positions. In *Wearable and Implantable Body Sensor Networks, 2006. BSN 2006. International Workshop on*, pages 4–pp. IEEE, 2006.

[66] J. K. Mi-hee Lee, I. L. Kwangsoo Kim, and S. K. Y. Sun Ha Jee. Physical activity recognition using a single tri-axis accelerometer. In *Proceedings of the world congress on engineering and computer science*, volume 1, 2009.

[67] E. Miluzzo, N. D. Lane, K. Fodor, R. Peterson, H. Lu, M. Musolesi, S. B. Eisenman, X. Zheng, and A. T. Campbell. Sensing meets mobile social networks: the design, implementation and evaluation of the cenceme application. In *Proceedings of the 6th ACM conference on Embedded network sensor systems*, pages 337–350. ACM, 2008.

[68] M. Mitchell, N. Lesh, H. Cranmer, H. Fraser, I. Haivas, and K. Wolf. Improving care-improving access: the use of electronic decision support with aids patients in south africa. *International Journal of Healthcare Technology and Management*, 10(3):156–168, 2009.

[69] D. S. Morillo, J. L. R. Ojeda, L. F. C. Foix, and A. L. Jiménez. An accelerometer-based device for sleep apnea screening. *Information Technology in Biomedicine, IEEE Transactions on*, 14(2):491–499, 2010.

[70] B. Najafi, K. Aminian, F. Loew, Y. Blanc, P. Robert, et al. Measurement of stand-sit and sit-stand transitions using a miniature gyroscope and its application in fall risk evaluation in the elderly. *Biomedical Engineering, IEEE Transactions on*, 49(8):843–851, 2002.

[71] N. Noury, T. Hervé, V. Rialle, G. Virone, E. Mercier, G. Morey, A. Moro, and T. Porcheron. Monitoring behavior in home using a smart fall sensor and position sensors. In *Microtechnologies in Medicine and Biology, 1st Annual International, Conference On. 2000*, pages 607–610. IEEE, 2000.

[72] J.-H. Park, H. J. Kim, and S.-J. Kang. Validation of the amp331 monitor for assessing energy expenditure of free-livingphysical activity. *Res. Quart. Exerc. Sport*, 77:A40–A40, 2006.

[73] D. M. Parkin, F. Bray, J. Ferlay, and P. Pisani. Global cancer statistics, 2002. *CA: a cancer journal for clinicians*, 55(2):74–108, 2005.

[74] R. K. Patra, S. Nedevschi, S. Surana, A. Sheth, L. Subramanian, and E. A. Brewer. Wildnet: Design and implementation of high performance wifi based long distance networks. In *NSDI*, volume 1, page 1, 2007.

[75] D. H. Peters, M. Kohli, M. Mascarenhas, and K. Rao. Can computers improve patient care by primary health care workers in india? *International Journal for Quality in Health Care*, 18(6):437–445, 2006.

[76] R. Philippaerts, K. Westerterp, and J. Lefevre. Doubly labelled water validation of three physical activity questionnaires. *International journal of sports medicine*, 20(5):284–289, 1999.

[77] D. M. Pober, J. Staudenmayer, C. Raphael, P. S. Freedson, et al. Development of novel techniques to classify physical activity mode using accelerometers. *Medicine and science in sports and exercise*, 38(9):1626, 2006.

[78] C. Randell and H. Muller. Context awareness by analysing accelerometer data. In *The Fourth International Symposium on Wearable Computers*, pages 175–176. IEEE, 2000.

[79] N. Ravi, N. Dandekar, P. Mysore, and M. L. Littman. Activity recognition from accelerometer data. In *AAAI*, volume 5, pages 1541–1546, 2005.

[80] P. C. Ribeiro and J. Santos-Victor. Human activity recognition from video: modeling, feature selection and classification architecture. In *Proceedings of International Workshop on Human Activity Recognition and Modelling*, pages 61–78. Citeseer, 2005.

[81] W. Saris and R. Binkhorst. The use of pedometer and actometer in studying daily physical activity in man. part i: reliability of pedometer and actometer. *European journal of applied physiology and occupational physiology*, 37(3):219–228, 1977.

[82] T. Sauer, J. A. Yorke, and M. Casdagli. Embedology. *Journal of statistical Physics*, 65(3-4):579–616, 1991.

[83] A. Schmidt, H. W. Gellersen, and M. Beigl. A wearable context-awareness component. In *iswc*, page 176. IEEE, 1999.

[84] L. Shu, T. Hua, Y. Wang, Q. Li, D. D. Feng, and X. Tao. In-shoe plantar pressure measurement and analysis system based on fabric pressure sensing array. *Information Technology in Biomedicine, IEEE Transactions on*, 14(3):767–775, 2010.

[85] B. G. Steele, L. Holt, B. Belza, S. Ferris, S. Lakshminaryan, and D. M. Buchner. Quantitating physical activity in copd using a triaxial accelerometer. *CHEST Journal*, 117(5):1359–1367, 2000.

[86] T. Stephens and C. Craig. The well-being of canadians: the 1988 campbells survey on well-being in canada. *Ottawa, Ontario: Canadian Fitness and Lifestyle Research Institute*, page 34, 1990.

[87] A. Subramanya, A. Raj, J. A. Bilmes, and D. Fox. Recognizing activities and spatial context using wearable sensors. *Proceedings of the 22nd Conference on Uncertainty in Artificial Intelligence*, 2006.

[88] F. Takens. *Detecting strange attractors in turbulence*. Springer, 1981.

[89] E. M. Tapia, S. S. Intille, W. Haskell, K. Larson, J. Wright, A. King, and R. Friedman. Real-time recognition of physical activities and their intensities using wireless accelerometers and a heart rate monitor. In *Wearable Computers, 2007 11th IEEE International Symposium on*, pages 37–40. IEEE, 2007.

[90] M. Uiterwaal, E. Glerum, H. Busser, and R. Van Lummel. Ambulatory monitoring of physical activity in working situations, a validation study. *Journal of medical engineering & technology*, 22(4):168–172, 1998.

[91] P. H. Veltink, H. B. Bussmann, W. De Vries, W. L. Martens, and R. C. Van Lummel. Detection of static and dynamic activities using uniaxial accelerometers. *Rehabilitation Engineering, IEEE Transactions on*, 4(4):375–385, 1996.

[92] WHO. Who global burden of disease, 2004.

[93] C.-C. Yang and Y.-L. Hsu. Development of a wearable motion detector for telemonitoring and real-time identification of physical activity. *Telemedicine and e-Health*, 15(1):62–72, 2009.

[94] J. Yang. Toward physical activity diary: motion recognition using simple acceleration features with mobile phones. In *Proceedings of the 1st international workshop on Interactive multimedia for consumer electronics*, pages 1–10. ACM, 2009.

[95] T. Zhang, J. Wang, L. Xu, and P. Liu. Fall detection by wearable sensor and one-class svm algorithm. In *Intelligent Computing in Signal Processing and Pattern Recognition*, pages 858–863. Springer, 2006.