DETECTION OF BEHAVIORAL MARKERS USING WEARABLE WIRELESS SENSORS

A DISSERTATION
SUBMITTED TO THE FACULTY OF THE GRADUATE SCHOOL
OF THE UNIVERSITY OF MINNESOTA
BY

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IN PARTIAL FULFILLMENT OF THE REQUIREMENTS
FOR THE DEGREE OF
DOCTOR OF PHILOSOPHY

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August 2014
Acknowledgement

This work was initiated and developed under the direction and support of Professor Ahmed Tewfik in 2006. The completion of the thesis was aided by project supervision of my co-adviser, Professor Lucy Dunne, and the advice of my dissertation advisor Professor Mostafa Kaveh. Their discussions, challenges and encouragements throughout the work have been most valuable. I also would like to thank Professor Anand Gopinath and Professor Ted Higman, for their discussions, advice, mentoring and willingness to be on the examining committee. I also would like extend my gratitude to Professor Nuri F. Ince for his invaluable and endless discussions and encouragements throughout the work.

I would also like to thank my friends and officemates, Sesan Srirangarajan, Yun-Sang Park, Vikrham Gowreesunker, Young-chun Kim, Nikhil Kundargi, Vijay Tadipatri, and Vimal Singh for all the discussions and good memories.

I would like to take this opportunity to thank the children, their family and care givers who participated willingly to this study. Without their support, this study would not have been possible.

Finally, I would like to thank my parents and my wife. I am deeply indebted to them throughout the studies for their support, encouragement and for believing in me throughout this journey.
Abstract

In this thesis, we propose new methods and systems to detect pseudo periodic behavioral patterns of people with physical and mental disabilities. We have defined the infrastructure of a non-intrusive, cost effective and user friendly system to assist patients with behavioral problems which may be due to cognitive impairments due to mental disorders such as Autism Spectrum Disorder (ASD), Traumatic Brain Injuries (TBI) or Alzheimer’s disease. This dissertation starts by describing advances in sensors and monitoring systems. The system is structured to monitor motions or motor patterns by obtaining sensor data from an in-home and wearable wireless sensor system, and to give reminders and feedback to users and assist therapists and caregivers. We then present the system’s applications and results in detecting and classifying the behavioral patterns in activities of daily living (ADLs). Unlike previous work which issues a reminder like an alarm clock, our system minimally intervenes with the user only when needed by detecting, classifying and monitoring the tasks. The system is flexible and can easily adapt to subject variability with minimal trainings, and the same algorithm can be used to adapt to new ADLs. To better assist cognitively impaired patients, the system detects incompletion and interrupted activities of the subject and issues a reminder/feedback in an intelligent manner. Our system uses three different sensor platforms to monitor and detect abnormal state to better assist the patients with right guidance at the right time.

To achieve the goals defined above, development of signal processing methods based on Gaussian Mixture Model (GMM) and Sequential Classifier from Time Domain and Frequency Domain features are discussed. Data fusion to optimally select, combine
and manage sensors from different platforms which possess various characteristics and sampling frequencies to collect data is addressed. A key contribution is the selection of a subset of sensors to be monitored and processed at any given time to reduce computation load and limit providing feedback to the patient only when needed. Sensor data fusion methods address how to combine the information obtained from selected sensors in an intelligent for analysis and classification. We explore automatic extraction of features across sensors in the time-frequency plane. We also investigate several behavior recognition strategies for comparison purposes.

Algorithm to detect novel patterns is proposed. The novel pattern detection algorithm to find patterns unknown to the system at the time of training is critical as behavioral patterns change or new patterns are developed. An on-line unsupervised learning method to detect and track novel patterns by analyzing features from Higher Order Statistics is also proposed. The proposed algorithm is tested over 60 hours of data collected across 20 subjects and 4 autistic patients with classification accuracy of 94.6%.

Finally, a different sensing platform was investigated to enhance the wearability and comfort level of the user for long term monitoring. We showed that using an array of stitched stretch sensors on every-day wear is feasible and demonstrated its potential for activity detection. We also showed that using a combination of different platforms to complement sensing modalities can be beneficial to improving the classification accuracy of the system.

We show that the proposed combination of Gaussian Mixture Model with a sequential classifier is efficient and allows potential for real-time application of the activity detection system. This thesis establishes that despite the similarities in the activities it is
possible to accurately detect and classify the specific behavioral patterns. The results are compared with the previously developed methods and show that the proposed method can detect the activities with high accuracy and also allows novel event detection to adapt to the behavioral patterns to a user.
# Table of Contents

Acknowledgement......................................................................................... i

Abstract........................................................................................................ ii

List of Tables .................................................................................................... ix

List of Figures ................................................................................................... xi

Chapter 1 Introduction..................................................................................1

1.1 Overview......................................................................................................1

1.2 Thesis Organization and Contributions..................................................3

1.2.1 Activity Detection with Time-Frequency Features Using Gaussian Mixture Model.................................................................3

1.2.2 Characterization and Detection of Behavioral Patterns and Novel Event in Children with Autism Spectrum Disorder..........................4

1.2.3 Application to Smart Clothing and Posture Detection.........................5

Chapter 2 Background....................................................................................7

2.1 Recent Development in Activity Detection..............................................8

2.2 Wearable Wireless Sensors........................................................................12

2.3 In Home Fixed Sensors.............................................................................14

2.4 Traumatic Brain Injury.............................................................................15

2.5 Autism Spectrum Disorder.......................................................................16

Chapter 3 Activity Detection Using Fixed In-Home and Wearable Sensors......19

3.1 Introduction................................................................................................20

3.2 Integration of Wireless Sensor Networks for Activity Monitoring..........23

3.2.1 Static In-home Wireless Sensors.........................................................24
### 3.2.2 Wearable Wireless Sensors

#### 3.2.3 Video and Audio System

### 3.3 Detection and Classification of Activities of Daily Living

#### 3.3.1 Early Morning ADL Data

##### 3.3.1.1 Data Collection

#### 3.3.2 Classification of Early Morning ADL Data

##### 3.3.2.1 Feature Extraction

##### 3.3.2.2 GMM Classifier and Preliminary Decision

##### 3.3.2.3 Post Processing and Final Decision

### 3.4 Results

### 3.5 Limitation and Future Work

### 3.6 Conclusions

### Chapter 4 Characterization and Detection of Stereotypic Behaviors in Children with Autism Spectrum Disorder

#### 4.1 Introduction

#### 4.2 Minnesota Wearable Accelerometer Based Sensor Platform Development

#### 4.3 Detection and Classification of Stereotypic Behavioral Patterns

##### 4.3.1 Subject Description

##### 4.3.2 Data Description and Experimental Setup

##### 4.3.3 Stereotypy Characteristics: Pseudo – Periodicity

##### 4.3.3.1 Temporal Feature Selection
4.3.3.2 Linear Predictive Coding.......................................................69
4.3.3.3 Template Matching and Dictionary Update..............................74
4.3.3.4 Data Balancing......................................................................75
4.4 Novel Event Detection via Unsupervised Learning of Sensor Signal
........................................................................................................75
4.4.1 Unsupervised Learning..............................................................77
  4.4.1.1 Statistical Unsupervised Learning........................................79
4.4.2 Novel Event Detection..............................................................80
  4.4.2.1 Higher Order Statistical Features........................................81
  4.4.2.2 Novel Event Detection and Dictionary Update.......................82
  4.4.2.3 Dictionary Alignment and Optimization by Pruning..............84
4.5 Results.........................................................................................85
  4.5.1 Processing Wrist Sensor..........................................................86
  4.5.2 Body Sensor Data Analysis......................................................87
  4.5.3 Audio Sensor Data Analysis....................................................89
4.6 Limitation and Future Work.......................................................91
  4.6.1 Limitations.............................................................................91
  4.6.2 Prediction of Problem Behavior.............................................92
Chapter 5 Applications to Smart Clothing and Posture Detection...........93
  5.1 Introduction..............................................................................94
  5.2 Background on Stretch Sensing................................................95
  5.3 Experiment Setup and System Validation....................................98
  5.3.1 Experiment Setup.................................................................98
5.3.2 Results..............................................................................................................101
  5.3.2.1 Movement Error...................................................................................101
  5.3.2.2 Drift Error..........................................................................................106
  5.3.2.3 Donning/Doffing Error.......................................................................107

5.3.3 Knee and Hip Sensor Characterization.....................................................110

5.4 Body Posture Detection via Sensor Integrated Clothing............................117
  5.4.1 Experiment Development and Results..................................................120
  5.4.2 Results....................................................................................................120
  5.4.3 Discussion...............................................................................................126

5.5 Conclusions and Future Work.......................................................................127

Chapter 6 Conclusions and Future Research Direction......................................129
  6.1 Conclusions................................................................................................129
  6.2 Future Research Direction.........................................................................132
    6.2.1 Algorithm Development for Garment Based Wearable Sensing........132
    6.2.2 Explore Sparse Representation and Subspace Clustering Algorithm
        Development for Garment Based Wearable Sensing..........................133
    6.2.3 Wearable Sensing Platform..................................................................133

Bibliography ........................................................................................................135
List of Tables

Table 3-1 Available Trials.................................................................32
Table 3-2 Classification accuracies of different feature sets ..................42
Table 3-3 Classification accuracies obtained from TD+FD combination with sequential classifier.................................................................42
Table 3-4 Classification accuracies obtained from TD+FD combination with majority voter post processing.................................................................42
Table 3-5 The confusion matrix for TD+FD combination and sequential classifier post processing for NoMix=2.................................................................43
Table 3-6 The confusion matrix for TD+FD combination and MV post processing for NoMix=3.................................................................43
Table 3-7 Classification accuracies (%) of different classifiers..................47
Table 3-8 The confusion matrix for LDC based classification system...........47
Table 4-1 Classification results for flapping, rocking, punching and hitting using proposed unsupervised novel event detection method.........................88
Table 4-2 Classification results for flapping, rocking, punching and hitting using LPC based template matching method.................................................................88
Table 4-3 Classification results for flapping, rocking, punching and hitting using ISI based clustering method.................................................................88
Table 4-4 Classification results for flapping, rocking, punching and hitting using K-SVD based learning method.................................................................88
Table 4-5 Classification results for flapping, rocking, punching and hitting using GMM based learning method.................................................................88
Table 5-1 Knee angle movement error: Difference between the reference (true) angle obtained from VICON and modeled angle from resistance……………….114
Table 5-2 Hip angle movement error: Difference between the reference (true) angle obtained from VICON and modeled angle from resistance……………….116
Table 5-3 Available trials………………………………………………………………121
Table 5-4 Sample resistance value range…………………………………………123
Table 5-5 Classification accuracy for posture detection…………………………124
Table 5-6 Classification accuracy for posture detection for Subject 1 and 2…………125
List of Figures

Figure 2-1 Home sensor setup..........................................................14
Figure 3-1 Schematic diagram of the proposed system..........................22
Figure 3-2 Schematic diagram of the proposed data acquisition and monitoring system .........................................................................................................................24
Figure 3-3 eNeighbor system...............................................................25
Figure 3-4 Crossbow wireless kits.........................................................27
Figure 3-5 Recordings from wrist worn accelerometer for brush, wash, shave........30
Figure 3-6 Schematic diagram of the proposed data acquisition and classification system ..........................................................................................................................34
Figure 3-7 Proposed classifier output...................................................44
Figure 4-1 Proposed data acquisition system platform that combines 2 different sensor platforms..........................................................56
Figure 4-2 Data recording system and wearable platform.........................57
Figure 4-3 Data analysis.........................................................................58
Figure 4-4 Typical recordings obtained from 3 channel sensor..................60
Figure 4-5 Schematic of the proposed training algorithm using LPC........67
Figure 4-6 Pole zero plot showing the locations of the pole (P=4)..............72
Figure 4-7 Pole zero plot showing the locations of the poles....................73
Figure 4-8 Temporal and frequency characteristics of a sample waveform.....76
Figure 4-9 Schematic of the proposed training algorithm using HOS and LPC........83
Figure 4-10 Acoustic features differentiating the vocalization and noise........90
Figure 4-11 Sensor readings showing arm movement prior to a tantrum........92
Figure 5-1 Looped conductor…………………………………………………………………………96
Figure 5-2 Coverstitch structure.. .................................................................97
Figure 5-3 Coverstitch applied to stretch pants...........................................97
Figure 5-4 Animatronic mannequin with stitched sensors................................. 100
Figure 5-5 Heat map representing the movement of the skin-tight clothes……….. 102
Figure 5-6 Heat map representing the movement of the loose form clothes……….. 102
Figure 5-7 Sensor response from hip............................................................104
Figure 5-8 Sensor response for the knee stretch sensor.................................... 108
Figure 5-9 Sensor response for the hip stretch sensor......................................109
Figure 5-10 Standard error plot against different polynomial degree for knee flexion and Extension..........................................................111
Figure 5-11 Standard error plot against different polynomial degree for hip......... 112
Figure 5-12 Recovery curves of the knee movement and model respective to resistance….. ..................................................................113
Figure 5-13 Extension curves of the knee movement and model respective to resistance….. .................................................................113
Figure 5-14 Knee movement trajectory with respect to movement angles and resistance….. ..........................................................................114
Figure 5-15 Recovery curves of the hip movement and model respective to resistance….. ..................................................................115
Figure 5-16 Extension curves of the hip movement and model respective to resistance….. ..................................................................115
Figure 5-17 Hip movement trajectory with respect to movement angles and resistance…..
Figure 5-18 Statistics from a work related injury………………………………………116
Figure 5-19 Stretch sensor array sensors on the coverall……………………………117
Figure 5-20 Example waveform of the knee and hip sensor response for the stand, squat 
and bend……………………………………………………………………………121
Figure 5-21 Coverall fitness issues shown……………………………………………122
Figure 5-22 Classifier and sequential detector output for the continuous postures for good 
and bad lifting postures……………………………………………………………125
Chapter 1

Introduction

1.1 Overview

In this dissertation, we discuss and evaluate solutions for intelligent activity detection especially related to Activities of Daily Living (ADL), and study its potential to assist people who are in need due to mental or behavioral disorder. We discuss the topics of behavior detection, monitoring and also the detection of new behaviors.

An intelligent system that uses a supervised learning approach analyzes the a priori information available at the time of training from the labeled information to target the designer’s intention [1, 2, 3]. An alternative approach is to allow the intelligent system to analyze information and generate reports from which the designer subsequently tries to extract its meaning i.e. the system tries to find hidden structure from unlabeled data. This approach is known as unsupervised learning in the literature. This research employs a hybrid approach which focuses on the design of a supervised learning method to detect predefined activities that also has the capability to learn from the data to detect
novel events as in unsupervised learning approach, so that the system could be applied to
detect normal and abnormal behaviors of the users of the intelligent systems.

Activity data from a human subject provides information about a person’s
behavior in the time and space domains. Therefore, the intelligent system focuses on
understanding the behavior of a person in space and time. Because of this, much of the
research effort to date has been in installing as many sensors as possible in a room or on a
person, and setting up body sensor networks for activity detection. The motivation for
this research is to create a simple solution to assist people who are in need of this
technology for independent living.

We focus on the problems of detecting, classifying and monitoring the progress of
activities of daily living in an indoor setting. While monitoring the behavior of an
individual for a certain period, we believe we can extract the general patterns of his/her
daily life and detect abnormal behaviors from it. Our system is flexible which can easily
adapt to subject variability with some training and the same algorithm can be used to
adapt to new activities. The system can detect beginning/ completion/ interruption of
activities with emphasis on frustration and behavioral pattern detection. To focus on these
issues, we propose methods for sensor fusion to bring data from different platforms with
various characteristics together in a novel approach in which they are intelligently
analyzed. Exploring the optimal location of sensors and sensor selection to reduce
computation, transmission load and power consumption is important aspect of this project.
We also address adaptive feature selection across the time-frequency plane. Finally, we
compare the performance of the proposed method with various other methods.
1.2 Thesis Organization and Contributions

1.2.1 Activity Detection with Time-Frequency Features Using Gaussian Mixture Model

In chapter 3, we present the design and evaluation of a flexible, low-cost, wireless in-home system to detect activities and to assist people with their daily activities. The system extracts time-frequency features from accelerometer data and classifies these features with a classifier that combines Gaussian Mixture Models (GMM) and a sequential classifier. The system can also monitor and track the activity in observance and check for completeness. Comparison of time-domain and frequency-domain features and its performance is analyzed. We also show that GMM based model outperforms commonly used models such as linear discriminant classifier. We show that within a subject, the proposed method showed classification rate of 97.9 – 100% for the activities studied. We also attempt to generalize the classifier across the subject and using the leave one subject out method and show that the average classification accuracy is 94.6%. In chapter 3, we describe the detection algorithm in more detail and explored possibility of optimizing the following parameters:

- Generalization: developed algorithm for a subject independent classifier.
- Personalization: developed algorithm for a subject dependent classifier
- Monitor completion/interruption of a task: developed algorithms to detect, classify and monitor execution progress of activities of daily living
- Construct strategies that use the behavioral models to assist subjects accomplish Activities of Daily Living (ADLs) or tasks selected by the clinicians, either by
providing directions and help as needed, or accomplishing these tasks directly.

Also monitor for abnormal behavioral pattern

- Issue warnings and monitor user’s response

1.2.2 Characterization and Detection of Behavioral Patterns and Novel Event in Children with Autism Spectrum Disorder

In chapter 4, we propose an efficient dictionary learning algorithm to detect behaviors from wearable sensors. It allows us to develop an unsupervised learning method which will be discussed in detail. Much research has been devoted to detection of behaviors using static sensors and wearable sensors but we are unaware of a system which uses such sensors and interacts dynamically with the subjects based on detection of an activity. Others have researched to understand the behaviors for long term treatment or understand the cause of such behaviors. But, in this study, we focus on a real time system which can interact with users. This is critical especially to patients with Autism Spectrum Disorder (ASD) or cognitive impairments since they cannot remember or are easily distracted away from their current tasks without completing them. We propose the following research to enhance the performance of the system and to contribute to the community in need of behavior and activity monitoring.

Our system allows real time detection and classification of accelerometer data using simple time-frequency analysis and observing frequency band powers. The methods studied based on statistically learning algorithms were resource intensive thus was not appropriate for real time applications. In order to enhance the performance, we
have developed a new algorithm to train the system based on extracting Higher Order Statistics (HOS) based temporal features. HOS features allow the system to explore novel patterns in the data adding more dimensionality to the classifier. We will describe the detection algorithm in more detail and explore possibility and optimize the following parameters:

- Generalization: develop algorithm to develop a subject independent classifier
- Personalization: develop algorithm to develop a subject dependent classifier
- Develop algorithms that can assess the abnormal state of a patient
- Monitor for abnormal behavioral pattern
- Issue warnings and monitor user’s response
- Preprocessing and explore new features: Higher Order Statistics

1.2.3 Application to Smart Clothing and Posture Detection

In chapter 5, we present a different type of activity sensing using a smart clothing platform. Due to the invasiveness of the devices and sensors, long-term monitoring is not possible. Therefore, researchers have looked into integrating the sensors into everyday clothing to improve the wearability and allow long term monitoring. We have integrated the sensors into textile and garment structures. Though, it is still at an early stage, clothing has a significant advantage over the strap-on devices. Many wearable sensing garments use a skin-tight garments or suit which allows a closer contact with the body. Therefore, the applications numerous and smart clothing is a perfect platform for
detecting body postures. In this chapter, we present our findings in validating the stitched sensor and modeling the sensor responses to joint movement. We also present our results on body posture to prevent back injuries at workplace. We believe it will be a low cost solution to effectively reduce posture related injuries in the workplace.
Chapter 2

Background

In this chapter, we discuss the concept of assistive technologies and devices which have gained popularity in recent years and also discuss its role in everyday monitoring of signs and symptoms. Recently, with the introduction of wireless technology and mobile computing, monitoring which were confined to hospitals or bedroom was expanded to monitor all Activities of Daily Living (ADL). With the introduction of pervasive computing [3], we review some of the work previously done in the areas of wearable and in-home sensors as well as the reminder/planner systems. With the development of technology, many different platforms were developed to monitor the physiological signs of human body, such as blood pressure, heart rate, ECG [4, 5, 6, 7, 8] as well as the physical activities of an individual [9, 10, 11, 12, 13]. These systems allow continuous monitoring of abnormal signs for early diagnosis of diseases or general health monitoring for the elderly population. Currently, two different platforms exist
independently to achieve the task of monitoring patients. The two platforms are in-home “fixed” sensors and wireless “wearable” sensors which we discuss briefly in this section.

2.1 Recent Development in Activity Detection

Much work has been done in the area of activity detection, especially for the elderly with the goal of assisting the elderly with their Activities of Daily Living (ADL). Others have studied the field with activity monitoring in general, studying postures, amount of body movements for energy expenditure, and studies to promote overall well-being by reducing obesity. In these studies, researcher used sensors to detect basic activities such as lying, sitting, standing, walking, and running [11, 12, 13, 14]. Observing such patterns for longer time periods allows researchers to determine subjects behavioral patterns allowing therapists or doctors to provide specific feedback based on the results. This basic system could be interconnected to a reminder system to give more timely feedback to clients [15, 16, 17]. Researchers from University of Minnesota have used a similar approach with an intelligent reminder system to dynamically give feedback to users of the system [18, 19]. The system was used to detect early morning activities and showed that they were able to detect the activities of interest with average accuracy of 96% [20, 21].

In order to detect the events of interest, we must start with the use of correct sensor platforms placed in right location. Challenges exist for patients and children with Autism that make use of body sensors difficult. Many children with Autism Spectrum Disorder (ASD) have severe sensory issues that include sensitive skin and intolerance of certain clothing or items touching their skin. Similarly, an inability to understand and
communicate can result in the child refusing to keep a sensor on their skin or body. Similarly, we must also target behavioral events sensors are able to detect and those that are most likely to benefit from a therapeutic intervention. Behavior patterns most widely seen in people with autism are flapping arms or hands, rocking body front to back or side to side, tapping/drumming, punching, and making repetitive vocal sounds such as “da da da da” or echolalia. In addition there are more subtle repetitive behaviors which are hard to detect such as tapping fingers, hair twisting, and repetitive blinking. While some children exhibit these behaviors when excited or agitated, some exhibit them to the extent that they interfere with their ability to learn. One of the goals of this project is to use technology to help children with ASD and their providers monitor their stereotypies and behaviors and identify interventions that successfully control those behaviors when desired.

A person who knows or have frequently been in contact with autistic persons can detect their affective states [22, 23, 24, 25, 26]. They observe various modalities such as facial expression, vocalization of word or non-word situations, gestures or physiological signs [10, 27]. They have used various sensor platforms to recognize the affect states by analyzing the signals from the sensors. Our research focus will be to automatically detect these modalities to predict extreme behaviors before they occur, so that clinical providers or parents may intervene or divert the child to an activity that may calm him/her down. In order to reach this goal, we tackle the detection problem by proposing a wearable sensor based solution to monitor and track behavioral patterns of children with ASD.

Research in automatic detection of behavioral patterns has surfaced only recently. This is mainly due to recent advances of micromechanical devices and embedded systems
that triggered the development of countless platforms that can monitor many different aspects of our lives. It also enabled ambulatory monitoring due to the advances in wireless communication protocols such as Bluetooth and devices that support these protocols. Such systems, when appropriately scaled and enhanced can be used for continuous monitoring of the behavioral patterns. Thus wireless wearable sensors were used to monitor their ADL [12, 28, 29, 30]. We have been successfully applying a similar technology to develop a system to assist people with cognitive impairments due to Traumatic Brain Injury (TBI) that require intelligent systems that can assist the person in carrying out their daily activities with intelligent reminders only when it is needed [31, 32, 33, 34].

Researchers from Georgia Tech have developed wearable wireless sensors based on accelerometer to detect and monitor repetitive behavioral patterns. They have used the sensor platform to detect 8 common repetitive behavioral patterns from a normal adult who mimicked these behaviors [35]. There also has been an effort to develop systems to detect autistic behaviors using accelerometer which showed promising results but analysis was done on recording from healthy adult subjects and no discussion of real data or explanation were explored. Although, the classification accuracy ranged from 80% - 100%, these patterns were mimicked. Another group has recently explored similar patterns from autistic children and has shown comparable results with our findings. This shows that the community has begun to understand the necessity of a system and methodologies that could be used to assist people with autism. Researchers in Groden Center, RI and UMN have independently studied and analyzed data collected from autistic children. Researchers at Groden Center studied data analyzed for hand flapping
and rocking from 6 subjects and showed that they were able to achieve 82% - 97% accuracy with average being 91.1% [36].

As briefly mentioned above, a number of computer based software programs and packages were developed for early intervention to assist children with autism. Among them, were programs to help improve attention, facial expression recognition [21], and social and communication skill development [21, 22, 37]. Several groups have developed prototype robots to interact with a child so that the child may learn social cues, social behaviors and other social skills needed to live a more independent life [24, 38, 39]. Others have used physiological recordings from people with autism for affect recognition to develop methods for computer based intervention. This concept is based on the work of researchers that developed methods to use computers as a medium to understand affective cues of persons that interact with computers. Computer based tutoring systems developed by several researchers [41] were used for affect recognition in normal subjects. Although these systems are designed for affect recognition, it is hard to find systems with high accuracy. Thus, several researchers have tried to increase the accuracy by correlating the underlying physiological parameters to aid affect recognition.

The majority of technology-based solutions or methods proposed above assist with education and long term goals. Since many the children with autism lack social cues, they are vulnerable to expressing excitement, anxiety or frustration [42, 43]. Often in a home, therapy or classroom environment, the parents, teachers and caregivers have to look for cues that could trigger repetitive or extreme behaviors, which can lead to over-excitement or frustration. Also, due to the general public’s lack of understanding the symptoms and behaviors of people with autism, it makes lives of people with autism
difficult. Parents are concerned about repetitive behaviors in a social environment, and sudden expressions, socially inappropriate gestures, stereotypic behaviors, vocal stereotypies make their child less socially accepted. These behaviors can also, make it difficult for a child to be in a group setting such as classroom learning environments. Our goal is to detect behavioral patterns in children with ASD correlate resolution of behaviors with specific interventions, and ultimately enabling children with ASD to live more independent lives.

2.2 Wearable Wireless Sensors

The birth of wearable wireless sensors was to overcome the limitation its predecessors possessed. Several decades back, monitoring of the physiological parameters could only be done in the clinical setting. It was used to monitor and detect abnormalities for diagnosis of the disease or illness. But, in order for the treatment to be effective, clinicians needed to observe the abnormalities. But, certain symptoms are not observable during a clinical visit and most patients are out-patients visiting the hospital once the symptom has been observed personally. Therefore there was a need for long term monitoring of the patients in a non-clinical setting.

Due to these reasons, there was a need to develop a system to continuously monitor the biological signals which can be carried by the patients throughout the course of their daily life. Many systems interact with Personal Digital Assistance (PDA) or other similar hand held devices where the sensor data is stored. Data itself is collected via wired sensors [12, 13, 45] and when collecting multi sensor data, patients carry a backpack equipped with amplifiers and PC to continuously record the data, which is
impractical. Recently, wearable wireless sensors were introduced which eliminated the wiring between the sensor and recording system and also allow wireless transmission of the data to the data center. This allows more flexibility and is less cumbersome to the patients [14, 15, 16, 17].

Other applications using the wearable sensors, such as an accelerometer, include activity monitoring and for energy expenditure estimation [8, 9, 11, 13, 18, 19, 45]. They focused mostly in monitoring walking, sitting, standing, lying, running, bicycling, driving/riding a car, etc. The amount of these activities subject was involved in would tell the researchers how much energy the subject has consumed in his/her daily life. Others report the use of EMG sensors for similar application [20].

Accelerometer gained popularity due to its simplicity and is widely used for clinical research to understand motion patterns after a stroke or being diagnosed with Parkinson’s Disease [13, 46, 47, 48, 49]. Since patients or users prefer non-intrusive and non-obtrusive system, small wearable sensor system gained attention among the researchers and designers. But, due to its form factor, extending the battery life becomes a critical factor in continuous monitoring.

For our research, among the few wireless senor systems, we use the wireless system developed by the Crossbow Inc. [http://www.xbow.com] which already incorporates, 2-axis accelerometer, magnetometer, thermometer, microphone and sounder.
2.3 In Home Fixed Sensors

In home based sensor systems uses fixed sensors attached to doors, rooms and throughout the home to monitor activities of daily living. Ogawa, Togawa [50, 51] and other researchers [52, 53] have developed a system for activity monitoring, health monitoring and behavior monitoring at home. Ogawa et al. used many different in-home fixed sensors, shown in Figure 2-1, such as motion, door, touch (contact), temperature, humidity and other sensors to monitor the activity of the subject to understand his behavioral patterns. On the other hand Celler at el. studied the design issues of a remote monitoring system [52]. They showed infrastructure and described that data can be collected which showed promising application in home monitoring. Based on this system, they were able to observe the behavioral pattern of the subject, such as when the subject wakes up, start to cook, have breakfast, leave home, come home, and etc. Such solutions are now popular that many of us have fixed in-home sensors to monitor home activity or home surveillance and have been commercialized to prevent theft and hazard.

![Figure 2-1. Home sensor setup shown in [51]](image-url)
2.4 Traumatic Brain Injury (TBI)

Traumatic Brain Injury (TBI) is one of the leading causes of death and permanent disability in the United States (US). According to the Center for Disease Control (CDC), the number of TBI patients in the US is 5.3 million [73]. About 2% of the US population has a long-term TBI and needs assistance to perform activities of daily living (ADL). This number is expected to rise with the increase in the elderly population. Males are twice as likely to sustain TBI compared to females. Furthermore, recent military actions in Iraq have led to a marked increase in TBI amongst active duty soldiers in the 18-25 age groups. For example, a Defense and Veterans Brain Injury Center’s report indicates that 62% of patients screened between July and November of 2003 were identified as suffering from brain injury [55]. Direct medical costs and indirect costs such as lost productivity of TBI totaled an estimated $60 billion in the US in 2000 [56]. The system that we describe here can decrease this cost while allowing TBI patients to lead independent and productive lives.

Traumatic brain injury is caused by a sudden impact or a penetrating injury to the head. In general, the frontal part of the brain is damaged in TBI cases. The frontal lobe is known to control higher cognitive functions. Therefore, TBI patients have difficulties with attention/concentration, planning, memory, execution and completion of activities.

Today, care for TBI patients is provided by health professionals. Initial treatment is given at hospitals. In late recovery stages, patients are moved from the hospital and assistance is extended into the home. Wellness monitoring of the patients becomes very important at this point. Unfortunately, with the shortage in care givers and rise in the
number of TBI cases, it is becoming increasingly difficult to provide the required level of human monitoring and assistance that TBI patients require.

2.5 Autism Spectrum Disorder (ASD)

Children with Autism Spectrum Disorder (ASD) lack social and communication skills and exhibit repetitive behaviors. Individuals with autism have symptoms that can range from mild to very severe. Although, lack of social and communication skills creates challenges, perhaps more disruptive are the repetitive behavioral patterns. Children diagnosed with ASD require intervention, regardless of the severity of the symptoms, to allow the child to function optimally.

Recent technology developments for ASD are primarily designed to assist either the individual with autism or caregivers (parents, doctors, teachers and therapists). A therapy method known as Discrete Trial Training (DTT) is the most widely practiced method to assist children with autism to learn basic skills in various areas of daily living. A child and a therapist/teacher meet in a one to one based session in which the therapist/teacher interacts with the solely with the child. The child learns through an interaction with the therapist by playing games or simply repeatedly learning the skills necessary. Depending on the severity of the child's needs, multiple therapists may be required to provide such things as Occupational Therapy, Physical Therapy, and Speech Therapy. At times therapists actively work together to provide a more efficient and intensive program for the child. Therapists log their observations and document their treatment sessions. This documentation serves as a report for other professionals, such as physicians and psychologists and as a billing document for insurance reimbursement.
Logged information is subjective and less desirable than non-objective quantifiable data, but the latter currently doesn’t exist. Pioneering work has begun to use video recording of the actual therapy session that can be stored and forwarded for discrete tasks. Researchers in Georgia Tech have developed an interface to record the video and give indices so that it could be reviewed in future sessions if necessary [57, 58]. The study showed that therapists relied more on objective measures compared to subjective recollections used previously. This method continues to rely on human observation to achieve the necessary information for evaluation.

Another area of assistive system development is in the area of analyzing the behavioral data. Children with autism exhibit stereotypic behaviors that are sometimes disruptive in social gatherings such as the classroom environment, restaurants, concerts, etc. It can draw attention or disrupt the activities that are occurring in an environment. These behaviors could be expression of their anxiety, frustration or over excitement. The expressions differ from one child to another. While most of the stereotypical behaviors are simple repetitive behaviors, some actions can induce self-inflicting wounds or injuries. These actions can be dangerous to the individual or threatening to others.

The Functional Behavior Assessment (FBA) is a tool used to diagnose specific behaviors, by first observing the behavior and then studying the antecedent to understand what may have led to such behavior. In the children that we observed, children appeared to use rocking as a way to express excitement while flapping seemed to be associated with anxiety. Children we observed, with and without verbal skills, escalated their intonations used a louder voice when frustrated. Researchers at Georgia Tech have studied the benefit of video recording based FBA used by teachers. Teachers reported
feeling less burdened during the class sessions because they could rely on video recordings if necessary [59, 60]. Therefore, in order to assist with the repetitive behaviors children with ASD experience, we first turn our attention to detecting these events using wearable sensors.
Chapter 3

Activity Detection Using Fixed In-home and Wearable Sensors

In this section, we describe a flexible, cost-effective, wireless in-home activity monitoring system for assisting patients with cognitive impairments due to traumatic brain injury (TBI). The system locates the subject with fixed home sensors and classifies early morning bathroom activities of daily living with a wearable wireless accelerometer. The system extracts time and frequency domain features from the accelerometer data and classifies these features with a hybrid classifier that combines Gaussian mixture models and a finite state machine. In particular, this chapter establishes that despite similarities between early morning bathroom activities of daily living, it is possible to accurately detect and classify these activities with high accuracy. It also discusses system training and provides data to show that with proper training data selection, accurate detection and classification are possible for any subject with no subject specific training.
3.1 Introduction

As indicated previously, an impact to the frontal lobe of the brain causes TBI patients to have difficulties in planning, organizing and completing activities. To assist TBI patients in planning their daily lives, several reminder/scheduler-oriented systems have been developed. In general, these systems are based on hand-held devices that deliver messages to the patient in an “open-loop manner”. For example, the Planning and Execution Assistant and Trainer (PEAT) [61] provides automatic assistance for task planning. It uses an integrated task planning and execution algorithm that is a spin-off from NASA's robotics research. Indeed, NASA's autonomous spacecraft and rovers on Mars require the same flexibility as people to accomplish goals in uncertain and changing situations. PEAT is an application of this technology on handheld computers for the purpose of cognitive rehabilitation. PEAT and similar calendar-type systems operate on a basic alarm clock strategy that does not account for the dynamic nature of a person’s daily schedule and needs. In the recovery stage, TBI subjects typically remember the daily activities that they are supposed to perform. Such subjects can find repeated alarm clock type reminders unnecessary and annoying. Despite its complexity and flexibility in scheduling, PEAT requires feedback from the user that could instead be provided by appropriate sensors. Within the architecture of PEAT, the monitoring of an execution of a delivered message or reminder can only be obtained by user feedback based on continuous interaction with the hand-held computer. This requires that the hand-held PC always be carried by the individual.

Fortunately, researchers and system developers are beginning to focus on monitoring activities with in-home sensor networks to complement such reminder
systems. In order to overcome the limitations of PEAT, a research group from the universities of Michigan and Pittsburgh has introduced a new type of planning system called Autominder [62] for cognitively impaired people. Autominder is a reminder and scheduling system involving a robot (Pearl) which has several on-board sensors to track the activity of the subject and to deliver visual and auditory messages [63] to the patient. However, the sensor strategy used in the system has several limitations. First, the robot is assumed to accurately observe the actions and location of the patient. This requires the robot to be able to move to each location with the subject. This may not be practical in real life situations and may be perceived by patients as intrusive. Indeed, our discussions with TBI experts indicate that most patients dislike systems that produce video or intelligible audio recording of their activities and are perceived as intruding on the patient’s privacy. A robot is also very conspicuous, adding to the stigma that TBI patients may feel. Second, the dynamic information which can be obtained from wearable wireless sensors as previously described is missing. Our experience indicates that such information is critical for accurate classification of ADLs. Finally, as with the sensor systems described above, the efficacy of such reminder/planner systems has not been studied. The literature provides evidence that to be useful and effective, a reminder or scheduler system must accurately classify and monitor the person’s activities. The two main contributions of this chapter are establishing that it is possible to detect and classify activities of daily living, despite their similarities, with a cost effective system and that the system requires little or no subject dependent training. We focus on the problems of detecting, classifying and monitoring early morning bathroom activities such as face washing, tooth brushing and face shaving to provide evidence to an intelligent
The system uses fixed sensors to locate the subject at home and track daily activities at a coarse level. Data from a wearable accelerometer is then used to detect and classify the precise early morning bathroom activity of daily living performed by the subject. The proposed system uses IEEE 802.11 and IEEE 802.15.4 standard compliant wireless sensor kits. The IEEE 802.15.4 compliant wearable sensors in particular provide low power and low data rate connectivity. They are used to monitor the execution of different activities at a detailed level. The wireless in-home fixed sensors are IEEE 802.11 compatible. In more complex systems designed to identify a larger set of activities of daily living, these fixed sensors can also be used to activate the proper wearable sensors that are best suited for recognizing activities of daily living performed in a given environment. The system uses Gaussian mixture models and a sequential classifier to classify the wireless sensor data. A block diagram of the proposed architecture is shown in Figure 3-1.

**Figure 3-1.** The schematic diagram of the proposed system
Subsequent chapters are organized as follows. In the next section we describe our sensor network to collect data and discuss in detail the architecture of the system. In section 3 we explain the experimental data and our classification strategy. Finally, in section 4, we give classification results obtained from seven subjects and discuss future directions.

3.2 Integration of Wireless Sensor Networks for Activity Monitoring

As mentioned earlier, the data acquisition system developed at the University of Minnesota integrates two sensor systems. The first sensor system is a collection of fixed wireless sensors. The second system relies on wearable sensors that provide data to complement the data collected by the first system. A schematic diagram of the system is given in Figure 3-2.

Note that other designs are also possible and may offer some advantages over the system that we constructed. For example, a system that relies exclusively on wearable sensors would be easier and cheaper to deploy. Such a system would substitute accurate localization based on wireless transmissions for the inputs obtained from the fixed wireless system that we are using. In most of the systems that we have investigated, accurate localization from wireless signal measurements requires using more than one base station and in some cases extensive signal strength surveys across a home, negating the savings achieved by not installing the fixed sensors
3.2.1 Static In-home Wireless Sensors

Many technologies have been developed for in-home activity monitoring. Most of these technologies use static home sensors which are activated by the user [50, 51]. These include thermistors positioned under the bed to measure body motion, infrared sensors to detect the presence of the subject in a specific location, magnetic sensors attached to appliances to detect their use, etc. The use of such sensors gives strong clues about the individual’s location and activities being performed. However, the wiring between the sensors and data center is a major issue for such a system. In our study we elected to use eNeighbor™ (eN), a wireless remote in-home activity monitoring system which was developed by RedWing Technologies and marketed under the name Healthsense™ [www.healthsense.com]. The eNeighbor wireless sensor network is based on the IEEE 802.11 standard. It had an Atmel Mega 128 microprocessor and includes server

![Figure 3-2](image-url)  
**Figure 3-2.** The schematic diagram of the proposed data acquisition and monitoring system. On the left side wireless networks to collect in home (eNeighbor) and wearable sensor data (xBow). The sensor readings are transmitted to a PC via the eNeighbor base station and MIB510 gateway. Synchronously, video and speech inputs are recorded with Matlab. These inputs are used to label the sensor readings.
technology applications for externally alerting and reporting monitoring information. This system comes with several sensors such as motion, bed, chair, and door sensors that enable it to track a broad range of daily activities at a coarse level shown in Figure 3-3. Each sensor communicates with the base station only in the case of an event. Therefore, the sensors have long battery life and can be used at home without maintenance for long periods of time. Each event received by the base station is exported in real time through the USB port to an external device for backup. We developed a USB port driver to capture the messages transmitted from the base station and save these messages on a PC with a time stamp to synchronize with the other sensors in the remaining system.

Figure 3-3. (a) The eNeighbor system. From left to right: The door sensor, base station installed with key fob and the motion sensor. (b) The software developed to capture the messages sent from eNeighbor via the USB port. (c) The GUI developed to dynamically visualize in-home sensor data. (d) Sample sensor data, recorded while a subject is going to the bathroom from the bedroom. (e) Wearable wireless sensor kit attached to the wright wrist.
3.2.2 Wearable Wireless Sensors

The eNeighbor gives binary information that provides clues about the activities carried out by the individual. There are many activities where interactions with these sensors do not occur. In addition, some activities may trigger the same sensors. For instance, the subject may enter the bathroom for a face washing, brushing activity. During these two activities the same subset of sensors is activated which makes it difficult to distinguish between wash and brush activities by examining the binary sensor data of the eNeighbor.

To get detailed information about the activity of the patient, we use wearable sensors attached to the wrist and installed on a wireless networked embedded system (See Figure 3-4). In particular, we selected the MICAz wireless nodes developed by Crossbow Technology Inc. [www.xbow.com] for wearable data collection. Data transmission and reception on the MICAz is handled by a Chipcon CC2420 radio chip, which is IEEE 802.15.4 compliant. It has a 250Kbps radio throughput rate. The onboard expansion slot enables the designer to interface several sensors to the microprocessor. The microprocessor runs TinyOS 1.1.7, a small open source operating system for the embedded sensor networks. The microprocessor is programmed with the NesC programming language to collect and transmit the sensor readings to the PC. NesC is a new programming environment for networked embedded systems. It significantly simplifies the efforts for application development under TinyOS [www.tinyos.net].

In our system, we used the MTS-310 multisensor board to record movement and environmental parameters. The MTS 310 has on-board light sensors, temperature sensors,
Figure 3-4. (a) The Crossbow wireless kits; on the left is the serial gateway MIB-510, two devices on the right are the MicaZ motes with MTS-310 sensor boards on top. (b) The mote kit attached to the wrist to collect data.

a 2-axis accelerometer, a 2-axis magnetometer and a microphone. These sensors are connected to the multi-channel 10 bit ADC of the mote kit.

In this section, we will restrict ourselves to the presentation and analysis of accelerometer data. The on board sensor is an Analog Devices ADXL202JE dual-axis accelerometer. The use of accelerometers for activity recognition is not new. Initial applications of accelerometers have concentrated on the recognition of sitting, standing and walking behavior [10]. The system used two biaxial accelerometers attached to waist and leg to estimate body position and lower limb gestures [10]. The accelerometer sensors are wired to a PDA for data collection. The wiring is a critical issue which limits the user activity in real life situations. In another system that consists of five biaxial accelerometers attached to several locations on the body has been used for activity recognition [45]. In order to remove the wirings between the sensors and data center, the system used hoarder boards. The data was locally stored with time stamps on these
boards and post processed offline for synchronization and classification. By using decision tree classifiers, the system was able to recognize 20 everyday activities with an overall accuracy rate of 84%. The studies showed that the flexible data collection is a critical step to give the subject the freedom to do his/her daily activities [10, 45].

In order to transfer accelerometer data to the PC we used an MIB510 serial getaway. The MICAz mote communicates with the MIB510-gateway using a wireless IEEE 802.15.4 link. The gateway transmits the received sensor readings to the PC through a RS-232 port. In the current system, the data communication rate is limited to 56 Kbps on the RS232 side. This data rate was high enough to transmit data from the sensors since the sensors outputs are sampled at the rate of 50 samples/sec. The reader can find detailed information about the DAQ system in [31].

On the PC side, we developed another serial port driver to capture the packets received from the MIB-510 gateway. We saved the sensor readings in an ASCII file with time stamps similar to those used by the eNeighbor system for further processing. We developed software to capture the serial messages transmitted by the eNeighbor system and the MIB510 using ActiveX components built on top the MS Windows application programming interface (WINAPI). This could have also been done using the Matlab™ (MathWorks Inc, Natick, MA) serial line programming interface in order to bypass detailed WINAPI.

3.2.3 Video and audio system

Video and audio are often used to label data during development to provide ground truth during the design and training of monitoring systems. During the training phase, the recording of daily activity is done continuously over long periods of time. To
collect ground truth information in an unsupervised manner, we used a USB port compatible webcam and a headset microphone. We have interfaced the webcam with the PC by using the Image Acquisition Toolbox of Matlab. The toolbox enables one to connect and configure the video hardware, preview the video, and stream images directly into Matlab for analysis and visualization. While collecting data from the fixed and wearable sensors, the system automatically records a video of the patient activity at a very low frame rate of 6 fps. We found this low frame rate adequate for the training data labeling task. The video frames are recorded in AVI format. Separately, the time stamp of each frame is recorded in another file. A program was developed under Matlab to read the video and other sensor data. All data was synchronized by utilizing the time stamp information. By examining the video and audio we are able to label the sensor data for training of classification algorithm.

3.3 Detection and classification of activities of daily living

In this section, we describe the data that we collected to design and test the system, and explain the classification procedure we constructed and finally discuss system training. As mentioned earlier, the system that we developed relies on a two phase approach for detecting, classifying and monitoring ADLs. In phase I, we localize the subject within a specific room of a home and perhaps on a specific piece of furniture using the fixed wireless sensors, e.g., eNeighbor in our case. This allows us to constrain the list of most likely activities that the subject may be executing. In phase II, we rely on the wearable accelerometer sensor to detect, classify and monitor the progress of ADLs. In this phase we rely only on accelerometer data.
3.3.1 Early Morning ADL Data

ADLs can be classified into 3 different categories: basic, instrumental and enhanced ADL. According to [64], basic ADL deals with personal hygiene and nutrition such as washing, toileting and eating. The authors state that all people living independently should be able to execute these basic ADLs. Instrumental activities can be managing a medication intake, maintaining a household etc. while enhanced ADLs involve activities outside one’s residence and social interactions. We have selected several basic early morning ADLs for initial investigation. Our initial studies and system design are based on healthy subjects since data collection from TBI patients is difficult and most TBI patients are not physically disabled.

3.3.1.1. Data Collection

![Graph showing typical recordings obtained from accelerometer sensor attached to the right wrist.](a)

**Figure 3-5.** Typical recordings obtained from accelerometer sensor attached to the right wrist. (a) brushing teeth (b) washing face (c) shaving face.
Figure 3-5. Typical recordings obtained from accelerometer sensor attached to the right wrist. (a) brushing teeth (b) washing face and (c) shaving face
In this section, we focus in particular on the classification of three ADLs. These are face washing, tooth brushing and face shaving. The data was recorded from seven healthy subjects with the system described above. A single mote kit is attached to the wrist to record hand movements. After a small training period, the wireless sensor system and user friendly data acquisition software installed on a notebook PC was given to the subjects to record the ADL data in their home setting. For privacy reasons, no audio or video data was released. In order to provide the ground truth for recorded wearable and static home sensor data, we conducted a single trial based recording paradigm. The subjects freely executed one of the three early morning activities listed above and the data was labeled manually after each recording. The number of available trials for each activity is given in Table 3-1. Sample signals corresponding to these activities are shown in Figure 3-5. In addition to the 3 distinct activities, subjects were also asked to record data related to activities that have no specific purpose or do not correspond to the three early morning activities listed above. Examples of such activities include changing a towel, arranging items on the sink, etc. All such activities are categorized as Other-Activity (OAct).

During the data collection process subjects reported that tooth brushing and face shaving were generally preceded and followed by a face wash activity. Although we attempted to record a single activity, many tooth brushing and face shaving recordings

<table>
<thead>
<tr>
<th>Activity</th>
<th>Brush</th>
<th>Wash</th>
<th>Shave</th>
<th>OAct</th>
</tr>
</thead>
<tbody>
<tr>
<td>Trials</td>
<td>182</td>
<td>199</td>
<td>107</td>
<td>40</td>
</tr>
</tbody>
</table>

Table 3-1. Available trials
included a short duration of face washing. Therefore, in our final decision evaluation, we ignored washing outputs when they are observed just before and after tooth brushing and face shaving activities.

3.3.2. Classification of Early Morning ADL Data

3.3.2.1. Feature Extraction

There are several possibilities for generating activity state models and ADL classification methods. In this study we use a hierarchical classification system as indicated in Figure 3-6 because of its simplicity and performance. The system combines Gaussian mixture models (GMM) and a sequential classifier as shown in Figure 3-6. We use GMMs to model the activities such as tooth brushing, face washing and face shaving. GMMs are widely used in continuous classification of EMG signals for prosthetic control and speaker identification problems due to their robustness and low computational complexity [65, 66]. The main motivation of using a GMM is that it provides a generative model of each task. The mixtures in the model are believed to represent the sub activities executed by the subject when engaged in a specific task. Furthermore, the number of mixtures can account for variability across subjects.

We extracted time domain (TD) and frequency domain (FD) features from the accelerometer data which were input to the GMM. The 2-axis accelerometer sensor provides two types of outputs for each channel. The DC component of the accelerometer sensor is related to the tilt information and the AC component is related to the acceleration signals. The time-domain features are extracted from raw data. We believe that it reflects the hand position. Frequency-domain features are extracted from the AC
Figure 3-6. (a) The schematic diagram of the proposed classification system which is based GMM followed by a sequential classifier. (b) The dyadic frequency bands used to extract frequency-domain features.
component measurement. Therefore, we combine both feature sets in the final classification. The time-domain features consist of the mean, root mean square and the number of zero crossings in a 64 sample time segment. After applying a first order high pass Butterworth filter, we calculate the frequency-domain features for the AC component of the acceleration signal. We extend the feature set with energies in different frequency bands. The Fourier transforms of the accelerometer data along the two axes are calculated from each 64 sample time segment along with the time-domain features. The time segments are shifted with 50% overlap across the signal. In each segment, we calculate the energy in dyadic frequency bands as indicated in Figure 3-6 (a). Frequency-domain features are then converted to log scale and combined with time-domain features related to the same time segment. This resulting feature vector \( x \) has a dimension of 16 in each time segment [67].

### 3.3.2.2 GMM Classifier and Preliminary Decision

A GMM probability density function (pdf), is defined as a weighted combination of \( N \) Gaussians,

\[
p(x|\lambda_k) = \sum_{k=1}^{N} w_k \eta(x|\mu_k, \Sigma_k) \quad k = 1, \ldots, K. \tag{3-1}
\]

Here, \( \lambda_k \) is the model, \( x \) is the feature vector, \( \eta \) is the \( D \) dimensional Gaussian pdf

\[
\eta(\mu, \Sigma) = \frac{1}{(2\pi)^{D/2} |\Sigma|^{1/2}} \exp\left(-\frac{1}{2} (x - \mu)^T \Sigma^{-1} (x - \mu)\right) \tag{3-2}
\]

with mean vector \( \mu \) and covariance matrix \( \Sigma \). Parameter \( w_k \) is the weight of each component and satisfies
A new observed feature vector can be assigned to one of the four classes (K=4) after evaluating the posterior probability of each GMM. Specifically, the label \( L \) assigned to an observed vector \( x \) is calculated as

\[
L = \arg \max_k p(x | \lambda_k) \quad k = 1, \ldots, K. \tag{3-4}
\]

Model order selection plays a big role in determining the performance in GMM based systems. While a low number of mixtures can poorly represent the geometry of the activity in a \( D \) dimensional space, a high number of mixtures generally over fit the data. We have found that by varying the number of mixtures from 1 to 6 we are able to find the optimal value for classification.

### 3.3.2.3. Post Processing and Final Decision

The evaluation in Equation 3-4 gives a class label for each time point. This corresponds to the continuous classification of the streaming data. However, we noticed that the arm movements during each task contain many sub-segments where the activity is not locally related to the task being executed. In addition, as we emphasized before, a single task can be executed by visiting many subtasks that also involve the 3 activities we focus on. For example, a face shaving task may start with face washing, then applying cream to the face, shaving with the razor and at the end again washing the face. Therefore, the GMM outputs give many local outputs that cause a high false positive recognition rate. In our previous work, we utilized a fixed window majority voter (MV) procedure to
remove local errors [67]. The majority voter used 16 points, approximately 10 seconds, windows to decide whether the observation sequence is related to any of the tasks of interest. Although several time points were used for voting, we noticed that the classifier performed poorly during state transitions. We also noticed that the execution times of the three tasks that being studied were quite different. A fixed window size does not provide flexibility to deal with these differences. To improve performance, we used a sequential classifier that acts as a finite state machine (FSM) as described below. Instead of calculating the posterior probabilities for each feature vector on the GMM outputs, first we evaluate the output probabilities over an 8 point time window with a na"ive Bayesian classifier to smooth the GMM outputs. Specifically, we compute

\[ p_k^N = \prod_{i=1}^{8} p(x_i / \lambda_k), \quad i = 1, 2, ..., 8 \]  

(3-5)

\[ L = \arg \max_k (p_k^N) \quad k = 1, ..., K. \]  

(3-6)

We calculate the posterior probabilities of each na"ive Bayesian classifier and then convert them to discrete symbols \( V \) that are processed by a sequential classifier. We remove observations which have low posterior probability at the input stage of the sequential classifier. Specifically, we use

\[ \text{post}_L^N = \frac{p_L^N \times \Pr_L}{\sum_k p_k^N \times \Pr_k} \]  

(3-7)
\[ V = \begin{cases} L, & \text{if } post^N_k > 0.7 \\ 0, & \text{else} \end{cases} \]  

(3-8)

where \( post^N_k \) is the naïve Bayesian classifier posterior probability of Brush=1, Wash=2, Shave=3 and OAct=4 nodes, \( Pr_L \) is the prior probability of each task and \( V \) is the input labels to the sequential classifier. Equation 3-8 removes outputs with low probabilities that occur at the beginning and end of each task, since these correspond to time intervals where uncertainty is high. This stage also converts the continuous input sequence to discrete labels such as \{B=1, W=2, S=3, OA=4 and no surviving activity-NoAct=0\}. These discrete inputs from the wash, brush, shave and OA nodes are processed by the sequential classifier as indicated in Box 1. The sequential classifier essentially tracks the states by counting the labels in the input sequence and deciding whether the resulting sequence is related to one of the four tasks that we study. If not, it provides a NoActivity (NoAct) output. Note that, rather than using a fixed window size majority voter, the sequential classifier provides a state tracking capability and flexibility in the task specific selection of the processing window size. Since we do not know where the real activity starts and ends, the sequential classifier provides great flexibility and accounts for the temporal variability in the data.

In a similar study, a Hidden Markov model (HMM) based approach has been used for activity modeling [68]. The authors have used a fixed size time window HMM and shifted the window along the signal to get classification outputs. In our study the sequential classifier works without any window size limitation on the observed sequence. The window sizes for a particular activity are adjusted to subject differences by observing the data. In our experimental studies we observed that in most cases the washing activity
takes much less time than the tooth brushing and face shaving activities. Furthermore, many segments of activities may involve similar movement of the arm. For instance, if a subject engages in the face shaving task, we often obtain brush labels in the beginning of the task due to common movement patterns between applying shaving cream to the face and tooth brushing. Both activities include circular hand movements which induces oscillatory components in the accelerometer sensor. A fixed size HMM can miss this when it is run in the beginning of a task. In the transition regions between states, the HMM may then provide several local errors. On the other hand, the sequential detector implements a sequential test. It waits until enough evidence has been collected before making a final decision. When an input is observed it waits until the system classifies the next state which will give further information about what task is/was being executed. For example, if a tooth brushing input is observed, the system waits to see if the next state is putting cream/shaving, in which case it would classify the entire activity as shaving rather than brushing.
**Box-1. Algorithm:** Sequential Classifier Module.

Discrete Input Sequence ($V$):
NNNNWWWBBBBWWWWWWWWWWWWWWWWNNNNN

**Transition Rules:**
- $Bc>8$, Reset($Wc$, $Sc$, $OAc$)
- $Wc>8$, Reset($Bc$, $Sc$, $OAc$)
- $Sc>8$, Reset($Bc$, $Wc$, $OAc$)
- $OAc>8$, Reset($Bc$, $Wc$, $Sc$)

- $Bc>15$, Set($TS=B$)
- $Wc>15$, Set($TS=W$)
- $Sc>15$, Set($TS=N$)
- $OAc>15$, Set($TS=OA$)

**Decision Rules:**
- **Brush Accept:** $Bc>32$ or ($TS=B$ and $Nc>15$)
- **Wash Accept:** $Wc>20$ or ($TS=W$ and $Nc>15$)
- **Shave Accept:** $Sc>20$ or ($TS=S$ and $Nc>15$)
- **OA Accept:** $OAc>15$

$Wc=Wash\ Count$, $Sc=Shave\ Count$, $Bc=Brush\ Count$, $OAc=Other\ Activity\ Count$, $Nc=No\ Surviving\ Activity\ Count$, $TS=Temporary\ State$
3.4 Results

In order to evaluate the performance of the extracted time-domain and frequency-domain features and their combination in classification, we conducted several “leave one subject out” (LOSO) experiments. In particular, we collected data from seven subjects and used the data of one subject for testing and the remaining subjects’ data for training the system. This procedure is repeated for all seven subjects to obtain classification performance and was averaged to obtain overall classification accuracy. The classification results obtained with the LOSO method provides information about the subject generalization capability of the proposed system. Table 3-2 provides classification results for time-domain features, frequency-domain features, and their combination.

The combination of time-domain and frequency-domain features yields better classification performance than using time-domain or frequency-domain features only. This suggests that the acceleration and the arm’s tilt data carry significant information for activity recognition. In addition, the classification performance of the sequential classifier was better than the majority voter approach. The classification results for different number of mixtures are given in Table 3-3 and Table 3-4 for the sequential classifier and majority voter approaches. We noticed that the best classification accuracy is obtained with 2 mixtures for the sequential classifier and with 3 mixtures for the majority voter approach. Increasing the number of mixtures for both approaches decreased the classification accuracy. A higher number of mixtures may result in over learning in the GMM stage. We believe that a low number of mixtures provides smoothness and enhances the correctness of the classifier. The confusion matrix related to the best
mixture indexes for the sequential classifier and majority voter based approaches are
given in Table 3-5 and Table 3-6 respectively.

Table 3-2. Classification Accuracies of different feature sets (%).

<table>
<thead>
<tr>
<th>Features</th>
<th>Brush</th>
<th>Wash</th>
<th>Shave</th>
<th>OAct</th>
</tr>
</thead>
<tbody>
<tr>
<td>TD</td>
<td>83.5</td>
<td>67.8</td>
<td>74.2</td>
<td>95</td>
</tr>
<tr>
<td>FD</td>
<td>96.7</td>
<td>16.6</td>
<td>12.1</td>
<td>97.5</td>
</tr>
<tr>
<td>TD+FD</td>
<td>96.1</td>
<td>93.5</td>
<td>93.5</td>
<td>95</td>
</tr>
</tbody>
</table>

Table 3-3. Classification accuracies (%) obtained from TD+FD combination
with sequential classifier. The NoMix stands for the number of mixtures in GMM.

<table>
<thead>
<tr>
<th>NoMix</th>
<th>Brush</th>
<th>Wash</th>
<th>Shave</th>
<th>OAct</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>95.6</td>
<td>77.4</td>
<td>82.2</td>
<td>97.5</td>
</tr>
<tr>
<td>2</td>
<td>96.1</td>
<td>93.5</td>
<td>93.5</td>
<td>95</td>
</tr>
<tr>
<td>3</td>
<td>95.6</td>
<td>90.5</td>
<td>91.6</td>
<td>95</td>
</tr>
<tr>
<td>4</td>
<td>94.5</td>
<td>88.4</td>
<td>90.6</td>
<td>95</td>
</tr>
<tr>
<td>5</td>
<td>93.4</td>
<td>87.4</td>
<td>88.8</td>
<td>95</td>
</tr>
<tr>
<td>6</td>
<td>92.8</td>
<td>86.9</td>
<td>90.6</td>
<td>95</td>
</tr>
</tbody>
</table>

Table 3-4. Classification Accuracies (%) obtained from TD+FD combination with majority voter post processing. The NoMix stands for the number of mixtures in GMM.

<table>
<thead>
<tr>
<th>NoMix</th>
<th>Brush</th>
<th>Wash</th>
<th>Shave</th>
<th>OAct</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>98.4</td>
<td>79.9</td>
<td>68.2</td>
<td>92.5</td>
</tr>
<tr>
<td>2</td>
<td>96.8</td>
<td>87.9</td>
<td>84.1</td>
<td>90</td>
</tr>
<tr>
<td>3</td>
<td>97.9</td>
<td>87.9</td>
<td>87.9</td>
<td>90</td>
</tr>
<tr>
<td>4</td>
<td>95.1</td>
<td>86.4</td>
<td>85</td>
<td>92.5</td>
</tr>
<tr>
<td>5</td>
<td>95.6</td>
<td>84.4</td>
<td>82.2</td>
<td>92.5</td>
</tr>
<tr>
<td>6</td>
<td>97.3</td>
<td>81.9</td>
<td>81.3</td>
<td>92.5</td>
</tr>
</tbody>
</table>
Table 3-5. The confusion matrix for TD+FD combination and sequential classifier post processing for NoMix=2.

<table>
<thead>
<tr>
<th>Tasks</th>
<th>Brush</th>
<th>Wash</th>
<th>Shave</th>
<th>OAct</th>
</tr>
</thead>
<tbody>
<tr>
<td>Brush</td>
<td>175</td>
<td>1</td>
<td>2</td>
<td>4</td>
</tr>
<tr>
<td>Wash</td>
<td>8</td>
<td>186</td>
<td>1</td>
<td>4</td>
</tr>
<tr>
<td>Shave</td>
<td>5</td>
<td>2</td>
<td>100</td>
<td>0</td>
</tr>
<tr>
<td>NoAct</td>
<td>0</td>
<td>0</td>
<td>2</td>
<td>38</td>
</tr>
</tbody>
</table>

Table 3-6. The confusion matrix for TD+FD combination and MV post processing for NoMix=3.

<table>
<thead>
<tr>
<th>Tasks</th>
<th>Brush</th>
<th>Wash</th>
<th>Shave</th>
<th>OAct</th>
</tr>
</thead>
<tbody>
<tr>
<td>Brush</td>
<td>183</td>
<td>0</td>
<td>4</td>
<td>0</td>
</tr>
<tr>
<td>Wash</td>
<td>11</td>
<td>175</td>
<td>0</td>
<td>12</td>
</tr>
<tr>
<td>Shave</td>
<td>10</td>
<td>2</td>
<td>91</td>
<td>4</td>
</tr>
<tr>
<td>NoAct</td>
<td>0</td>
<td>1</td>
<td>3</td>
<td>36</td>
</tr>
</tbody>
</table>

As mentioned earlier, in our experimental studies we noticed that there is a significant overlap in the feature space between the activities of tooth brushing, putting soap and applying shaving cream to the face. All of these segments include circular hand movements that cause sinusoidal waveforms in the accelerometer. As can be seen from the confusion matrices, the face washing and face shaving activities are mostly classified as brushing in these regions. In particular, putting soap or applying shaving cream is locally recognized as a tooth brushing activity. A representative trial is shown in Figure 3-7. The sequential classifier eliminated many of these false positives by using different time window thresholds. For the brushing activity, a higher brush-count (Bc) is used for final decision.

It should be noted that in our final evaluation of the classification performance face washing outputs preceding and following brush/shave activities are ignored. Most of the time, subjects washed their faces prior to shaving or rinsed after brushing.
Figure 3-7. (a) The Bayesian posterior probabilities of the classifiers during a washing task. (b) The input votes (V) entering the sequential detector. Note that the putting soap section is locally classified as tooth brushing.
Figure 3-7. (c) The Bayesian posterior probabilities related to brush activity and the input votes entering the sequential detector (d). Note that tooth brushing task is followed by a washing activity due to giving rinse. They are ignored in final evaluation.
Note that the OAct decisions are not evaluated as false positives. Such decisions are ignored because it is possible that the subjects can interrupt the main task for a short while. In addition, it takes several seconds for the subjects to start with the main task. For instance, when subjects grab the brush or the shaver, the classifier mostly produced an OAct or NoAct output. Therefore, OAct and NoAct outputs are merged in the final evaluation and are not evaluated as a false positive if they are locally present. As indicated previously, the main purpose of including OAct trials into the dataset is to account for activities where the subjects are not really performing the ADLs that we studied here.

In order to assess the efficiency of the GMM, we replaced it with a linear discriminant classifier (LDC) that models the feature vectors corresponding to each activity as Gaussian vectors with identical covariances and activity dependent means. In this way we could evaluate the recognition accuracy of a discriminative approach working in the lower level of the system. In particular we used a pair-wise classification strategy by constructing several linear discriminant classifiers. Each discriminant classifier discriminates a single task from another. Each feature vector is then processed by the pair-wise linear discriminant classifier bank. Then each time point was stamped with a discrete label by evaluating the linear discriminant classifier outputs. As in the GMM case, the discrete sequence was then fed to a sequential classifier for final decision.

The classification results obtained with the linear discriminant classifier are compared with the GMM approach using one or two mixtures (denoted as GMM-1 and GMM-2 respectively) in Table 3-7. Interestingly, the linear discriminant classifier provided very high recognition accuracy for the face shaving activity and outperformed
the results obtained with a single component GMM while recognizing the tooth brushing, face washing and face shaving activities. However, we noticed that the results obtained with the linear discriminant classifier are worse than the GMM-2 based results. Furthermore, the OAct trials are misclassified as face shaving activity. The results that we obtained thus indicate that the linear discriminant classifier based approach is biased towards the shaving activity.

### 3.5 Limitation and Future Work

During the experimental studies we noticed that some subjects changed their active hand during task execution. For instance, one of our subjects switched his hand during brushing trials. This behavior eliminated the accelerometer observations and the system went to OAct state. When the instrument used to perform the activities that we studied is electric, the measured patterns change. Electric tooth brushes and shavers need to be treated in a different manner. Another possibility is to use tiny modules which

<table>
<thead>
<tr>
<th>Features</th>
<th>Brush</th>
<th>Wash</th>
<th>Shave</th>
<th>OAct</th>
</tr>
</thead>
<tbody>
<tr>
<td>LDC</td>
<td>87.9</td>
<td>88.9</td>
<td>100</td>
<td>75</td>
</tr>
<tr>
<td>GMM-1</td>
<td>95.6</td>
<td>77.4</td>
<td>82.2</td>
<td>97.5</td>
</tr>
<tr>
<td>GMM-2</td>
<td><strong>96.1</strong></td>
<td><strong>93.5</strong></td>
<td><strong>93.5</strong></td>
<td><strong>95</strong></td>
</tr>
</tbody>
</table>

Table 3-7. Classification accuracies (%) of different classifiers

<table>
<thead>
<tr>
<th>Tasks</th>
<th>Brush</th>
<th>Wash</th>
<th>Shave</th>
<th>OAct</th>
</tr>
</thead>
<tbody>
<tr>
<td>Brush</td>
<td>160</td>
<td>5</td>
<td>14</td>
<td>3</td>
</tr>
<tr>
<td>Wash</td>
<td>7</td>
<td>177</td>
<td>11</td>
<td>4</td>
</tr>
<tr>
<td>Shave</td>
<td>0</td>
<td>0</td>
<td>107</td>
<td>0</td>
</tr>
<tr>
<td>NoAct</td>
<td>0</td>
<td>0</td>
<td>10</td>
<td>30</td>
</tr>
</tbody>
</table>

Table 3-8. The confusion matrix for LDC based classification system.
include an accelerometer and a radio attached to the electric shaver or brush. When the electric shaver or brush is turned on, accelerometer data is transmitted to the system.

We also noticed that the face washing of different subjects exhibited two distinct motion patterns. In particular, we observed that one group of subjects were applying soap, drawing water and rinsing the face. The other group of subjects washed their face by simply splashing water onto the face. Although few different patterns were observed within each group, in general, any washing activity involved one of the two patterns mentioned above. We noticed that when the training data was biased to one group, then the classification accuracy corresponding to face washing was much lower compared to when the training data was balanced. This shows that unless similar patterns are present in the training set, the classifier will not be able to correctly classify activities. One solution to overcome this problem is to refine the classifier with a small number of trials from the user or the subject himself. This allows the system to adapt to the unique patterns [32].

Wearable wireless sensors are one of the main components of this system. The continuous monitoring task involves continuous packet exchanges between the computational center and the wearable sensors. It is well known that the power consumption of wireless embedded systems increases while communicating. A straightforward online data transfer can decrease the battery life dramatically. In such a case the wearable system will need frequent maintenance. Therefore, an intelligent and adaptive data collection and communication strategy is necessary. In-home static sensors can be used to decide when and how to collect wearable sensor data. Furthermore, after a
certain period we expect to capture the lifestyle of the person so that the system can then infer from this information adaptive data collection strategies.

3.6 Conclusions

In this chapter, we described the infrastructure of an in-home activity monitoring system based on wearable and fixed wireless sensors. The system is intended to assist people with cognitive impairments due to TBI. In particular, we focused on the problems of detecting early morning bathroom activities of daily living at home. The proposed system uses IEEE 802.11 and IEEE 802.15.4 standard compliant wireless sensor kits. Finally, the data collected from both sensor networks are processed by intelligent algorithms. We showed experimental results from seven subjects engaged in face washing, face shaving and tooth brushing activities. Our results are quite promising. In the next chapter, we discuss the application to stereotypic behaviors and how the technology can be applied to aide people with Autism Spectrum Disorder.
Chapter 4

Characterization and Detection of Stereotypic Behaviors in Children with Autism Spectrum Disorder

This chapter describes a method to automatically detect behavioral patterns of patients with autism. Many stereotypical behavioral patterns hinder their learning ability as a child and patterns such as self-injurious behaviors (SIB) can lead to critical damages or wounds as they tend to repeatedly damage one single location. Custom designed accelerometer based wearable sensor can be placed at various locations of the body to detect stereotypical self-stimulatory behaviors (stereotopy) and self-injurious behaviors of patients with Autism Spectrum Disorder (ASD). A microphone was used to record sounds in order to understand the surrounding environment and video provided ground truth for analysis. Analysis was done on four children diagnosed with ASD who showed repeated self-stimulatory behaviors that involve part of the body such as flapping arms, body rocking and self-injurious behaviors such as punching their face, or hitting their
legs. The goal of this study is to devise novel algorithms to detect these events and open possibility for design of intervention methods. This chapter discusses time domain feature extraction with Higher Order Statistics (HOS) of the data to detect and classify these stereotypic behavioral events. Also, novel event detection using online dictionary update method is discussed. The goal of detecting novel events relies on the fact that the limitation of training data and variability in the possible combination of signals and events also make it very difficult to design a single algorithm to understand all events in natural setting. In addition, ASD children may develop new repetitive behavior as they grow and at times develop injurious behaviors. Therefore, unsupervised method to discover and track novel events in a multidimensional sensor data becomes an important topic in classification and detection problem in children with ASD. This chapter discusses how the HOS features can be used to design dictionaries and to detect novel events in a multichannel time series data.

4.1 Introduction

Autism spectrum disorder is a development disorder that leads to cognitive impairment, including deficiencies in social interaction and communication [42]. The heterogeneity of ASD has been attributed to the structure and misuse of diagnostic systems. The Centers for Disease Control (CDC) show that 1 in 68 births are diagnosed with autism [43]. Autism is becoming the fastest growing (10-17% annual growth) development disability which affects 1 to 1.5 million in U.S. For autism management, it costs over $90 billion annually in the U.S. alone and it is estimated that the cost related to autism will increase to $200-400 billion in 10 years [43].
One is diagnosed with ASD when any combination of several symptoms with certain degree of severity is logged. There are no medical tests to diagnose autism but it is diagnosed based upon the Diagnostic and Statistical Manual of Mental Disorders – Fourth Edition (DSM-IV) and relies on understanding the behavioral patterns. Therefore, treatment or unified care has been very difficult to find, leaving families with wide variety of choices of therapies, treatments that use drugs or dietary programs. Often times, the treatment varies from one doctor to another and families become worn out trying to find what works best for their children. Due to the wide range of categories and uncertainty in the reasons behind autism, there has been no quantitative measure to diagnose and treat autism not to mention the monitoring the progress of the treatment. Symptoms of autism differ between individuals. They may also differ in a single individual over time. Research indicates that early diagnosis and intervention is critical for successful long term management. Therefore, clinicians often try different interventions simultaneously. Families face difficulties because the treatment varies from one therapist to another and families become worn out trying to find a treatment that works best for their children.

Although there is no known cure for autism, many researchers agree that intensive early intervention does improve the conditions of the child. Methods for intervention is not unified nor agreed upon, but, it has been discovered that certain methods of alternate treatments do work for certain children [69]. Although these methods are effective, there are no unbiased measures to quantify the effectiveness of the treatment. Therefore, researchers have adapted available technologies to better understand autism and assist the patients and doctors. It ranges from developing systems to help therapists automate their
paper work process [58] computerized programs to teach the social contexts by allowing interactions with the computer to detecting facial expression of those children to understand their behaviors [24].

Previously, technologies were built around the patient such that others can better interact or reduce burden on therapists or families [58]. But, these results only provide long term solutions or are more focused on assisting the therapists. This study explores methods to meet their immediate needs by detecting behavioral patterns and generating feedback. This feedback can be immediately directed to the user and caregiver to meet urgent needs of the user. It can also be used by both caregivers and patients for developing behavior reversal programs. It may enable them to modify their own behaviors which may interfere with their daily lives and eliminate such behaviors which may interrupt them from concentrating and learning.

Research in automatic detection of behavioral patterns has surfaced only recently. This is mainly due to recent advances of micromechanical devices and embedded systems that triggered the development of countless platforms that can monitor many different aspects of our lives. It also enabled ambulatory monitoring due to the advances in wireless communication protocols such as Bluetooth and devices that support these protocols. Such systems, when appropriately scaled and enhanced can be used for continuous monitoring of the behavioral patterns. Thus wireless wearable sensors were used to monitor their ADL [29, 30, 34, 37]. Researchers at the University of Minnesota have successfully applied a similar technology to develop a system to assist people with cognitive impairments due to Traumatic Brain Injury (TBI) that require intelligent
systems that can assist the person in carrying out their daily activities with intelligent reminders [30, 31, 32, 33] and stereotypies of people with ASD.

Researchers at from Georgia Tech have developed wearable wireless sensors based on accelerometer to detect and monitor the repetitive behavioral patterns. Researchers from Georgia Tech have used the sensor platform to detect 8 common repetitive behavioral patterns from a normal adult who mimicked these behaviors [35]. There also has been an effort to develop systems to detect autistic behaviors using accelerometer which showed promising results but analysis was done on recording from healthy adult subjects and no discussion of real data or explanation were explored. Although, the classification accuracy ranged from 80% - 100%, these patterns were mimicked. Another group has recently explored similar patterns from autistic children and has shown comparable results with our findings. This shows that the community has begun to understand the necessity of a system and methodologies that could be used to assist people with autism. Researchers from Groden Center, RI with researchers at MIT and UMN have independently studied and analyzed data collected from autistic children. Researchers at Groden Center studied from data analyzed for hand flapping and rocking from 6 subjects showed that they were able to achieve 82% - 97% accuracy with average being 91.1% [22, 24, 36].

Despite these efforts, solutions or methods proposed above is intended to educate the child with a long term goal and does not meet their immediate needs for assistance. Since many children with autism lack social cues, they are vulnerable to expressing excitement, anxiety or frustration [82]. Therefore, often in a home, therapy or classroom environment, the parents, teachers and caregivers have to look for cues that could trigger
repetitive or extreme behaviors which include SIB or others. As humans are very well trained detection systems, they can observe certain trends in behaviors to predict what may come. Therefore, in therapy or training sessions, they push the limits or challenge them often causing frustration build up on the children. But, since they can predict the children’s behavior, if they observe over excitement or frustration builds up, they will stop so that they may avoid extreme situations. Therefore, proposed system has added features into the system to be able to detect such frustration and stop such behaviors from happening by intervention methods. This is especially important due to the general public’s lack of understanding the symptoms and behaviors of people with autism. Therefore, by real time intervention using the system, will make lives of people with autism much less difficult and help them control their sudden expressions, socially inappropriate gestures, stereotypic behaviors, vocal stereotypies to make their lives more socially agreeable.

A person who knows or have frequently been in contact with autistic persons can detect their affective states. They observe various modalities such as facial expression [22, 37], vocalization of word or non-word situations, gestures or physiological signs [24, 38, 39]. Researchers have used various sensor platforms to recognize the affect states by analyzing the signals from the sensors. Our research focus will be to automatically detect these modalities and to predict extreme behaviors before they occur, so that an intervention can be made or divert the patient to an activity that may calm him/her down. In order to reach this goal, the detection problem is targeted by proposing a wearable sensor based solution to monitor and track behavioral patterns of autistic patients and a
user feedback is given through the device by vibrating the sensor. The user is then trained to stop the behavior upon receipt of the feedback.

4.2 Minnesota Wearable Accelerometer based Sensor Platform (MinWaSP) Development

In order to visit the patients and meet the needs of data recording, new recording devices and platform as shown in Figure 4-1 was planned and developed using the Bluetooth technology. Bluetooth was chosen so that the platform would be able to interface to laptops and mobile phones. Our custom designed wireless accelerometer sensor with Bluetooth module is able to pick up movement information as they may be worn by users of the system. As shown in Figure 4-2, the sensor system can be worn on
wrist, chest, waist and ankles. The sensor system can also be clipped onto shirts and hats to detect movement of the body or head. Most of the large motor functions can be detected but fine motor skills such as movement or use of fingers and toes cannot be detected. Our wearable sensor system is equipped with a 3-axis accelerometer, microcontroller and Bluetooth module for wireless communication with the base station.

Using the on-board microcontroller, it can sample and quantize the analog accelerometer output at high sampling rate (up to several kHz). Sensor readings are exported from the sensor system to a PC in real time and no data is stored locally on the

Figure 4-2. (a) Data recording system (b) Wearable wireless sensor kit enclosed in a wrist band. (c) Wearable body sensor strapped to upper body.
wearable system. The second system is the audio and video sensors which are microphones and webcams. In this system, sensor readings are exported from the sensor system to a PC in real time. For the behavior detection purposes, it does not require high sampling rate, therefore the accelerometer signal is sampled at 50 Hz rate and transmitted to base station and stored on the PC using the user interface shown in Figure 4-3. Data from wearable sensors alone are not sufficient to understand the behavioral patterns of people with autism. For this reason, MinWaSP has added feature to simultaneously record audio and video recordings at 22kHz and 30fps respectively. The audio sensor, which can detect sounds or vocalization of the subject helps with behavior recognition and video recordings provide ground truth during the initial studies to understand the behavioral patterns so that an intelligent assistive system can be developed.

**Figure 4-3.** MinWaSP data acquisition platform with a user interface that receives sensor data. This interface allows real time tagging of events observed by pressing predefined buttons on the GUI.
To better understand the behaviors of people with repetitive patterns, therapists often use video to understand the context, cause and effect of certain behaviors. But, it is very difficult for them to review and analyze the video recordings due to the time consuming nature of the video analysis procedure. To alleviate this burden, our system allows automatic labeling of the detected events. This will allow the behavior and video clip to be synchronized with respect to time and event. Tagging can be done by anyone and the GUI could be modified to accommodate different behavioral patterns of a patient. Then, doctors and therapists can randomly access only the events they prefer to view reducing the burden of video analysis. The performance of the system depends on how well the system detects the events of interest and if the system has the capability to predict certain events.

4.3. Detection and Classification of Stereotypic Behavioral Patterns

We underwent a University of Minnesota’s Institutional Review Board (IRB) in order to enroll children with ASD to participate in the study. For this particular study, researchers collected 4 types of accelerometer sensor data from 4 autistic children labeled as S1, S2, S3 and S4. Recorded data include several self-stimulatory patterns and many other daily activities. As shown in Figure 4-4, self-stimulatory patterns such as hand flapping (F) and body rocking (R) were observed. Also, several SIB patterns such as punching one’s own face (P) and hitting (H) one’s laps were also observed. S1 showed fast stereotypic flapping with arms raised while S2 showed short durations of jitter like flapping patterns with arms partially raised or lowered. This shows that the system needs
to be flexible in order to be able to tailor to the different behaviors of different patients. Flapping, punching and hitting events were recorded from the wrist worn accelerometers while rocking actions were recorded from the sensor placed on the back using flexible straps. The frequency and speed of the arm movement contribute to different frequency characteristics and associated band powers in the frequency domain while the different

Figure 4-4. Typical recordings obtained from 3 channel (x, y, z axis) sensor. (a) Sample waveform from a body worn sensor. Due to the mechanical coupling of the body, some behaviors can be detected from the body worn accelerometer sensor. From left to right: Rocking, standing, flapping and walking. (b) Hand flapping accelerometer readings from a wrist worn sensor.
position of the arms generate different DC values in the accelerometer data in time domain. Therefore, this is also an important piece of information in understanding and distinguishing different arm positions and involved activities. In following sections, we analyze data recorded from our subjects and compare the detection accuracy.

4.3.1 Subject Description

As mentioned earlier, subjects S1 – S4 showed different repetitive patterns for flapping, which corresponds to studies in the literature. S1 showed fast self-stimulatory repetitive flapping patterns with arms raised while S2 showed short durations of jitter like flapping patterns with arms partially raised or lowered. This showed that system may categorize them as different patterns although both behaviors fell under the name “flapping”. Therefore, the automatic detection system and behavior intervention therapy needed to be flexible in order to be patient specific. This is consistent with studies in the literature [69]. Flapping actions were recorded from the wrist worn accelerometers while rocking actions were recorded from the sensor placed on the back using flexible straps. Data was recorded from both in therapy and in home sessions. The in home session recordings was necessary because, children only engage in a limited number of activities during the therapy sessions and we needed to know if there were any activities that produce similar sensor readings compared to their self-stimulatory behaviors. In most cases, we were able to observe that the self-stimulatory repetitive behavioral patterns were different from their everyday patterns. In this study, we endeavor to detect and distinguish the self-stimulatory patterns from all other daily activities. This allows us to monitor and keep track of number of events and duration of each repetitive behavior.
These quantified results can be used to monitor the progress of behavioral intervention. Activities other than flapping and rocking were labeled as Other Activity (OA).

Four children diagnosed as autistic participated in the study. 3 subjects were male and 1 subject was female. The female was 12 years old while male subjects were 9, 10 and 16. The 16 year old male and the 12 year old female subject lacked verbal communication skills but possessed few sign languages to express their desires. The 9 and 10 year old children possessed verbal skills and could express themselves verbally. But, their verbal skills were delayed and were not quite their own age group. All four children did possess self-stimulated repetitive behaviors from hand flapping, body rocking, vocalization and echololia. But, all four children possessed different frequency of stereotypy and different form of flapping, vocalization or repetitive behavioral patterns. They also showed subject specific patterns such as hitting objects, punching face and banging head on the wall.

4.3.2. Data Description and Experimental Setup

In the previous chapter the experiments were performed in a controlled environment in which subjects were given a queue to perform specific tasks. But, with the ASD patients such experiment was not possible. Therefore, continuous recordings were made for different subjects and part of the data from each subject was used for training while other data was used for testing.

Since the subjects showed flapping, rocking, punching, banging and vocalization, accelerometer based sensors were placed on subject’s wrists and on the back of the upper body to acquire acceleration of wrists, arm and body movements. A microphone was
placed facing toward the subject to detect the vocalized sounds, speech and environment sounds. This data was also annotated by a video recording to provide ground truth of the events that occurred during the time of experiment while the data was being recorded. The sensor system includes wireless transmission module that transmits data to a base station which was connected with a laptop computer to record and analyze the data. More sensor nodes could be placed such as waist, ankles, etc. but only wrists and body sensors data were analyzed for this purpose. Sensors were woven into a wrist band and were worn by the children. Body sensor was placed on the back of the upper body using a strap. Two children did not adapt well to wearing a strap on the body. Therefore, this sensor was placed on the subject by sewing a pouch with Velcro on the vest or a hoodie to be worn by the children.

The accelerometer sensor detects continuous acceleration of the movements. And the on-board ADC digitizes the data with 10 bit resolution and 50Hz sampling rate. It is well known in the research community that 50 Hz is high enough to detect human movements. Also, microphone was used to record sounds and speech produced by the subjects to analyze their behavioral patterns and responses to external stimulus or environmental changes. The acoustic data was recorded at 22 kHz with single channel (mono) 8 bit resolution. The microphone and the webcam was placed along with the laptop to better observe the surroundings and followed the children around if the subject was moving around. At the base station (laptop), data from different sensor platforms are saved after each event so that the audio and accelerometer data could be analyzed to detect events that occur.

Each recording session lasted from 1 – 2 hours and several breaks were given
during the session when children seemed unwilling to wear the wrist sensor or clothes. Data were recorded during their therapies and while they were home. Duration of recordings was balanced between work (study, therapy) and leisure (rest, play). During their therapies, they go through their routine work which can be speech therapies (learning to pronounce short noun and verb words) or physical activities (learning gross and fine motor skills).

4.3.3. Stereotypy Characteristics: Pseudo-Periodicity

In the previous chapter, under the controlled experiment, the classification system was trained from a set of data collected from the subjects. But, due to the fact that the recordings from autism patients is a continuous recording, data must be extracted from the labeled data and training data set needs to be generated from the set of recordings. In this section, a method to extract and set up training data is discussed.

The fundamental characteristics of the stereotypic behavior patterns involve repetition of events. Although behavioral patterns repeat similar to waving of a hand, they may not necessarily be periodic or repeat in a continuous form. That is, an event may occur with seconds, minutes or even hours in between the repeating events. Some event may repeat at a faster pace while other event may repeat slower. The amplitude of a repeating event may differ from time to time. In this chapter, we target to detect and quantify stereotypy and SIB events in a natural setting. The stereotypic patterns exhibit great regularity but are not periodic as in mathematical terms.

A signal $x(t)$ periodic with period $T$ for all $t$, if

$$x(t) = x(t + T).$$ (4-1)
Many researchers have taken this concept to an extent to model the idea of pseudo periodicity, periodic transforms and almost periodicity [70, 71]. It was widely studied in the areas of music periodicity detection [72, 73], in which periodicity, near periodicity was studied for beat detection, music classification and labeling. And, a signal \( y(t) \) may be called pseudo periodic when

\[
y(t) = \alpha x(\beta t + \gamma),
\]

in which \( \alpha, \beta \) and \( \gamma \) represents, scaling, dilation and translation parameters independently. Scale parameters change the amplitude in the signal, dilation parameter stretches or shortens the signal while the translation parameters moves the origination of the signal allowing non-uniform arrangement of the signals. In similar problems found in musical signal processing, \( \beta \) refers to pitch and \( \gamma \) refers to beat respectively. Therefore, the repeating signal \( R(t) \) is a combination of a signal with varying \( \alpha, \beta \) and \( \gamma \) parameters.

\[
R(t) = \sum_i y_i(t) = \sum_i \alpha_i x(\beta_i t + \gamma_i)
\]  \hspace{1cm} (4-3)

In the problem we target to model, the \( \beta \approx 1 \) and \( \gamma \approx T_i \). For detection of the repeating patterns, we do not need to necessarily fit all patterns to above form nor estimate the model parameters [74]. But, find key features from the signal which will be understood by the algorithm and find enough separation so that similar repeating signals can be grouped into clusters or modeled with error less than some threshold for classification purposes. Therefore, we generate templates based on the several samples of repeating signals we observe. First, signals from training data are sampled and then we find \( \alpha, \beta \)
and $\gamma$ parameters from the sampled data. We then vary the parameters by adding a uniformly distributed random noise to generate similar templates with varying factors. These templates are used in the following sections to generate dictionary atoms.

4.3.3.1. Temporal Feature Selection

We are interested in detecting both forms of stereotypy continuously repeating stereotypy and short transient stereotypic behaviors, the accelerometer data is first analyzed in the time domain by segmenting the signals into short duration of segments of 32 samples which is 0.64 second duration with 50Hz sampling rate. We have analyzed window sizes of several lengths (128, 64, 32, 16) and have found window size of 32 to best suit for our purpose for wrist worn sensor in which we may capture both the shorter and longer repeating events (maybe will need to put in supporting results summarized in a table). We have used a smaller window size which is a size of 2 seconds. We believe they have chosen the larger window size due to the fact that they have focused on finding the longer repeating patterns such as flapping and rocking. We chose the shorter window size as it was observed during the data recordings that not all stereotypies are continuously repeating as flapping or rocking. Especially, SIB patterns which may bring more stigma to patients that we also target to detect usually are short transient events, and may not be detected or be masked by other activity that occurs within the longer time window. If the event is longer than the window size, the event will be picked up in several consecutive windowed signals. For the body sensor to detect rocking events, we used a longer window to capture the much slow frequency body rocking patterns. Due to the slow frequency of this motion, we needed a longer window to capture the repeating
rocking motion. Therefore, we used a segment size of 1.28 seconds for rocking. This translates to a window size of 64 which is then shifted along the data with 50% overlap.

We extract statistical features in a sliding window such as its mean, variance and rms. The mean values infer the position or the orientation of the sensor, i.e. position of the arm or body. Variance gives the variability in the 3-axis directional signals captured. rms gives the measure of varying quantity in the windowed data and infers if an event in

**Figure 4-5.** (a) Schematic of the proposed training algorithm using LPC. (b) Schematic of the proposed testing algorithm using LPC.
search is on-going. We also extract zero crossing rates and zero crossing intervals within a segment to obtain periodicity of sign changes in the signal. In order to detect repeating events, we first extract several features from time domains which have shown to provide good distinguishing characteristics for acceleration based sensors. One of the critical information an acceleration based sensor provides is the tilt information of the sensor. Due to the effect of gravity, the DC values of the acceleration sensor changes causing different offset for each axis depending on the tilt of the sensor relative to the ground. This can inform the position of the hand enabling the distinction between hand waving and hand flapping in a subject’s arm motion.

The waveforms are high pass filtered to remove the DC bias. As mentioned before, the DC values and extracted features associated with the windowed data are separately stored. Change in DC value shows the variation of the arm or torso movement. For known events, we randomly select waveforms from training data and design an initial dictionary with waveforms from each category such as flapping, rocking, punching face and hitting/banging using the training data. The basic waveforms from training data $x(t)$ are also stretched and translated using a function shown below, where $\alpha$, $\beta$ and $\gamma$ represent scale, stretch and translation factors;

$$r(t) = \sum \alpha x(\beta t + \gamma).$$  \hspace{1cm} (4-4)

The initial dictionary now consists of basic waveforms and scaled, stretched and translated versions of a basic waveform.
4.3.3.2. Linear Predictive Coding (LPC)

Stereotypical behavioral pattern signals from accelerometer sensors are complex signals, which may be represented by using sinusoidal models with additive noise. Due to their pseudo periodic nature, behavioral signal $x(n)$ can be modeled as below

$$x(n) = \sum_{m=1}^{M} a_m \sin[(n - n_0)\omega_m] + v(n)$$

where, $n_0$ is the event onset time, $M$ is the number of sinusoids, $a_m$ is the amplitude, $\omega_m$ is the frequency component of the signal and $v(n)$ is the additive noise which may represent imperfect movement of the body, movement of the sensor and also quantization noise in the accelerometer sensor. In natural setting, the event waveforms actually appear as a variation of the signal $x(n)$, also due to change in motion frequency. Similar waveform patterns are seen in speech detection and classification applications. We modeled the stereotypic behaviors using the Linear Predictive Coding (LPC) model which is an all-pole Autoregressive (AR) model. This was possible due to the consistency of behavioral patterns observed within a subject and correlation observed in the nature of the behavioral patterns. Using the pole locations obtained from the LPC model allowed us to extract the dominant frequency component in the signal. We have also shown that detection performance of the system using LPC model out performs detection accuracy of other system such as clustering and machine learning type of methods which are widely applied in the literature.

Linear Predictive Coding (LPC) has been very successful especially in the area of speech processing and has also been used in variety of applications [75]. LPC uses a p-th
order linear predictor that predicts current value using the past p samples of data, 
minimum error in the least square sense. Therefore, the coefficients can be found using 
the dictionary atoms. Using the coefficients, we can find estimate of the incoming data, 

\[ e(n) = x(n) - x'(n) \]  

(4-5) 

where, \( e(n) \) is the error between the original signal and LPC predicted signal. Therefore, 
using the pole-zero plane, we are able to observe the locations of the poles. The intuition 
behind this approach is that if the input signal is close to dictionary atom, the error would 
be small and the frequency content would be similar. Also, the match can be found by 
calculation of the cross correlation between the dictionary atom and incoming signal. 

The coefficients can be found using the dictionary atoms. From the polynomial 
and coefficients, we find the roots of the polynomial. The roots give us location of the 
pole which reveals the frequency content in the data. Using the coefficients, we can find 
estimate of the incoming data. We optimize the order of the LPC by finding optimal point 
in which the complexity and performance of the system trades off. We also calculate the 
ergy of the error signal on the 32 sample data. This is calculated over the series of 
windowed sample data. We refer to the LPC coefficients for i-th segment as, 

\[ a_i = \{a(0), a_i(1), a_i(2), a_i(3), a_i(4)\} \]  

(4-6) 

Where \( a(0) = 1 \), and the energy of the i-th segment is calculated as 

\[ E_i = \sum_{n=n_0}^{n_0+31} x^2(n) \]  

(4-7)
Where \( x(n) \) is the high pass filtered signal and \( n_0 \) is the index of the initial sample in the \( i \)-th segment. We then continue to calculate the energy differences between the segments of interest to the reference classes in the dictionary.

\[
D_E(j) = \frac{|E_i - \bar{E}(j)|}{\sigma_E(j)}
\]  

(4-8)

Where \( j = 1, 2, \ldots, k \) represent different class of event.

Similar to previous chapter, the time domain and frequency domain features will be extracted. Time domain features such as mean, standard deviation, smoothed signal mean, standard deviation and number of zero crossings will be analyzed. We, further obtain additional features from the location of the poles by finding the Euclidean distances between the dictionary atoms and segments as shown in below. The angles are calculated from the pole location. Angles represent frequency content in the segment and the angles are sorted in ascending order. The frequency information observed from the location of the poles represent frequency characteristics of an event and it is used as an important feature to classify one event from another.

\[
D_{i_{\text{min}}} = \min |D_j - D_i|
\]  

(4-9)

where, \( j \) represents different class of events from dictionary while \( i \) represents the \( i \)-th segment. \( D_{i_{\text{min}}} \) represents the minimum distance measure between the dictionary atoms and each segment.
Figure 4-6. Pole-zero plot showing the location of the poles. Poles in darker shades (blue) are from actual flapping events in the training set. Poles in lighter shades (red) represent poles from testing data. (a) shows flapping patterns observed for S1 and (b) shows flapping patterns for S2. Note that encircled poles represent lower order poles. (a) Figure of pole locations that were detected as flapping. (b) Figure of pole locations that were rejected as flapping.
Figure 4-7. Pole-zero plot showing the location of the poles. Dominant pole location from the figure show that the similar approximation can be done by using lower order AR model to detect dominant frequency components in the windowed signal. (a) Figure of pole locations using 4 LPC coefficients (b) Figure of pole locations using 8 LPC coefficients
It is well known in filter design, angles and radius of the poles and zeros define characteristics of a filter. Similarly, pole locations as shown in the pole-zero planes show the frequency content in the windowed signal (see Figure 4-6). We use Euclidean distance measure and angle differences to define the proximity of the poles of the dictionary atoms to input signal and determine the signal as candidate of a predefined event. The threshold used for similarity testing was empirically obtained. Also, due to the frequency limitation of arm motions and body motions, pole locations above certain frequency level does imply that events associated with high frequency are unlikely to be associated with repeating stereotypy.

Another important factor is the order of the parameters to accurately model the stereotypic events, as was shown in Equation (4-6). Although, higher the order of the polynomial would better fit the dictionary atoms this would over fit the dictionary atoms and would generate higher error in the residual signals. We have tested the order of the LPC and its associated performance was analyzed on a small set of stereotypic events which is used as the training data for the system and have found out that the LPC of order 4 is the least number of poles that can be used to represent and distinguish stereotypic events analyzed in this study (see Figure 4-7). The pole location and error energy are used to find candidates for stereotypy. This stereotypy candidate is checked for dictionary matching in the following step discussed below.

4.3.3.3. Template Matching and Dictionary Update

From the training data, it showed that using lower order of LPC coefficient is sufficient to model the stereotypic events and to identify the major frequency content within the windowed data. Once the potential candidates are identified, we take into the
consideration the correlation between the dictionary atom and the signal in analysis and perform template matching. Cross correlation is used to obtain a match between the signal and dictionary atom. Although the dictionary atom and signal do not match but if the correlation coefficient is above 0.85, the dictionary is updated by adding this signal into dictionary atom. The threshold 0.85 was empirically obtained by testing on the training data.

4.3.3.4. Data Balancing

Dictionary trained from training data is comprised of flapping, rocking, punching, hitting and other events. Other events dictionary is composed of all non-stereotypy events. Due to the nature of stereotypy, compared to other events, are far less frequent events throughout the course of the day. Therefore, in order to train the dictionary, the input training data had to be balanced, i.e. we use the same number of events from each category for training. But, our analysis with from the testing data (naturally recorded) show that stereotypic events are at approximately 2% of the total data recorded. An interesting fact is that once a flapping is detected from a windowed sample data, the probability of finding another flapping within next 5 seconds was approximately 81%. This shows that once the stereotypic events occur, it continuously occurs with high probability over a limited time.

Our goal of detecting novel events relies on the fact that it is impossible and impractical to design an algorithm to detect every type of events that may occur in natural setting. The limitation of training data and variability in the possible combination of signals and events also make it impossible to design a single algorithm to understand all.

Figure 4-8. Temporal and frequency characteristics of a sample waveform. (a) x and y axis data for the flapping event. (b) x and y axis data for the punching event.
events in natural setting. Therefore, an unsupervised method to discover and track unknown events in a multidimensional sensor data rises as a very important topic in classification and detection problems. In this section, we explain our methods to detect novel events in a multidimensional time series data and combine the proposed supervised learning method by adopting the advantages of both algorithms to increase the classification and detection accuracy. We, compare our results to the supervised methods that we have explained in the previous chapter and show that although unsupervised method do not achieve better performance compared to supervised methods, it can efficient find new events and anomalies in multi-dimensional time series data.

4.4.1 Unsupervised Learning

Unsupervised Learning is highly preferred in many applications such as time series clustering, scene change detection and anomaly detection [76, 77, 78]. It is especially desired in detection of behavioral patterns or Activities of Daily Living and in the areas of wearable sensors and their applications. It attracts researchers due to the dynamics of sensor locations and high variation in the subject dependent actions and variety of activities and motions. Among many different reasons for choosing unsupervised learning, following are few reasons why unsupervised methods are preferred.

First, due to the high variability in activity detection, it is almost impossible to design a system to define and train the system to detect and track the various actions and activities. We have proposed a model in the previous chapter to accurately detect such events but we may only be able to model finite number of events in training stage.
Similarly, the actions of stereotypy and SIB have variability but are still quite consistent within a subject compared to inter subject while there is a great variability among subjects. Also, within a subject, one stereotypy may disappear but another stereotypy or SIB may develop, with an intervention or therapy. Therefore, it is critical for behavior detection and monitoring system to have the capability of unsupervised learning of the data to detect novel events.

Second, assuming that one can generate all models priori, we still need a specialist such as medical experts or therapists to interpret each and every activity. This may be done on site which may be impossible as not all actions may be seen in a finite time. Interpretation may be done by watching a video recording which may be very costly that requires hours and days of video to put meanings to actions in priori. But, with unsupervised learning methods, similar actions can be grouped and interpretations become much easier and less costly in terms of time, resource and labor.

Third, as we will show in this section, in most cases, supervised learning outperforms the unsupervised learning methods due to the fact the system has the prior knowledge about the event that the system is detecting or classifying. Therefore, intelligently fusing both methods can maximize the detection rate by combining the advantages of both methods.

More importantly, during the behavior reversal therapy, therapists often succeed in modifying undesired behaviors but some patients start to develop new repetitive behaviors which seem to replace the existing behaviors. But, in general, the community agrees that behaviors can be modified and if new patterns are detected and treated at an early stage, behavior reversal can be done. Therefore, it becomes our objective to detect
novel behaviors before it becomes a repetitive behavior.

Due to such advantages of unsupervised learning, we integrate this concept into our methods of LPC modeling that we have studied in the previous section. It is explored in this section and applied to multi-dimensional and multi-channel data for novel event detection.

4.4.1.1 Statistical Unsupervised Learning

The statistical learning approaches use models that is generated by the statistical properties found from the training data that is used to define the characteristics of the data. Similarly, statistical unsupervised learning also relies on the statistical properties of the data in testing. It finds characteristics that are not found in the training data or characteristics it had not observed previously. The performance of this method of learning depends on how well it minimizes the false detection of known events while maximizing the detection of novel events.

In the statistical method, the model uses distribution of a density function to recognize the classification to a known class of events. The threshold is applied to the probably estimate to decide as a known event or not. Other approaches are based on the distance measure from the distribution mean which is also thresholded to decide if it belongs to a known event. The distribution itself could be in feature space which is used for classification as was discussed above.

During the behavior reversal therapy, we often succeed in modifying undesired behaviors but some patients start to develop new repetitive behaviors which seem to replace the existing behaviors. But, in general, the community agrees that behaviors can
be modified and if new patterns are detected and treated at an early stage, behavior reversal can be done. Therefore, it is our objective to detect novel behaviors before it becomes a repetitive behavior.

We take the approach to novel event detection which learns the density function from the data observed [79, 80, 81]. We therefore keep simple time domain statistics such as mean, variance, energy, number of zero-crossings to track incoming signal for repetition of any event. And, by generating the histogram and observing histogram changes, we may update the dictionary.

Also, the system must be able to distinguish between stereotypical events and SIB. SIB requires much more attention compared to stereotypy due to its nature. It may significantly injure the subject that may involve brain damage or self-inflicted wounds. Therefore, SIB related events must be updated to the dictionary at an early stage, so that, the system can trigger alerts. SIB events are characterized with high signal energy. The injury occurs due to the impact of the fist/hand or foot to the body. The fact that the amount of energy delivered at the time of the impact is much higher than those of stereotypy. The dictionary is designed by normalizing the incoming waveforms which are then quantized in a linear scale. The resulting output is the optimized waveform which represents the location of zero crossings of the incoming signal and also represents the global view of the signal change characteristics in a much simpler domain.

**4.4.2. Novel Event Detection**

In this study, we present additional work on dictionary design methods utilizing HOS features in an unsupervised classification method which is discussed in the
following subsections. We also discuss methods to optimize the dictionary and faster searching strategy.

### 4.4.2.1. Higher Order Statistical Features

Many time domain features such as mean, variance and zero-crossing rate have been used in many classification applications. Other features such as energy or log energy have widely been used in speech detection applications as well [83]. Higher Order Statistics have also found its application in number of signal processing applications. Especially in speech processing applications, it has found wide attention [84].

In this study, in addition to mean and variance, we have utilized skewness and kurtosis of the frequency distribution in the analysis of a data segment. Skewness \( s(n) \) describes the asymmetry of the distribution about the sample mean \( \mu \) and is defined as follows,

\[
s(n) = \frac{E(x - \mu)^3}{\sigma^3}
\]  

(4-10)

Skewness is the 3\(^{rd}\) moment about the mean. And, skewness along with mode and mean shows us how the distribution is biased within a given data. The positive skewness represents a distribution is spread out to the right of the mean, while negative number represents the distribution is spread to the left of the mean.

Kurtosis \( k(n) \) describes the peakedness of a distribution about the sample mean \( \mu \) and is defined as follows,

\[
k(n) = \frac{E(x - \mu)^4}{\sigma^4}
\]  

(4-11)
Kurtosis is the 4th moment in statistics and finds the peakness of the distribution. The higher the kurtosis, more of the variance is the result of infrequent extreme deviations. For each 32 sample segment data with 50% overlap, we perform 128 sample FFT to obtain frequency distribution, from which we obtain frequency content of a data segment. Therefore, repeating events or signal with periodicity will produce a different skewness and kurtosis values compared to those signals that do not repeat. This information along with LPC model described below is used to generate dictionaries for event detection.

4.4.2.2. Novel Event Detection and Dictionary Update

In previous sections, we described our approach to dictionary generation and event detection using supervised method by utilizing HOS features and clustering similar segment data to generate dictionary atoms for event detection. Although the actions of stereotypy and SIB are quite consistent within a subject for using supervised learning approaches to model and detection of events, there is a great variability among different subjects. Also, studies show that even within a subject, with intervention therapy, one stereotypy may disappear but another stereotypy or SIB may develop. Therefore, it is critical for behavior detection and monitoring system to be equipped with the capability to learn new events from the data to detect novel patterns. Our approach is a semi-supervised method in which we initially learn from part of training data to generate models for few known events then use the other training data to learn new events in an unsupervised method using the HOS and LPC.

In our previous study, we took the non-parametric approach to novel event detection which learns the density function from the data observed. System analyzed and
stored simple time domain statistics such as mean, variance, energy, number of zero-crossings to track incoming signal for repetition of any event. And, by generating the histogram and observing histogram changes, to detect novel events and updated the dictionary to detect when it occurred again.

In this study, we have taken the parametric approach as the events can be modeled using the Gaussian model along with the HOS features to generate labels for novel event

**Figure 4-9.** (a) Schematic of the proposed training algorithm using HOS and LPC. (b) Schematic of the proposed testing algorithm using HOS and LPC.
detection. System generates and adds a new Gaussian mixture when a novel event occur over 20 instances. We add additional cost function to an event with high energy as such events are likely to be self-injurious behaviors (SIB). Such behaviors may expose patients to brain damages or self-inflicted wounds. Therefore, SIB related events must be updated to the dictionary at an early stage, so that, the system can trigger alerts as the injury occurs due to the impact of the fist/hand or foot to the body.

### 4.4.2.3 Dictionary Alignment and Optimization by Pruning

Part of variability in the dictionary atoms and detection performance comes from the fact that the data segment and dictionary atoms are not aligned. This is due to the fact that the length and start of the event is different. For example, we do not know when the flapping event begins or the duration of this event. Therefore, we design the dictionary by aligning the data so that the beginning of the data is a non-zero element. One method of aligning the data is using the resampling techniques and selecting the samples to generate a dictionary. But, in this study, we use the features we found in the first stage of the algorithm, which turns out to be as effective as the resampling technique. If the features such as variance and energy are greater than a threshold which we found from the analysis of the training data, we shift the window by 2 to find a zero-crossing location with a sign change. We then search for the nearest positive or negative peak. Thus both the dictionary atom and the signal are now aligned at a peak. This guarantees us that the dictionary atom and windowed signals both starts with certain characteristics reducing the variability allowing faster detection of the dictionary matching process.

For the events in this study, we do not update the dictionary when the signal and dictionary atoms have correlation coefficient greater than 0.9. And, also keep history of
number of times a dictionary atom has been accessed. Based on the distribution of the number of hits, we prune dictionary atoms with small frequency of hits. We may then dynamically set optimal dictionary size for different events.

As part of the optimization process, we do not allow the dictionary to continuously grow with the incoming of new data. For the events in this study, we do not update the dictionary when the signal and dictionary atoms have correlation coefficient greater than 0.9. And, also keep history of number of times a dictionary atom has been accessed. Based on the distribution of the number of hits, we prune dictionary atoms with small frequency of hits. We may then dynamically set optimal dictionary size for different events.

4.5. Results

The extracted features and proposed method showed a good separation in feature and has great potential for continuous detection of the location and duration of the self-stimulatory behaviors. We have recorded over 60 hours of annotated data from 4 children with autism with flapping and rocking events, from subjects S1, S2, S3 and S4. From the analysis of this data we were able to detect the self-stimulatory patterns with the accuracy shown in Table 4-1. Authors in [85] have reported activity classification accuracy of 73 - 100% depending on the activity. Especially for hand flapping and body rocking, they reported 80% and 100% respectively. Although our data is from real patients, we were able to obtain comparable performance to their findings.

Also note that the focus on minimizing the False Negatives (FNs) while maximizing the True Positives (TPs) so that SIBs are not missed as it is more important
to reduce false negatives then reducing false positives. On the average, we are able to
detect the self-stimulatory patterns with the average of 92.7%.

4.5.1 Processing Wrist Sensor

As mentioned in the previous section, we used Linear Predictive Coding and
template matching to train the wearable accelerometer data. LPC models the waveforms
and using the features extracted, we can assign activity labels depending on the model
parameters, pole locations and templates matching which were created for each activity.
Signals may show similar oscillatory patterns, but, the frequency content and different
DC levels from respective channels were good discriminating factors to classify 4
different stereotypic patterns. We then observed the classifier outputs to determine if a
repeating pattern was correctly detected by the classifier.

In order to detect hand flapping events, sensors were worn on the wrists of autistic
patients. Flapping events produced high frequencies along the y-axis while the other axis
data showed considerably less information. This information was distinctive from other
daily patterns shown by the subject. Randomly selected events from labeled training set
were used to generate separate dictionaries for flapping, punching, hitting events
Another training set which includes data from other daily activities were used to generate
one other-activities dictionary. All event and non-event data were processed by
generating a series of segments which used window sample size of 32 with 50% overlap.

When larger windows were used, we missed instances such as single flapping or
single rocking due to short duration of the events. But, the proposed method is able to
detect such instances. This is partially due to use of smaller window for analysis but also
taking the characteristics of the stereotypy events into the detection and monitoring system rather than blindly applying various machine learning approaches [38, 48, 53]. Using the short window would also naturally increase the false positives but prediction with LPC and template matching allows those false positives to be minimized compared to our previous study. The system then observes the sequence of these labels to decide whether the observed pattern was flapping or not. Same strategy is used to detect rocking.

4.5.2 Body Sensor Data Analysis

In order to detect rocking events and body motions, the sensor system was worn on the back of autistic patients using an elastic strap. Similar to the wrist sensor case, we extracted same features such as mean, variance and zero crossing rates. We did not use time domain features because of the posture of the body. The body position during the day was mostly in the upright position. Due to this, combining the time domain features such as mean value did not add any discrimination factors to the detection of events. We discovered that the body sensor tightly attached to the back can also be used to record flapping events. This is possible because the arms are coupled with the back via the shoulder and certain arm motions are directly propagated to the back where the sensor picks up related motion. But, these signals are absorbed by the body and these signals have lower amplitude compared to those detected by the wrist sensors.

Similar to the above case, we generated 2 dictionaries from rocking and non-rocking training set. For the body worn sensor, we used a longer 128 sample window with a 256-pt DFT due to the slow rocking nature of the movement. We then used the same approach as above, to classify the observed patterns as rocking or non-rocking.
Table 4-1. Classification results for flapping, rocking, punching and hitting using proposed unsupervised novel event detection method.

<table>
<thead>
<tr>
<th></th>
<th>flapping</th>
<th>rocking</th>
<th>punching</th>
<th>hitting</th>
</tr>
</thead>
<tbody>
<tr>
<td>Subject 1</td>
<td>92%</td>
<td>95%</td>
<td>NA</td>
<td>NA</td>
</tr>
<tr>
<td>Subject 2</td>
<td>88%</td>
<td>96%</td>
<td>NA</td>
<td>NA</td>
</tr>
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<td>96%</td>
<td>NA</td>
<td>96%</td>
<td>NA</td>
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<tr>
<td>Subject 4</td>
<td>89%</td>
<td>NA</td>
<td>NA</td>
<td>95%</td>
</tr>
</tbody>
</table>

Table 4-2. Classification results for flapping, rocking, punching and hitting using LPC based template matching method.

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<thead>
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<tbody>
<tr>
<td>Subject 1</td>
<td>94%</td>
<td>95%</td>
<td>NA</td>
<td>NA</td>
</tr>
<tr>
<td>Subject 2</td>
<td>89%</td>
<td>96%</td>
<td>NA</td>
<td>NA</td>
</tr>
<tr>
<td>Subject 3</td>
<td>96%</td>
<td>NA</td>
<td>96%</td>
<td>NA</td>
</tr>
<tr>
<td>Subject 4</td>
<td>92%</td>
<td>NA</td>
<td>NA</td>
<td>95%</td>
</tr>
</tbody>
</table>

Table 4-3. Classification results for flapping, rocking, punching and hitting using ISI based clustering method.

<table>
<thead>
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<th></th>
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<th>punching</th>
<th>hitting</th>
</tr>
</thead>
<tbody>
<tr>
<td>Subject 1</td>
<td>89%</td>
<td>95%</td>
<td>NA</td>
<td>NA</td>
</tr>
<tr>
<td>Subject 2</td>
<td>78%</td>
<td>96%</td>
<td>NA</td>
<td>NA</td>
</tr>
<tr>
<td>Subject 3</td>
<td>84%</td>
<td>NA</td>
<td>96%</td>
<td>NA</td>
</tr>
<tr>
<td>Subject 4</td>
<td>83%</td>
<td>NA</td>
<td>NA</td>
<td>95%</td>
</tr>
</tbody>
</table>

Table 4-4. Classification results for flapping, rocking, punching and hitting using K-SVD based learning method.

<table>
<thead>
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<th>rocking</th>
<th>punching</th>
<th>hitting</th>
</tr>
</thead>
<tbody>
<tr>
<td>Subject 1</td>
<td>89%</td>
<td>95%</td>
<td>NA</td>
<td>NA</td>
</tr>
<tr>
<td>Subject 2</td>
<td>79%</td>
<td>96%</td>
<td>NA</td>
<td>NA</td>
</tr>
<tr>
<td>Subject 3</td>
<td>85%</td>
<td>NA</td>
<td>96%</td>
<td>NA</td>
</tr>
<tr>
<td>Subject 4</td>
<td>83%</td>
<td>NA</td>
<td>NA</td>
<td>95%</td>
</tr>
</tbody>
</table>

Table 4-5. Classification results for flapping, rocking, punching and hitting using GMM based learning method.

<table>
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<td>86%</td>
<td>92%</td>
<td>NA</td>
<td>NA</td>
</tr>
<tr>
<td>Subject 2</td>
<td>84%</td>
<td>91%</td>
<td>NA</td>
<td>NA</td>
</tr>
<tr>
<td>Subject 3</td>
<td>NA</td>
<td>NA</td>
<td>96%</td>
<td>NA</td>
</tr>
<tr>
<td>Subject 4</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>95%</td>
</tr>
</tbody>
</table>
We have compared the performance of the proposed method to several different approaches commonly found in the literature. We also show comparison results from studies done using different methods. Due to the difference in dataset exact comparison with other research group is difficult but we can see from the tables above that results are slightly better than the recent studies in the literature where the results vary from 82% - 97% accuracy with average being 91.1%.

4.5.3 Audio Sensor Data Analysis

Another class of stereotypy observed in children with Autism is vocal stereotypy. One form of vocal stereotypy is known as echolalia which is observed in children that are vocal. These children can express themselves in words but may lack appropriate age level speech skills. These children have tendency to repeat words or sentences which may hinder their learning abilities. But, we are more interested in another form of vocal stereotypy often observed in children with Autism. This is especially seen in children that are non-verbal who are not able to express their thoughts in words. This is important as it serves as an indicator for children’s frustration build up that may sometimes evolve into problem behaviors such as SIB or tantrum.

As the LPC was initially used to detect vocal sounds and many applications, it fits very well for this purpose. Vocal stereotypy is detected in the same procedure as the accelerometer signal. The characteristics of the vocal stereotypy can be defined as a similar sounds being repeatedly made by the patient. The characteristics of these sounds are different from speech but are closer to uttering and screaming with represents their frustration.
For vocal stereotypy detection, 22KHz sampling rate was used for voice/sound recording. Due to the high sampling frequency, we used a sample window size of 4096 with 2205 sample shift (approx. 50% overlap), which corresponds to 0.1 second shifts. We extend the feature set with energies for acoustic signals. Acoustic data recorded from microphone was also analyzed to extract features. The audio recordings were recorded at 22kHz rate. Since the audio data is recorded at much higher rate compared to accelerometer data, we processed them independently. But, since the data recorded at constant rate, the features from accelerometer data and acoustics data can be synchronized for processing. We observed that in all subjects, as the stress levels increased for each individual, they exhibited different behaviors and vocalization of non-word sounds. We thus trained 2 different dictionaries to differentiate between

**Figure 4-10.** Acoustic features differentiating the vocalization and noise. Encircled areas denote locations which vocalized stereotypic behaviors.
vocalization (source) and non-vocalization sounds (noise) which include speech and other sounds from the surrounding environment. We extracted source and noise manually from the recorded data and generated separate dictionaries for source (\(D_{src}\)) and noise (\(D_{noise}\)). Both the source data and noise data were segmented with \(N=512\) samples of segment size with 50% overlap. The window used was a Hanning window and an \(N\)-point DFT was used. For each source K-SVD algorithm was used [86]. Our dictionary consists of coefficient matrix created from the algorithm and two dictionaries are concatenated. First \(m\) elements are noise atoms and next \(n\) elements are source atoms. We then use Orthogonal Matching Pursuit (OMP) algorithm that sequentially selects the best matching dictionary atoms [87]. The resulting dictionary had the size of vectors 4879 for \(Nx1\) dictionary and 1402 \(Nx1\) dictionary.

### 4.6. Limitations and Future Work

#### 4.6.1 Limitations

We have found that when sensors are placed in the right location, using one sensor on the subject’s upper back can be used to detect flapping information as well. As can be seen in Table 4-6, flapping detection rate for both S1 and S2 decreased 6% compared to that of the wrist sensor. But, when flapping was detected from the body sensor, we noticed the reduction in false positives. This is due to the sensor location which caused the signal to be attenuated across the body. Thus, reducing many hand related movements causing FPs. Using the single body sensor, we were able to observe 5FPs and 15FPs for flapping respectively and no FPs for rocking events. Our system currently misses instances such as single flapping or single rocking due to short duration
of the events. It is difficult to decide if it is a behavioral pattern of an autistic child or just a random action that is also observed in normal children but we expect to achieve higher detection rate as we begin to better understand the uncertainty in the behavioral patterns and study the events before and after the behavioral pattern.

4.6.2 Prediction of Problem Behavior

We further analyzed the data and found correlation between the stereotypy and problem behaviors. In many cases, intensified behavioral stereotypy which we believe is frustration often times led to shouting or a tantrum. Therefore, if we can detect the signs of frustration build up, we may be able to divert the attention of a child or meet child’s request before the tantrum occurs. This is done by tracking the intensity of the vocalization at the detection of each event. The energy and duration of the vocalization is tracked such that when the frequency and intensity goes above a threshold, the system acknowledges it as a potential problem and can generate an alarm. This allows the children to learn to control their behavior with the assistance from the system. This could be very useful in a classroom environment.

![Figure 4-11](image_url)

**Figure 4-11.** Sensor readings showing arm movement prior to a tantrum
Chapter 5

Applications to Smart Clothing and Posture Detection

Wearable body sensing is critical to many personal sensing applications including Human-Computer Interface (HCI) applications and ambulatory medical applications for smart personal illness management. Over the past 10 years, much progress has been made in the development of personal devices and sensor systems that allow long term personal monitoring. But, due to the invasiveness of these devices and sensors, truly pervasive use has been resisted by users. Therefore, researchers have looked into integrating sensors into everyday clothing to improve their wearability and allow long term monitoring. Possibilities have arisen especially from the sports and sports clothing industries to measure signals such as step frequency and heart rate. But, these applications are a simple, requiring minimal sensing, and are wearable only in the attachment of discrete hardware sensor modules onto clothes. Researchers such as Dunne and her group have integrated the sensors into textile and garment structures, to expand the potential for body sensing
and to improve wearability. This approach allows many sensors to be distributed over the body surface, improving the specificity of activities sensed. However, garment-integrated sensing presents a more difficult challenge for activity recognition due to the error introduced into sensor data by movements of the clothing.

5. 1 Introduction

Wearable sensing via e-textiles and fabric has been an increasingly popular topic for research in the pervasive computing community. It has a wide range of applications from biomedical sensing to Human-Computer Interaction. With the increasing popularity of garment-integrated sensing, “second-skin” or skin-tight garments have become very popular especially in the sports industry. Skin-tight clothes allow a closer contact with the body compared to looser clothing, which generally increases the accuracy of garment-integrated sensors. But, there is a trade-off to this type of clothing as it does not seem to be popular to all consumers for every-day wear. It is unfortunate that the characteristics that promote comfort and ease of use are usually opposite to the characteristics that promote accuracy of the worn sensor. This fact is one of the most significant obstacles in promoting the wide adoption of wearable sensor systems. A good balance between social acceptance in the sensing garment, improved wearability for long term wear and garments that produce high quality data must be achieved.

Therefore, in this chapter, sensor characterization and error analysis to reinforce garment based sensing is done specifically for looser-fitting and stretchy garments. Garment based sensing is a logical platform for detecting body postures and for monitoring physiological parameters such as breathing [88, 89], body functions that can
be detected and measured through changes in surface dimensions or geometry. Other parameters such as heart rate monitoring, affect or emotion monitoring via electro-dermal sensors require tight direct contact with the skin and are not of the scope in this research. The tighter the clothes, the easier it is to sense applications which are reflected through dimension changes in the clothing. Skin tight garments conform tightly to the body, enabling higher resolution of stretch or bend signals. For this reason, our research began with integration of sensors into a skin tight garment to measure movement of the body. We then extend the study to loose garments to characterize and detect postures.

5.2 Background on Stretch Sensing

There are several different types of sensing methods for detecting stretch that are integrated into fabric. In one approach, stretch sensing is measured through piezo-electric sensors integrated into the garments [90, 91, 92, 93, 94] that respond with change in resistance to stretch or bending of the fabric.

Another approach uses the looped conductor approach. This method uses a looped conductor of R Ohms per unit length, in which the loops of the conductor pass in and out of contact as the garment is stretched or relaxed. Typically, when loops are in contact, the electrical length is shorted causing the resistance value to decrease, while when the loops are opened, the length increases and the resistance increases (see Figure 5-1). But, note that depending on the structure of the loop, stretch can either bring the loop into or out of contact causing the resistance to decrease with the stretch. The looped conductor approach has been implemented in many different applications [94, 95, 96, 97, 98, 99], in which the loops are formed by knitting, and are either closed or opened with the
Figure 5-1. Loop conductor. (a) relaxed position (b) stretched position (c) delta-Y configuration [94]

stretch to the knitted structure. An alternative approach is to create loops through stitching using machine stitches that already use looped threads to form the stitch.

Stitched stretch sensors have the flexibility to be stitched onto textile or garment surface at any location, even to a fully fabricated garment. Depending on the application, they can be customized at-will. They also have an added benefit of using common commercial fabrication equipment, which requires minimum changes to existing process and technology.
Figure 5-2. Coverstitch structure [94]

Figure 5-3. Coverstitch applied to stretch pants. (a) on the hip with reflective markers (b) stretch pants on the mannequin
The stitch used for the construction of the sensor used here is made using a Juki MF-7723, a high speed, flat-bed coverstitch machine. It produces a standard industrial two-needle coverstitch with top and bottom cover. It uses two needle-threads with a bottom looper thread and top looper thread, and forms a two-thread lockstitch. The stitch structure is illustrated in Figure 5-2 and shown in Figure 5-3. This type of stitch is commonly used in seaming and finishing knit garments. In order to form a stretch sensor, the bottom cover thread is replaced with a conductive yarn with a measurable resistance per unit length.

In the following sections, our approach to modeling the sensor output using a motion capture system in parallel, in which the sensor output is modeled by solving a curve fitting problem in least squares sense is described in more detail. Finally, the stretch sensor was integrated to a personal protective wear called coverall and sensor application for lifting posture detection is evaluated.

5.3 Experiment Setup and System Validation

5.3.1 Experiment Setup

Following the procedure in [100, 101, 102], Shieldex conductive silver-plated Nylon yarn with a measured resistance of 0.81 ohms/cm was used to create the sensors using an industrial flat-bed coverstitch sewing machine. This yarn was stitched to a fabric consisting of 82% polyester and 18% Lycra. The sensors were stretched and tested to characterize the resistance response when stitched to a fabric. Researchers have previously characterized the stitch sensors on cotton denim and lycra-blend fabrics [100,
In the experiment presented in this chapter, bottom-thread cover stitched stretch sensors stitched to the knee and hip were evaluated using a VICON Motion Capture System to test their validity and to correlate the amount of stretch as measured by the garment-integrated sensors to the joint movement angles.

An electronic running mannequin (Cyberquins, UK) was used to repeat a running motion while wearing the sensor stitched skin tight pants. A VICON IR motion capture system (VICON Nexus with Bonita Optical family of cameras) with retro-reflective markers was used to capture the running mannequin’s motion. 6 video cameras were used to model the running motion of the mannequin wearing only its base garment (a skin-tight Lycra bodysuit) and joint angles were estimated. VICON-generated angles were used as references to map the amount of stretch as measured by garment-integrated sensors to angle variations. A digital multimeter (DMM, BK Precision, 2831E) was directly connected to the stitched sensors to record the sensors’ resistance response. Similar to motion capture systems widely used in the movie and gaming industry, reflective markers were carefully placed on the body segments to create a line through the thigh and another line through the shin. VICON outputs XYZ coordinates of each marker and calculates the position of the markers in 3D space. We can then select the markers in the 3D space to create lines and calculate the angles between 2 lines. This process is performed for both the knee and the hip generating knee and hip reference models for the stitched sensors.

The repeating motion of the mannequin generates a periodic gait cycle over time which is represented as a periodic waveform in a 3D space. Marker traces were aligned by using reference markers at the waist (Marker 0) and the heel (Marker 1). Marker 0
Figure 5-4. Animatronic Mannequin with stitched sensors. Resistance variation recorded via direction connection to DMM. (a) shows the location of the sensors for the knee and the hip (b) shows the multiple sensor placement to determine the sensor with maximum stretch.

serves as the global reference due to its location. This marker is the only static marker on the mannequin, for which spatial position does not change with respect to time (this marker filters vertical bounce in the mannequin, caused by its suspension from a bar at the right waist.) Marker 1 serves as the dynamic reference marker, which is never occluded from the camera’s view and is used to align gait cycles. Therefore, along with Marker 0, other markers use this marker as a reference point in 3D space. On the stretch pants, an array of 7 sensors, 6 inches long were stitched to the front of the knee and array of 9 sensors, 10 inches long, ½ inch apart were stitched to the hip area. In order to analyze the larger hip area, longer and more sensors were stitched to the hip.
5.3.2. Results

Unlike the sensors which achieve tight coupling to the body with straps, adhesives or a skin-tight garment, loose forms of clothing cannot achieve similar mechanical coupling. Poor mechanical coupling results in movement or slippage of the sensor which may generate inconsistency in the sensor signal. Therefore, in this section, following the study of error analysis on denim jeans different types errors of the positioning, drift and donning/doffing error is described [100, 101, 102]. In order to deal with such issues, redundant sensors have been explored as a means to improve accuracy in a noisy sensors configuration [100]. With the analysis described in section 5.3.2, sensor selection was done from the array of sensors (see Figure 5-3) was used to select a single sensor which generated the maximum response.

5.3.2.1. Movement Error

Dunne et al. have performed error tests to explore how much and in what way the garment moves relative to the body during body movement [101]. In their study, movement error was detected by identifying the difference in 3D spatial position between the sensor and a corresponding body location. Movement error analysis on the mannequin’s base body suit was performed and a heat map was generated. They showed that depending on the location of the body it moved between 1 mm to 8mm (see Figure 5-5), with the maximum movement occurring at the mannequin’s shoulder and hip [101].

More loosely-fitted pants, i.e. jeans, were also studied. Studies showed that movement of 15 – 111mm were observed (see Figure 5-6). Similar to the skin-tight body suit, maximum movement error occurred at the hip area. [101].
Figure 5-5: Heat map representing the movement of the skin-tight suit (in mm) [101]

Figure 5-6: Heat map representing the movement of the jeans (movement in mm) [101]
For this study with the stretch pants which is worn over the skin-tight body suit, above mentioned values act as lower and upper bound for the garment movement. Therefore, it was decided that the sensors stitched to the stretch pants should not be more than 0.5 inch (11 mm) apart to capture the effects of the movement of the stretch pants (see Figure 5-3). Sensors were labeled from 1 to 9 from left to right. In the figures below, sensor responses from Figure 5-3 are shown in Figure 5-7. Figure 5-7 (a) is from sensor 1, (b) is from sensor 5, (c) is from sensor 9, and (d) corresponds to recordings from sensor 7. Using this information, the sensor with optimal response (sensor 5) was selected from the sensor array configuration to model sensor response discussed in the following sections.
Figure 5-7: (a) recording from sensor 1 in Figure 5-3(a). (d) recordings from sensor 5 in Figure 5-3(a). (c) recordings from sensor 9 in Figure 5-3(a). (d) recordings from sensor 7 in Figure 5-3(a).
Figure 5-7 Cont’d: Shortest sensor in (d) gives minimum response. According to the figure, sensor 9 in (c) shows largest response but this is due to the folding of the sensor where the sensor lower half of the sensor touches itself causing the overall resistance to decrease during the recovery stage of the leg movement.
5.3.2.2. Drift Error

An interesting observation was the notion of an error, which is called, drift error [102]. Once the mannequin begins to run, the sensor readings show a drift in values. This error reflects the movement of the pants as well as the stitched sensors as they settle and conform to the body and the movement of the mannequin. It also shows that the pants are slowly pulled down with movement due to gravity and friction with the body. Drift error decreases and settles in several cycles with the increase of the experiment runs as the pants settle in. In a study, error analysis was performed on trousers made from different denim fabrics, evaluating movement in different body locations [102]. They showed that the average drift of different fabrics was between 0.8 mm to 4.6 mm. It was also noted that between the different markers placed on the pants, the displacement ranged from 0.8 mm to 20 mm.

Drift error on the stretch pants was less severe as it stays closer to the body. A lighter and flexible fabric is more likely to buckle and may be less likely to maintain a consistent garment shape, quickly conforming and settling down on the body. Also, due to the lycra content and loosely fit lighter fabric, the drift is not as significant as the jeans in the previous study. It was shown that the loose clothing showed less drift error and stabilizes after 2 or 3 gait cycles. Loose garments created less friction between the body and therefore would cause smaller drift error.
5.3.2.3 Donning / Doffing Error

In this section, we present the effect of variability of sensor positioning error due to donning and doffing to evaluate the sensor accuracy of a garment integrated stretch sensor used to measure joint angle of the knee and hip. Donning and doffing produces different location of the sensors. In this study, 5 consecutive trials of donning and doffing were tested. For each trial, 10 consecutive running gait cycles were recorded with VICON. Resistance change was also recorded with the DMM used in the previous study. The first trial was used as the reference and resistance values from 4 other trials were aligned with the first trial for comparison.

Figures 5-8 and 5-9 show the response from the knee and the hip which includes all the error mentioned previously. Due to the joint size difference between the knee and the hip, more response is generated from the hip compared to the knee. It should also be noted that the shorter sensor length on the knee creates a different resistance response compared to the hip which can be confirmed from the figures.

Variability in the sensor output due to initial placement of the pants were studied and showed that error in the sensor was approximately between 8 – 10 degrees. Also, as seen in the previous movement error analysis, the hip area showed more error due to more movement.
Figure 5-8. Sensor response for the knee stretch sensor. (a) sensor response shown in ohms (b) normalized sensor response. Figures show excellent consistency between trials.
Figure 5-9. Sensor response for the hip stretch sensor. (a) sensor response shown in ohms (b) normalized sensor response. Figures show excellent consistency between trials.
5.3.3 Knee and Hip Sensor Characterization

In this section, we discuss the model used to characterize the stitched sensors on the stretch pants. From the data collected from VICON, we calculated 2 separate lines passing through 3 reflective markers. That is, the line passing through marker 1 and marker 2 creates line 1 while line 2 passes through marker 2 and marker 3. It then calculates the angle between the 2 lines. Knee flexion and extension phases were found after alignment with the reference angle calculated from VICON captures. Internal VICON function called “angle between three points” was used to compute the angle estimates. 5 trials of 15 cycles of mannequin movement were recorded in which the 1st trial was used to create a model and the next 4 trials were used to compare to the model. The model is found by solving the curve fitting problem in the least squares sense. Model parameter was tested and we chose the polynomial degree equal to 4 for both flexion and extension phases (see figure 5-10) which error is minimized. We used an error calculation in which for each data point the difference between the bend angle predicted by the model and the reference bend angle for the trial that is acquired from the VICON function. The difference in the bend angle is the error to compare sensor response. This approach models a real-world scenario in which the sensor response is calibrated based on a calibration routine and subsequent movements are measured using the model.

Similar testing was performed for the hip sensors. The model for the Hip sensor was found by solving the curve fitting problem in the least squares sense. Model parameter was tested and chose the polynomial degree equal to 4 for both flexion and extension phases for comparison against the knee. (see Figure 5-11). As shown in previous section, more error is noticed around the hip joint.
As previously discussed, due to the complex movement of the hip compared to the knee, we were able to observe more angle error in the hip sensors. Nevertheless e-textile sensors enable the best practical approach to providing comfortable, long term body sensing through everyday clothes. It minimizes the invasive and bulky devices required in traditional electronic sensing, allowing the true sense of long term monitoring to be possible.

Figure 5-10. Standard error plot against different polynomial degree for Knee Flexion and Extension
As it can be seen from the figures below, the model created from the data shows how well the model fits subsequently-collected data points. Tables 5-1 and 5-2 shows the angle error between the VICON generated “Reference Angle” and estimated angle from resistance values. In Tables 5-1 and 5-2, more error is observed from the hip joint. This is expected as our earlier studies show that most of the observed positioning and movement error occurs around the hip joint. Another important factor to note is due to the shape of the hip joint on the mannequin. Unlike the human hip, it is segmented into 2 regions, localizing the surface elongation into one place rather than spreading it over the entire surface as in the human body, causing the line approximation to be less perfect compared to the knee.

**Figure 5-11.** Standard error plot against different polynomial degree for Hip
Figure 5-12. Recovery curves of the knee movement and model respective to resistance

Figure 5-13. Extension curves of the knee movement and model respective to resistance
In Table 5-1, we show the variation in the angle estimation error in different trials which originates from the different sensor location while donning and doffing. The error shows the range of expected variation in angle estimation in the real world activity detection.

**Table 5-1.** Knee angle movement error: Difference between the reference (true) angle obtained from VICON and modeled angle from resistance

<table>
<thead>
<tr>
<th>Trials</th>
<th>Knee Angle Estimation Error</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Resistance [Ohm]</td>
</tr>
<tr>
<td>1</td>
<td>Flexion = 9.50°</td>
</tr>
<tr>
<td></td>
<td>Extension = 13.12°</td>
</tr>
<tr>
<td>2</td>
<td>Flexion = 15.09°</td>
</tr>
<tr>
<td></td>
<td>Extension = 10.55°</td>
</tr>
<tr>
<td>3</td>
<td>Flexion = 4.91°</td>
</tr>
<tr>
<td></td>
<td>Extension = 7.43°</td>
</tr>
<tr>
<td>4</td>
<td>Flexion = 5.08°</td>
</tr>
<tr>
<td></td>
<td>Extension = 5.92°</td>
</tr>
</tbody>
</table>

*Figure 5-14. Knee movement trajectory with respect to movement angles and resistance*
Figure 5-15. Recovery curves of the hip movement and model respective to resistance

Figure 5-16. Extension curves of the hip movement and model respective to resistance
In Table 5-2, we show the variation in the angle estimation error in different trials which originates from the different sensor location while donning and doffing. The error shows the range of expected variation in angle estimation in the real world activity detection.

**Table 5-2.** Hip angle movement error: Difference between the reference (true) angle obtained from VICON and modeled angle from resistance

<table>
<thead>
<tr>
<th>Trials</th>
<th>Hip Angle Estimation Error</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Resistance [Ohm] case</td>
</tr>
<tr>
<td>1</td>
<td>Flexion = 8.06° Extension = 11.17°</td>
</tr>
<tr>
<td>2</td>
<td>Flexion = 7.78° Extension = 4.73°</td>
</tr>
<tr>
<td>3</td>
<td>Flexion = 8.67° Extension = 4.73°</td>
</tr>
<tr>
<td>4</td>
<td>Flexion = 9.63° Extension = 5.10°</td>
</tr>
</tbody>
</table>
The above result sets an expectation of aggregated error due to positioning, drift and donning/doffing across different trials of data collection. This means that for activity detection, there would be a lower bound of resistance values where discrimination of different postures would not be feasible. In the next section, we show how this result affects in a posture detection application.

5.4 Body Posture Detection via Sensor Integrated Clothing

In previous sections, we explored and characterized the performance and the potential for stitched sensors on pants for joint movement analysis and characterization in order to understand the error in garment-integrated sensing that may affect activity recognition. In this section, we discuss and analyze the application of the stitched stretch sensor for the prevention of posture related injuries. According to a recent document, a news release from the Bureau of Labor Statistics by the U.S. Department of Labor, the most common workplace injuries were related to “overexertion in lifting or lowering” and back injuries were by far the most common injuries.

Figure 5-18: Statistics from a work related injury. Back injuries are the most common form of injury in a workspace in U.S. [104]
Back injuries occur due to the amount of force that is applied to the back when lifting objects with bad posture. When a person bends to pick up an object, the back acts as a lever, while the legs acts as the fulcrum. Therefore, when the fulcrum moves to the end it takes 10 times more force to life the objects. As an example, when lifting a 10 pound object, you are actually lifting 110 pounds including the weight of average human torso. Now, with the fulcrum at the other end of the lever, one could easily put 1100 pounds of pressure on your lower back. Given such fact, repetitive lifting and bending can cause back injuries.

Therefore, we present a solution to automatically assist workers to reduce the injury in the workplace. Many workers working in the industry that involve heavy lifting wear what is known as a coverall, a loose form of clothing that acts as a simple protective barrier, worn over their outdoor clothes. We target to design a low cost wearable platform, to monitor postures and prevent injuries, that could be easily worn and be disposable.

Therefore, an array of sensors was stitched to the knee and hip area to record the amount of bend on the sensors. Each array consists of 6 sensors, with the sensor length of 9 inches (see Figure 5-19). For each individual, during the initial training, we recorded sensor readings from the entire array of stitched sensors and processed readings to determine the sensor with maximum range from a subject’s data.

There were several issues that we noticed while developing the smart posture detection system on the coverall. We noticed new issues that we did not observe while testing the stitch sensor on the stretch pants. Firstly, similar to the baggy jeans, the coverall does not fit the user tightly as the stretch pants do. Secondly, coveralls are more generically fit and come only in standard S, M, and L type of sizes. Therefore, depending
Figure 5-19. Stretch sensor array sensors on the coverall. (a) Sensor array on the knee (b) Sensor array on the hip
on the size of the coverall and the level of fitness, sensors fall in vastly different body locations, creating different resistance readings for the subject. It was also noticed that due to the differences in a subject’s body shape, a sensor that showed maximum response in one subject did not show maximum response in other subjects.

In the following sections, we describe the data that we collected to design and test the system and explain the classification procedure we have established in previous chapters. The data collected from two different joints, i.e. knee and hip, was used to detect lower body posture for lifting posture.

5.4.1 Experiment Development and Results

We have recorded data from 6 subjects for both knee and hip joints. Due to the limitation of the recording system, each subject was asked to lift a moderately heavy box with good and bad postures for each knee and hip recording. Also due to the injurious behavior of this test, each subject was asked only to repeat 10 times for each posture. They were asked to do equal number of good postures (Squat) and bad postures (Bend). For the experiment, they were asked to repeat stand – squat – stand – bend – stand procedure with 6 a second delay for each of the posture. Other activities include walking and running. Table 5-3 shows the number of trials per subject for the lifting task.

5.4.2. Results

Because the garment is very loosely fitted and the fabric of the coverall is very thin, if the subject were to stand with straightened joints, the sensors may not also be in a straight position -- it does not mean that the fabric will fall smoothly as it might in stiffer
garments or skin-tight clothes, making it difficult to have good representative data for each posture across the subjects. In Table 5-4, we see the value range for each of the postures. Especially there exists significant overlap between the bend and stand postures.

**Figure 5-20.** Example waveform of the knee and hip sensor response for stand, squat (good lifting posture), and bend (bad lifting posture).
Table 5-4. Sample resistance value range

<table>
<thead>
<tr>
<th>Subject</th>
<th>Activity</th>
<th>Stand</th>
<th>Squat</th>
<th>Bend</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Knee</td>
<td>100 – 120</td>
<td>70 – 90</td>
<td>90 – 110</td>
</tr>
<tr>
<td></td>
<td>Hip</td>
<td>110 - 140</td>
<td>50 - 70</td>
<td>90 – 120</td>
</tr>
<tr>
<td>2</td>
<td>Knee</td>
<td>105 - 125</td>
<td>85 - 105</td>
<td>100 – 120</td>
</tr>
<tr>
<td></td>
<td>Hip</td>
<td>115 - 140</td>
<td>40 - 95</td>
<td>85 – 110</td>
</tr>
<tr>
<td>3</td>
<td>Knee</td>
<td>105 – 125</td>
<td>85 - 105</td>
<td>100 – 120</td>
</tr>
<tr>
<td></td>
<td>Hip</td>
<td>110 - 140</td>
<td>90 – 110</td>
<td>100 – 120</td>
</tr>
<tr>
<td>4</td>
<td>Knee</td>
<td>105 – 130</td>
<td>80 – 100</td>
<td>100 - 120</td>
</tr>
<tr>
<td></td>
<td>Hip</td>
<td>120 – 140</td>
<td>80 – 100</td>
<td>100 – 120</td>
</tr>
</tbody>
</table>

**Figure 5-21** Coverall fitness issues shown (a) sensors not correctly in line with knee – leg (b) sensors not in a straight position with the leg (c) sensor array remains bent after standing up from a squat.
As can be seen from Table 5-4, the values overlap across subjects and between the stand and bend postures. But, there exists a good distinction of good lifting posture. Therefore, although it may be difficult to “warn” when a poor posture is detected, the system can be designed to find good postures and generate a reward as opposed to providing a warning. We believe that generating a positive reward system can similarly tell the subject that he/she needs to squat down more before the object can be lifted up.

We have used the same GMM model and sequential detector structure used in chapter 3 for classification. Due to the dominant DC component values in the sensor readings, signals with noisy behavior such as walking and running were well clustered within the model. But, as mentioned earlier, overlapping DC values in the data played negatively to the classification results (see Table 5-5). In order to enhance the classifier performance, additional data needed to be observed. The orientation of the upper body also changes when lifting objects, therefore addition of an inertial sensor was sought. Sensor fusion and data fusion of 2 different sensing modalities was performed as was done in previous chapters and a preliminary study has been performed on 2 subjects. The inertial sensor used only the DC values and binary classifier of 45% bend or more, which showed an enhanced classification rate opposed to the lower body sensing. The inertial sensor used only the DC values and binary classifier of 45% bend or more. More thorough experiment must be conducted to validate the claim. But, with the addition of the inertial sensor, the classifier was able to detect with high accuracy as shown in Table 5-6.

| Table 5-5. Classification accuracy for posture detection |
|-----------------|-----------------|-----------------|-----------------|
|                 | OA  | Stand | Squat | Bend |
| Accuracy        | 97% | 81%   | 87%   | 73%  |

- 124 -
Table 5-6. Classification accuracy for posture detection for Subject 1 and 2

<table>
<thead>
<tr>
<th></th>
<th>OA</th>
<th>Stand</th>
<th>Squat</th>
<th>Bend</th>
</tr>
</thead>
<tbody>
<tr>
<td>Accuracy</td>
<td>97%</td>
<td>98%</td>
<td>97%</td>
<td>99%</td>
</tr>
</tbody>
</table>

Results showed an enhanced classification rate opposed to the lower body sensing only. However, more thorough experiments must be conducted to fully validate this claim.

Figure 5-22. Classifier and sequential detector output for the continuous postures for good and bad lifting postures. It demonstrates that the classifier can detect good postures during daily work
5.4.3 Discussion

The classification result shown in Table 5-6 is a preliminary results from 2 subjects. But, the upper body positioning coupled with the garment integrated sensing to detect postures would not be much different from one person to another and we expect that our system would be able to detect good lifting postures from the bad. One other aspect to consider is that the experiment was performed in a controlled scenario exercising finite number of activities. This is especially true since many different scenarios could occur in a real workplace causing a person to bend or move their upper body. Depending on the work place, different postures may act as a dominant posture. For example, in an office setting, more sedentary postures may be dominant with frequent leaning of the torso. Such factors must be incorporated into the design when developing the posture detection system.

In order to validate the claim, the experiment needs to be extended to include all the subjects in the study and results must be evaluated. Also, additional data needs to be collected from more subjects to extend the data size.

But, this study also shows that the addition of a different sensing modality can bring added information to a classifier to improve its classification accuracy. The downside of this system is that the augmented sensing module requires an attachment to the subject’s upper body, which can be very invasive when worn for a long time. However, this strap-on module could be attached to or placed on the garment and also serve as the processing unit for the sensors stitched to the disposable coverall, such as a mobile phone with inertial sensor, allowing the coverall itself to remain disposable.
Currently sensing of joint positions is performed only on the lower body. But, during lifting postures, both arms are extended. Therefore, additional sensors to detect position of the shoulder or stretching of the garment around the shoulders would be able to enhance the classification accuracy of the system and with the added sensing capability we may be able to create a subject independent classifier.

5.5 Conclusions and Future Work

Although there is a great interest in the development of wearable sensing, not much attention has been given to textile based sensing. Only recently, garment based sensing has gained popularity. While it is widely acknowledged that movement, positioning and drift of the sensors on the body can be critical to accuracy of the sensing capability not much research has been conducted in the area to understand the variables and underlying causes that contribute to this kind of error. Two types of error, movement and drift error have been analyzed similar to the previous work of Dunne and Gioberto. The influence of these types of errors did impact the posture detection. Thus far, error analysis have been implemented and tested on the mannequin. But, it would be interesting to see if the same behavior would hold for human subjects.

In this chapter, we first showed that resistance variation of the stretch sensor on the garment can be used to model the amount of bend/motion on the lower body joint. We then showed that the stretch sensor could be used for posture detection. Finally, we showed that the sensors can be placed in an intelligent way to accommodate the difference in body size and clothes sizes to circumvent the positioning, movement and drift errors. We placed an array of sensors to collect multichannel data. Finally, we
showed that intelligent sensor and data fusion can be coupled with the garment based sensing to improve the classification accuracy of a posture detection system.

We believe that by moving from strap on type of sensors to the e-textile based sensing modality, we can improve the comfort level of the person allowing for true long term monitoring of activities and maybe for extension of long-term monitoring to biomedical and physiological monitoring as well.
Chapter 6
Conclusions and Future Research Direction

The work presented in thesis other than Chapter 5 were initiated and developed in 2006 – 2010. Therefore, no mention or comparisons are included with more recent approaches and development.

6.1 Conclusions

In this thesis we presented new methods and overall system architecture to continuously recognize the activities of behavioral patterns. Integration of In-home fixed sensors and wireless wearable sensors was performed to intelligently localize the location of the subject in a room and detect the activities performed for early morning. In a controlled experiment setting, Gaussian Mixture Model with a Sequential Classifier was integrated to classify the different early morning activities in the bathroom. A mechanism for a potential feedback is possible through the sequential classifier to inform completion or incompletion of the executing task.
The system was then extended to detect behavioral markers of autistic children that exhibit repetitive behaviors using wearable wireless accelerometer sensors and audio/video sensors. The system was used to detect hand/arm and body motions. We presented a method to characterize the stereotypical movements and dictionary design methods based on LPC and HOS algorithm to detect and update dictionary dynamically based on the characteristics of the incoming data. This would enable the system to automatically adapt to the behavioral patterns of the subject which in turn maybe used to characterize and categorize the subjects based on their behavioral patterns.

Although the actions of stereotypy and SIB are quite consistent within a subject, there is a great variability among subjects. Also, within a subject, one stereotypy may disappear but another stereotypy or SIB may develop, with an intervention or therapy. Therefore, it is critical for behavior detection and monitoring system has the capability of unsupervised learning of the data to detect novel events. We took a non-parametric approach to novel event detection which learns the characteristics from the data observed. We therefore keep simple time domain statistics such as mean, variance, energy, number of zero-crossings to track incoming signal for repetition of any event. And, by capturing higher order statistic value changes, we update the dictionary.

There is an outstanding task of enrolling more patients and also studying further fusion of audio and accelerometer data to understand the interaction between the patient and its surroundings to improve the classification accuracy. Due to the potential privacy issues, video will serve as a means to provide ground truth. But, there is no question that fusing video would provide another dimension in understanding their behaviors.

We have shown that both accelerometer based wrist sensor and body sensors can
provide information regarding their self-stimulatory behaviors and we were able to use
detect them for detecting stereotypy such as rocking and flapping and SIB patterns such
as punching face and hitting legs. Using the results from this study, our contribution was;

1. Provided an unbiased objective measure to detect amount of self-stimulatory
   behavior autistic children exhibited
2. Provided a study results on using unsupervised methods to detect stereotypy
   and SIB patterns.

We believe this allows system to be adapted to users which accommodate all
different motions ASD patients exhibit. This information combined with audio/video
recordings would also provide us with information on what triggers the self-stimulatory
patterns for the autistic children and how the intervention strategies could be designed to
best suit an individual. In addition, our capability to generate alarm or immediate
intervention based on the detection of the stereotypy and SIB greatly benefits the users of
the system. Therefore, through this study, we have opened up a possibility for real time
monitoring and intervention system.

Finally, a different sensing platform was investigated to enhance the wearability
and comfort level of the user for long term monitoring. We showed that using an array of
stitched stretch sensors on every day wear is feasible and demonstrated its potential for
activity detection. We also showed that using a combination of different platforms to
complement sensing modalities can be beneficial to the improving the classification
accuracy of the system.
6.2 Future Research Direction

Wearable computing and machine learning is a very rich area of research and in this thesis we have shown that there exists very exciting areas for research in this field. It reaches into an area of novel sensing platform, communication and networking of the sensors, and algorithm development from the data acquired from the platforms.

6.2.1 Algorithm Development for Garment Based Wearable Sensing

In this thesis, the algorithm developed in chapters 3 and 4 were used to detect body postures in garment based sensing. With the addition of multichannel and multimode data, an influx of data is expected. To handle the vast amount of data, algorithms to mimic DNA sequence detection will be investigated.

1. The sensor values will be quantized to create motifs. The motifs will act as a dictionary and the system will focus on motif discovery. This could be of interest due to the fact that the signal of interest in ADL and stereotypies in ASD, have pseudo-periodic nature.

2. Motif discovery can also be extended to the activity sensing in garment based wearable sensing as it analyzes patterns in the movement of the joints.
6.2.2. Explore Sparse Representation and Subspace Clustering Algorithm Development for Garment Based Wearable Sensing

Previous investigation of a use of sparse representation with subspace learning and clustering methods for the applications in chapters 3 and 4 but it did not deliver any improvement over the GMM-sequential classifier especially with respect to computational load. Improvements can be studied in the following areas:

1. Improvement of computational load: The main computational bottleneck was in dictionary orthogonalization step in the Orthogonal Least Squares (OLS) sparse coding algorithm.

2. With the high dimensional spaces, we may have many subspaces that need to be optimized, tracked and updated to incorporate new data. Especially to incorporate on-line learning of the data for novel event or anomaly detection.

6.2.3 Wearable Sensing Platform

The current sensor system does not include on-garment processing, and therefore can only record single trials of data using a DMM, a significant limitation. An implementation of a single board to transmit multichannel data from various nodes to the base station can greatly reduce handling the data and complexity in wearable sensing. To improve data collection process and classification accuracy, following steps are proposed:
1. With the expansion of the sensors to multiple joints, effects of sensor positioning, drift, donning and doffing related to different joints must be evaluated to model the movement.

2. The current sensing is performed only on the lower body. But, during the lifting posture, both arms are extended. Therefore, additional sensors to detect stretch on the shoulder would be able to enhance the detection rate and we may be able to create a subject independent classifier.

3. Develop and expand the current stretch sensing platform to multiple joints on the body and create a single wireless platform to send multichannel data from the stretch sensor from the garment.

4. Develop methods to collect data from the array of sensors to rank and sort to find correlation and extract meaningful information from multiple arrays of sensors.

With the construction of loose form clothing, there is a potential for further study with the ASD patients. It is significant that that the sensors could be woven into their everyday clothes, fully transparent and unrecognizable to the children with autism. This is partially due to the fact that the spectrum of autism so wide that some patients cannot tolerate any form of tight coupling of an object to their body, while some enjoys the compression on the body. Such form of wearable sensing would open the horizon for new sensing and understanding of behavioral markers. However, while ASD patients may be an extreme case for the effects of clothing discomfort, it affects all humans in more subtle ways. Following the principles of universal design, solving the problem of wearability in activity monitoring can benefit everyone.
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