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Activity Analysis and Detection of Repetitive Motion in Autistic Patients

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***Abstract* — There is no doubt today that autism is both neurodevelopmental and behavioral – a multifactorial disease characterized by impaired social skills and lack of efficient communication. In order to support more efficient development and improve communication, many directions in science have been and still are on clinical trials. We compared repetitive motion patterns with patterns characteristic of normal everyday activities and isolated the key elements of each that allow distinguishing between the two motion patterns. The Principal Component Analysis technique was used to reduce the dimensionality of the motion data collected. A kNN classifier was also used to determine the two classes of motion apart with 100% sensitivity and specificity. We present here a uniquely designed alarm system that can help with autistic children's difficulties on a real-time basis. The uniqueness of the system is that it can be extended or applied to other situations of even non-autistic children that suffer some health disturbances or particular situations that need a specific assistance. Beside the system's design description and methodological details, further work on improving it to the higher level is proposed.**

Keywords—Repetitive Motion, Autism, Activity Analysis

I. INTRODUCTION

Autism Spectrum Disorder (ASD) is a complex range of neurodevelopmental, behavioural disorders affecting a significant percentage of the population of the United States. Characterized by impaired social development, impaired communication skills, and restricted interests with repetitive behavior, the disease manifests itself in the form of classic Autism (the most severe and also the most common form), Asperger's Disease (a milder form) and a range of other manifestations together known as pervasive developmental disorder not otherwise specified (PDD-NOS) [1]. Fig.1 presents and explains the latest classification.

Research indicates that 1 out of every 88 children in the United States has some form of ASD [2] [12]. Based on surveillance year 2008, data from The Centers for Disease Control shows a 26% increase over 2006 and a 71% increase over 2002 [3]. Though it is not known how much of the increase is due to improvements in detection and diagnosis of the disease, it is clear that the disease represents a growing challenge to health care professionals responsible for caring for affected children.

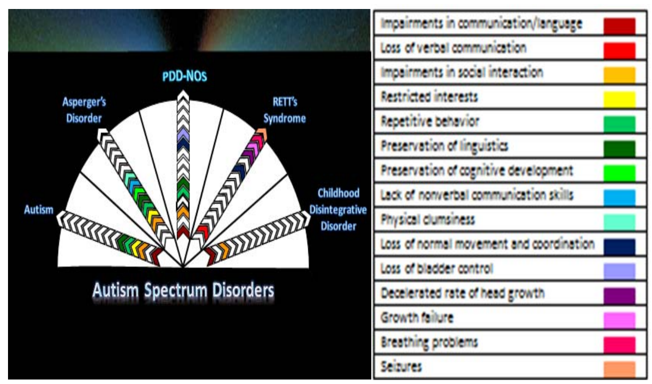

Fig.1: The newest classification of Autism

Background:

Autistic children often develop unusual habits and in some cases they could be unsafe or even dangerous to themselves and other family members. Their behavior can be characterized by impaired social development, impaired communication skills, and restricted interests coupled with bouts of unabated repetitive motion.

Persons afflicted with autism often display severe bouts of repetitive motion, which if left uninterrupted could lead to injury to the patient and to others, and in many cases could also lead to worsening of the disease. Several treatment options have been explored [7] [8] [9] [10], but none with overwhelming success [11].

This article identifies the critical relationships between activities of daily living (ADL) and repetitive motion and demonstrates how observed movements can be classified with a high degree of accuracy. A new device is proposed which can be used to detect repetitive motion in autistic children. It is a portable device that can be worn by the child and will collect motion data on a real time basis, detect and deter repetitive motion and provide appropriate alerts to caregivers.

In the rest of this article we review related work in section II, discuss the proposed repetitive motion detection system in section III, present and analyse the data collected in section IV, and present the conclusion and direction for future work in section V.

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II. Related Work

In their studies of repetitive motion detection in the workplace, Lu and Ferrier [4] used a dynamic model to classify workplace motions. In their approach they determined the class identities based on the data obtained, as opposed to determining ahead of time what the classes would be. In that sense, they allowed the motion classes to be dynamically determined.

They decomposed the motion classification problem into two primary parts: first they used a multi-dimensional segmentation algorithm to segment the observed motion of the subject without relying on any a priori knowledge of the type of motion that is being performed; then they performed model fitting on the identified segments to determine which sequence of segments represented a complete repetitive motion.

Their approach, though plausible when there are expectations that the subject is performing some type of repetitive motion, does not take into account the possibility that the subject may be performing ADL mixed in with any sequences of repetitive motion. In fact, for the autistic motion case the overwhelming majority of the motions performed are expected to be ADL, with only a small number of repetitive motions interspersed among them. Therefore their solution, though appropriate for a workplace environment in which the subject is expected to be continuously performing some type of repetitive motion, such as for example cranking a handle, may not be appropriate for use in identifying repetitive motion in autistic individuals.

Polana and Nelson [5] also devised a method to identify specific motion sequences without any prior knowledge of what those motions might be. Using computer vision techniques their proposed solution extracts motion features form grayscale images of the moving subject and classifies these motions based on known motion patterns.

They were able to deduce the occurrence of periodic motions based on observed peaks in the motion's fundamental frequency as highlighted by the discrete Fourier transform of the periodic signal recorded from the subject. They were then able to use a nearest centroid classifier to recognize the repetitive motions based on the extracted features.

This approach seems suitable for adaptation for use in identifying repetitive motion in autistic individuals, as it is able to identify periodic movements while not relying on the assumption that the motion is periodic to begin with.

III. Repetitive Motion Detection System

This section discusses the overall system requirements, basic features implemented in this study, and extended features that may be incorporated into a full-function comprehensive health monitoring system.

A. System Requirements

The system is intended to be a wearable device, capable of detecting repetitive movements in the person wearing the device. It must be small and compact, such that it will not interfere with the daily activities of the user. It is expected to be used primarily for detecting repetitive motion in autistic children, and as a consequence special consideration must be given to the limitations of the typical autistic child.

In particular, the device must not depend on the co-operation of the child for its success. Even though the device is designed for the good of the child, he or she may not understand the significance of that and may tamper with or in other ways interfere with the proper functioning of the device.

For the same reason the device must be robust and tamper-proof, so that it is allowed to function uninterrupted. If, for example, the child attempts to dismantle the device, an alarm should sound to notify the relevant parties that such an attempt is being made. The alarm should also have the dual purpose of distracting the child and discouraging that activity. The alarm should ideally be local, such as for example the house alarm so that quick remedial action by a caregiver can be performed, but it may also be beneficial to collect statistics of such actions remotely for further analysis.

Also to reduce the risk of tampering, the device must be minimally intrusive or observable by the child. If the child is unaware or only minimally aware of the presence of the device, the chances are greater that he or she will not tamper with it. This could be challenging for a body-worn device, but disguising the device or hiding it in the child's clothes may be helpful, therefore care must be taken to make the device such that it can be camouflaged among the child's clothing or in some other way appropriate for the circumstances.

In the same way, the device must also be difficult for the child to remove or disable, in the event that he or she tries to remove or disable it. If the device is worn directly on the body, it must be located such that it is inaccessible by the child, such as for example behind the child's back or hidden in the child's clothing. Therefore the device should remain in its intended position regardless of the child's efforts to remove it.

The device must present no health risks to the child. Since the device is intended to be wearable, it must not be able to produce any harmful radiation or in any way harm the child whether during normal operation or if it is tampered with or broken in any way.

It must be possible to refresh any power sources used, such as batteries, etc, with minimal intervention or disruption. For example, batteries used may be long-lasting, needing to be replaced only after a long period of use. In such cases battery replacement could be scheduled and performed as needed. Alternatively, batteries may be refreshed in a non-intrusive manner such as remotely by an inductive device located under the child's bed and performed when the child is asleep.

Communication between the device and any monitoring node to which it is connected must be real-time, both incoming and outgoing. The device is intended to be used to provide alerts and calls for help on an emergency basis. Since failure to complete an emergency alert on a real-time basis may result in serious harm to the child and possibly even death, it is imperative that all communication mechanisms upon which the device relies perform efficiently and at an optimum level. Nevertheless, consideration should be given for giving preference to local alerts that require less critical communication resources, such as a house alarm that could attract the attention of an on-the-scene care giver.

The communication link between the device and any connected node must be reliable, dependable and secure, to ensure that only correct information is transmitted, to ensure that information requiring emergency responses is received in a timely manner, and to ensure that information is not accessed or altered by unauthorized individuals. Information security in this environment must be maintained at the highest possible level. Any compromise of security could lead to serious harm to the child or even death, for example if the system detects harmful repetitive motion and issues an alert that due to a security breach is either not transmitted or transmitted too late. Also, breaches in security could be exploited to use the stimulus generating capabilities of the device to provide harmful stimuli to the child, for example by increasing to a harmful level the sound that is played to distract the child from a harmful activity.

B. System Features

The system continually monitors the user's activity and determines when the user is performing any repetitive motion activity or is otherwise in any danger that it is capable of detecting. The device provides a reliable means of monitoring the user to detect any undesirable conditions, alerting parents or other caregivers on a real-time basis to enable rapid response, and providing local stimuli to the user to help break habits that can lead to worsening of his or her condition.

Although the primary function of the device is to detect harmful repetitive motion of the user, it is equipped with other diagnostic capabilities that could together provide useful information on an emergency basis to caregivers to prevent harm to the user. The activity monitor is the primary subsystem responsible for detecting repetitive motion, but other subsystems, such as for example the heart monitor subsystem, could be used to provide a comprehensive suite of information transmitted in an alert that could lead to improved performance in providing emergency help for the user. The basic device block diagram shown in Fig.2 comprises the following subsystems:

The Activity Monitor subsystem uses movement and orientation sensors to detect any abnormal motion or sequence of motions, such as waking up in the middle of the night and jumping on the bed in the dark, which may cause the child to fall and get hurt. Also, during the daytime, autistic children often develop some form of repetitive motion such as skip jumping and/or spinning their hands or bodies in a very abnormal way. Parents are often too busy to prevent these repetitious movements, which in the long run worsens the child's behavior unless it is definitely stopped by distracting the child from such movements. When such repetitive motions are detected, the device not only alerts the parents but it issues a corrective response such as a loud audible sound or electric muscle stimulation pulse to distract the child and break the repeated cycle.

The Communication subsystem uses an SMS Modem to send text messages to parents to report various conditions of interest, both normal and abnormal. It also receives corrective orders or control actions.

The Controller uses a Real Time Operating System to make the device time sensitive, and adds intelligence to the way all sensors and actuators are controlled, such as the frequency of sensors detection and level of acceptable threshold, the loudness of alarm, and so on. The Controller also provides Intelligent Battery Control including inductive recharging and low battery alarm.

The House Alarm interface connects to the house alarm and triggers an alarm when the child is in danger, as sensed by the various monitoring subsystems.

The Data Storage Unit captures all pertinent health events of the child. In addition to recording emergency health events, it records normal events and creates a log that can then be transmitted to a physician or other caregiver upon request.

The Local Stimulus subsystem is the interface used by the device to send intervention signals to the child. These signals may be a loud noise, music, other sounds, or a vibrating pulse to distract the child from performing any harmful activity, or to waken the child to stop the progress of any harmful health event such as choking while asleep.

A prototype of the Repetitive Motion Detection System is shown if Fig.4. A multi-sensor small digital IC comprising a gyroscope, accelerometer and magnetometer is used to obtain activity measurements from the subject. Each sensor provides 3-dimensional measurements of the subject's motion.

A more full-function comprehensive health monitoring system may also include the following extended-function features:

The Temperature subsystem monitors the child's body temperature and the ambient temperature. Some autistic children sometimes get too cold or too hot in their own homes but the parents are unaware because the child does not speak out. This subsystem triggers an alarm when the body temperature goes outside a pre-defined acceptable range.

The Heart Monitor subsystem monitors the child's heartbeat to detect heart dysfunction such as abnormal rhythm. It observes changes in heart rate and triggers an alarm in the event of any observed irregularities.

The Sound Monitor subsystem monitors the child for sound that they can produce and which can be a warning sign for caregivers. While sleeping, some children may choke on their own saliva and they may make unusual sounds but not loud enough to wake up their parents. This device will detect any unusual sounds or breathing, and issue an alert upon detection.

The Ambient Control subsystem monitors the child's surroundings for potentially hazardous equipment or tools, such as may be present for example in a kitchen or garage. If the child is unsupervised, these hazards could possibly harm the child. This subsystem disables or locks these hazards when the child is in the vicinity.

The Location Monitor subsystem uses a GPS sensor to help locate the child, or learn about any special environmental aspect of the child's current location and surroundings.

All communication is on a real time basis. The system has the ability to accurately record data produced by any of the above sensors, and report on a real time basis to parents or to the monitoring facilities of a caregiver.

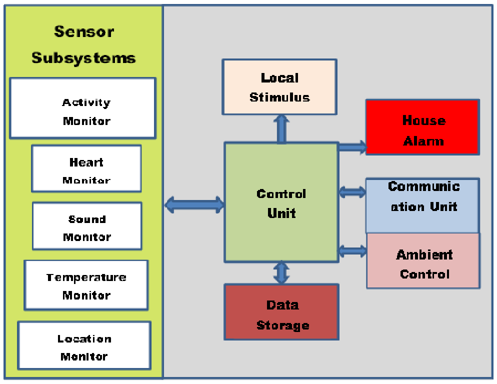

Fig.2 Repetitive Motion Patient Monitoring System

C. Design Methodology

The system continually measures the values of the x, y and z sensor data of the gyro, accelerometer and magnetometer. It does so in a 25 Hz loop (Fig.3). After each new reading is obtained, it updates a FIFO buffer and compares the entire contents of the buffer with stored values of known repetitive motion activities lasting for 3 seconds. Consequently the size of the FIFO buffer must be able to accommodate 75 samples. If the data representing the contents of the FIFO buffer does not match any of the stored repetitive motion activities, then the system continues in the loop searching for a match. However, if it finds a match then it determines that the user is performing repetitive motion and issues all appropriate alerts and stimuli.

Several alerts may be needed, including any required local alerts as for example to on-the-scene caregivers such as parents or medical staff, alerts to remote medical response centers, or alerts to remote data collection and monitoring facilities.

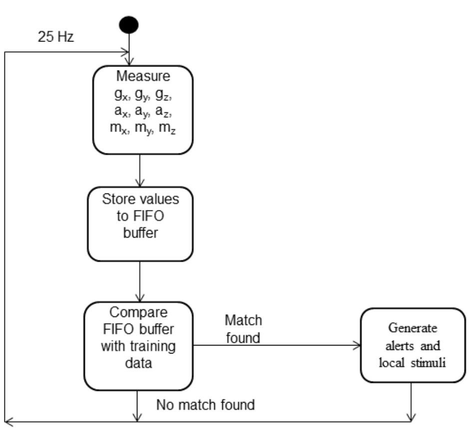

Fig.3 Repetitive Motion Detection System Diagram

Stimuli may be in the form of an alarm or loud noise, music, flashing lights, a small voltage discharge or any appropriate

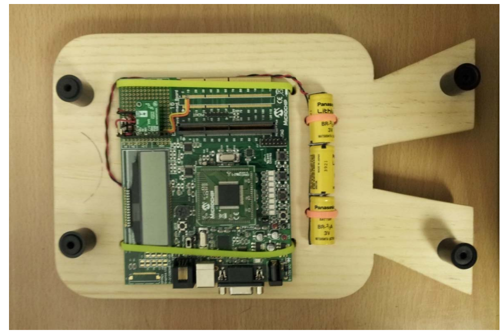

Fig.4 Repetitive Motion Detection System Prototype

stimulus designed to distract the child from performing the detected repetitive motion activity.

IV. Experimental Results

This section describes the data collected and the analysis performed.

A. Data Collection

In this study we analysed many types of ADL and repetitive motion, studying the sensor recordings obtained from carrying out several use cases of each type of activity. We used the results of this analysis to calculate the accuracy of determining for each activity recorded by the sensors whether it is repetitive motion or ADL. For both the ADL and repetitive motion data collection procedures, the device prototype (see Fig.4) was worn by one of the authors of this paper, who performed various types of movements, each lasting for 3 seconds, and recorded the resulting sensor readings generated. The sensor readings were recorded on the EEPROM memory that comes standard on the Explorer 16 development board, saved onto an SD card by running a small C program on the MPLAB X IDE platform, and exported to Matlab for further processing.

A third class of motion – falls – was also included in this study and a close similarity of the motion data patterns between falls and repetitive motion was observed. The repetitive and ADL motion types studied are as shown in Table I.

In this study measurements from the accelerometer were recorded and analysed. Measurements from the gyro and magnetometer were recorded and will be analysed and discussed in future work.

B. Analyzing ADL Motions

Activities of daily living (ADL) are normal activities like standing, lying, sitting, walking and so on, and are generally characterized by smaller changes in angular rate, acceleration and direction than falls and repetitive motion. Such changes can be accurately measured by inertial sensors such as accelerometers, gyroscopes and magnetometers, which will generally record comparatively larger values of inertial change for falls and repetitive motion than for ADL.

The ADL data collected are represented in part by the graphs shown in Fig.5. The graphs show the values of acceleration measured for the specified activity along the x, y and z axes of the body's movement. The red curve represents the x component, the green curve represents the y component, and the blue curve represents the z component of the acceleration of the subject in performing the specified activity. Acceleration due to gravity is measured along the z-axis of the graph. Each activity lasts for 3 seconds.

In examining the ADL graphs, it can be observed that for ADL the values of acceleration for each axis vary only within a very small range. For the 'sit down' class of activities, the x value of acceleration remains very close to 0 G, the y value remains near -0.5 G and the z value remains close to -1 G.

The graphs of Fig.5 show how the value of acceleration along each axis responds to changes in the direction of the body's movement. Acceleration values measured along the x axis fluctuate in direct response to the right/left movements of the body as can be observed by examining the 'walk forward wobbling from side to side' graph. Positive values of x indicate movements to the left, as can be seen from the 'sit down normally leaning left' graph, which shows relatively large positive values of x. And negative values of x indicate movements to the right, as can be seen from the 'sit down normally leaning right' graph, which shows relatively large negative values of x.

Acceleration values measured along the y-axis indicate forwards and backwards movements. For most of the ADL movements performed there is not much variation in y. However, in the 'walk forward wobbling from side to side' graph, y ranges between -0.5G and 0.5G (a full 1 G), which is easy to understand given the fact that there is a relatively large forward-backward swing in performing this type of movement.

The z-axis measurements offer the most significant information in the ADL group. Here it can be seen that though the acceleration measured for z is around -1G for most movements, this value could increase significantly for some movements, approaching as much as 1.5G for walking normally, 2.3G for walking forward and turning around and 2.8G for running forward. The higher value of acceleration for walking forward and turning around versus merely walking forward is explained by the fact that the subject was required to walk at a faster pace when the movements required turning around, especially considering that the entire movement had to be completed in 3 seconds; therefore the measured values of z when the movement involved walking 4 steps and turning around versus walking only 2 steps and turning around are slightly higher. For running, the measured value of z reached as high 2.8 G. Also, the choppiness of the z curve increased when the movements were faster, as can be seen from the graphs of 'walk forward (brisk)' and 'run forward'.

TABLE I. TYPES OF MOTIONS STUDIED

Motion Category	
ADL	***Repetitive Motion***
Sit down normally	Rock from side to side
Sit down normally leaning left	Jump up and down
Sit down normally leaning right	Spin counterclockwise
Walk forward wobbling from side to side	Bang head against the wall
Walk forward normally	-
Walk forward 4 steps and turn around to the right	-
Walk forward briskly	-
Run forward	-

However, the main lesson learned from the ADL graphs is that z, the up-down component of acceleration, is normally around |1| G for ADL, but could range as high as around |2.8| G depending upon the type of movement being performed. This fact has serious implications when it comes to the ability of the system to distinguish between ADL and repetitive motion.

C. *Analyzing Repetitive Motions*

Various types of repetitive motions were performed, including jumping up and down repeatedly, spinning, rocking from side to side, running in place and head banging, and as expected, the measured values along all axes of body movement were very high as compared with ADL. The repetitive motion data collected are represented in part by the graphs shown in Fig.6. The graphs show the values of acceleration measured for the specified activity along the x, y and z axes of the body's movement. As in the previous cases, the blue curve represents the z component (up-down measurements), the green curve represents the y component (forwards-backwards measurements), and the red curve represents the x component (right-left measurements) of the acceleration of the subject in performing the specified activity. Acceleration is measured along the y-axis of the graph, and is measured in units of G. Each activity lasts for 3 seconds.

In examining the repetitive motion graphs, it can be seen that the up-down component value of acceleration, as measured by the blue curve, could have a range from as small as just over 1G (for example as in the 'rocking from side to side' graph) to as large as 6.5 (as in the 'running in place' graph). These high values provide excellent discriminative capabilities for the system to be able to distinguish between repetitive motion and ADL. And for movements where the range of values of z is toward the low end, other discriminating factors such as time and the values of the other acceleration components could be used to provide the proper discriminative capability.

In summarizing the experimental findings from the analysis of the repetitive motion data, it is clear that for the movements in which the z component of acceleration exceed 3 G a repetitive motion can be inferred, but for movements in which the z component of acceleration is less than 3 G, other factors including the x and y components of acceleration and time could be used to distinguish between repetitive motion and ADL.

D. *Data Analysis*

Principal component analysis (PCA) was used to extract characteristic features from the incident data, which was then classified using a 3-class k-nearest neighbour classifier. The 3

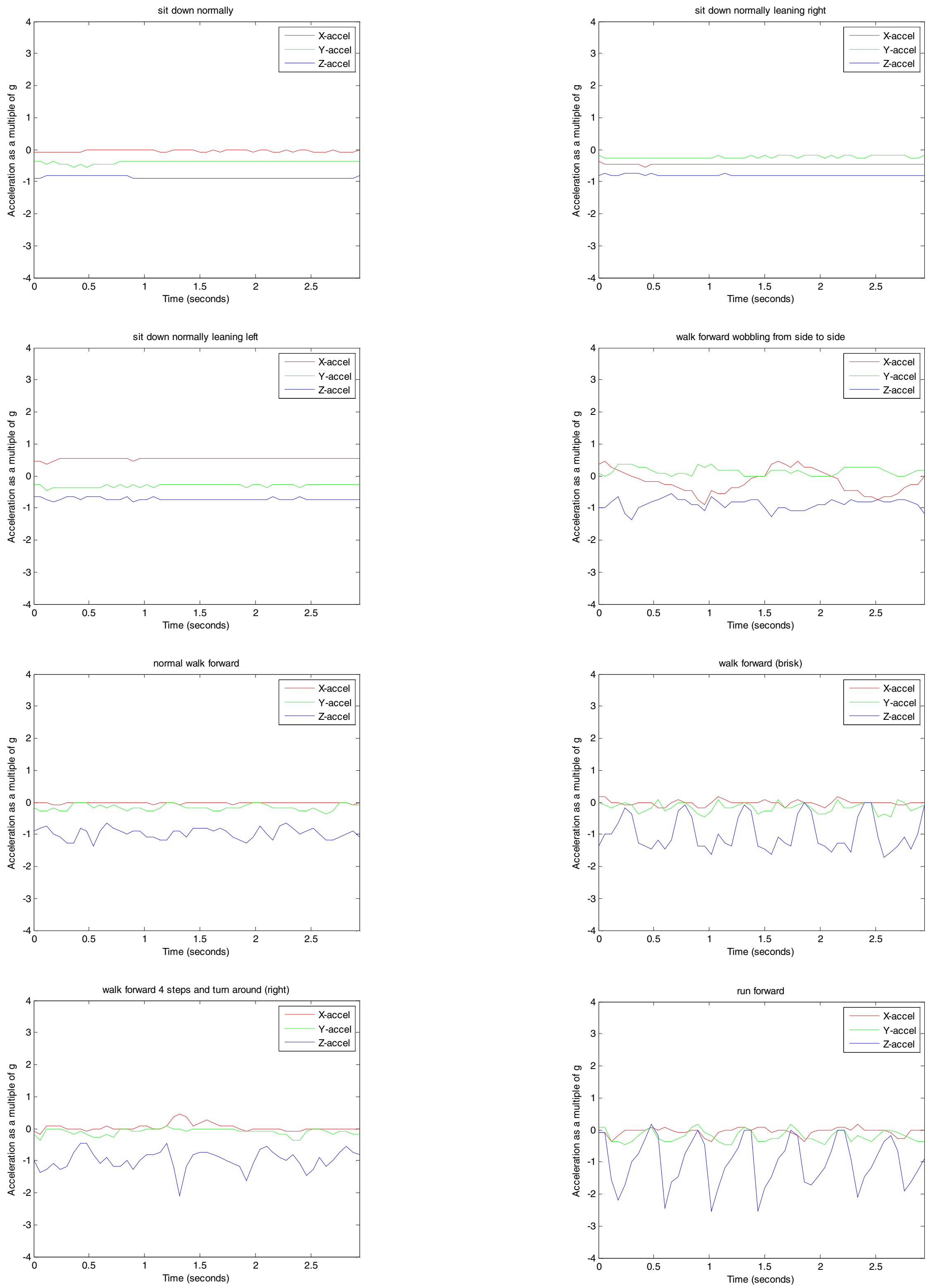

Fig.5 ADL motion graphs

classes considered were ADL, repetitive motion, and falls.

MATLAB was used to create PCA models of the data, which was then partitioned into training and test samples: 50% as training samples and 50% as test samples, all selected randomly. The kNN classifier was then used to estimate the accuracy of the models in determining the correct class of each incident, that is, whether it should be classified as a repetitive motion, an ADL or a fall. The data was created by performing several experimental falls, repetitive motions and ADL, each lasting for at least 3 seconds, to generate the data samples.

The starting initial total sample size was 75 incidents. Of these, 22 samples were known to be ADL, 26 samples were known to be falls, and 27 samples were known to be repetitive motions. With these samples, classification accuracy was good, ranging from 83% at the low end to as high as 92%.

Next, 25 more ADL incidents were added to the data set and the classification accuracy improved, ranging from 88% to 96%. Finally, adding 25 additional fall incidents caused the accuracy to drop slightly to the 82%-95% range. The results are as shown in Table II.

The experiments were then repeated with the samples divided into 2 classes representing ‘ADL’ and ‘others’. This caused the classifier accuracy to go up sharply to a consistent 100%, proving that this method successfully distinguishes ADL from repetitive motion and falls, which produce motion data that very closely resemble each other though they differ markedly from ADL motion data.

V. CONCLUSION

The complex problem of monitoring individuals at risk of engaging in harmful repetitive motion activity was examined in this paper. A new portable medical device was proposed that would be worn by at-risk individuals and would have the capability of collecting activity data on an ongoing basis and determining in real time when a bout of repetitive motion is occurring, and initiating any necessary remedial activity on behalf of the patient. An advanced feature extraction technique, principal component analysis (PCA), was used to extract identifying features from the collected data and these features were provided as input to a kNN classifier in order to determine if the observed motion was ADL or repetitive motion. Experimental results showed that the proposed medical device could discriminate between activities of daily living (ADL) and non-ADL with 100% accuracy. ADL motions typically were measured in a range of acceleration less than 3G, whereas repetitive motions were measured in a range of acceleration greater than 3G. The proposed device would employ this discriminating characteristic to distinguish between ADL and repetitive motion. In summary, the proposed device fills a need within the medical community for a reliable portable repetitive motion detection device capable of not only detecting bouts of repetitive motion, but also providing appropriate alerts to caregivers to inform them of the detected events.

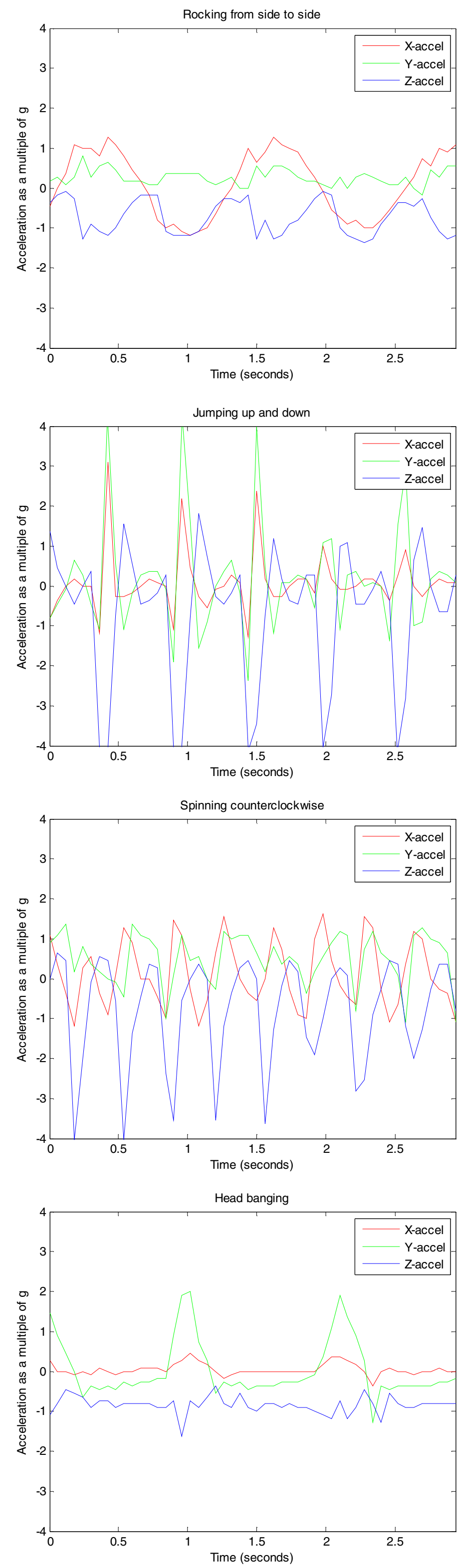

Fig.6 Repetitive motion graphs

TABLE II. MOTION CLASSIFICATION RESULTS

Classes	No. of samples	Percentage of samples			Accuracy (%)
		ADL	*Falls*	*RM*	
ADL/non-ADL	150	31	34	35	100
ADL/Falls/RM	75	29	35	36	83-92
ADL/Falls/RM	100	47	26	27	88-96
ADL/Falls/RM	125	37	41	22	82-95

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BIOGRAPHY:

Dr. Bassem Alhalabi's primary research is the development of pragmatic industrial, consumer, medical, and educational systems with emphasis on Embedded Systems, Web-based and Smart Controls, and Distance Education & Remote Labs. He Co-founded the CADET research center in 1999, and has been co-directing/ directing it since. Through his private consulting company, Dr. Alhalabi works with inventors on their feasibility study, design specification, system architecture and integration, prototypes and proof of concepts, and design for production. Dr. Alhalabi received a BS and an MS in electrical engineering from Ohio University and Purdue University, respectively, and an MS and a PhD in computer engineering from the University of Louisiana at Lafayette. He holds a US patent and others are pending. He is a member of IEEE and various other professional and honor organization, and a recipient of various academic awards.

Clyde Carryl received a B.S. in electrical engineering from Howard University and a M.S. in computer engineering from Florida Atlantic University. He is currently working towards the Ph.D. degree in computer engineering at Florida Atlantic University. His research interests include physical access control systems, embedded systems security, software defined networking security, and dedicated short-range communications. He is a member of the Tau Beta Pi Engineering Honor Society and IEEE.

Dr. Mirjana Pavlovic, MD, PhD a Researcher and Adjunct Professor in the CEECS Department, FAU, Boca Raton, Florida, USA, is with the Bioengineering Program within the CEECS Department. Her teaching assignments include Chemistry for engineers, Introduction to bioengineering, Stem Cell Engineering, Nature-intersections with engineering and Tissue Engineering courses. She has research and clinical experience with an excess of 150 papers and abstracts. Target interest includes translating lab data to clinical arena, and her efforts are directed toward autoimmune diseases and stem cells (fundamental, research, computational approach, clinical applications). For ten years, work on stem cell application, lupus anti-DNA antibodies: structural, functional and pathogenic features including mechanisms of DNA hydrolysis/ cytotoxicity) has been her main research direction. Her interest is also focused to molecular and biochemical aspects of Autism and bioengineering solution to the specific manifestations of the disease. She has got her MD, MS and PhD degrees in Belgrade and Yugoslavia (Serbia).