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Optimal Sensor Location for Body Sensor Network to Detect Self-Stimulatory Behaviors of Children with Autism Spectrum Disorder

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Abstract— **In this study, we investigate various locations of sensor positions to detect stereotypical self-stimulatory behavioral patterns of children with Autism Spectrum Disorder (ASD). The study is focused on finding optimal detection performance based on sensor location and number of sensors. To perform this study, we developed a wearable sensor system that uses a 3 axis accelerometer. A microphone was used to understand the surrounding environment and video provided ground truth for analysis. The recordings were done on 2 children diagnosed with ASD who showed repeated self-stimulatory behaviors that involve part of the body such as flapping arms, body rocking and vocalization of non-word sounds. We used time-frequency methods to extract features and sparse signal representation methods to design over-complete dictionary for data analysis, detection and classification of these ASD behavioral events. We show that using single sensor on the back achieves 95.5% classification rate for rocking and 80.5% for flapping. In contrast, flapping events can be recognized with 86.5% accuracy using wrist worn sensors.**

I. Introduction

Autism is a Pervasive Development Disorder which causes a person to have severe difficulties in the areas of cognitive and social development [1]. Due to the wide range of impairments, it is also known as Autism Spectrum Disorder or Autistic Spectrum Disorder (ASD). Autism falls under a category of neurological development disorder and brings disabilities in communication, learning, development and social skills. Recent statistics from the Centers for Disease Control (CDC) show that 1 in 150 births are diagnosed with autism [2]. The ratio is even higher for boys of which 1 in 94 is estimated to be autistic. 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 [2].

Treatment or unified care has been very difficult to find, leaving families and therapists with wide variety of choices of therapies, such as treatments that use drugs or dietary programs. It is known that early intervention is effective. However, not much is understood about the underlying causes of autism. Therefore, implementing an effective treatment is difficult for therapists, families and patients. 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. Therapists also face difficulties. They monitor patient's behaviors or review lengthy video recordings to find the best treatment for a patient, which can be a very time consuming process. Using technology to quantify, automate or minimize these steps would benefit both families and therapists.

One aspect of the treatment is behavior correction, since many people with autism exhibit self-stimulatory repetitive behavioral patterns. Parents who have autistic children are very concerned about these behavioral patterns which set them apart from others. Along with long term treatments to cure autism they seek immediate treatment to correct or modify behavioral patterns exhibited by their children.

There has been an effort to develop systems to detect autistic behaviors using accelerometers [3], which showed promising results but analysis was done on data recordings from healthy adult subjects and focused on assisting therapists. In this paper, we explore methods to meet their immediate needs by detecting repetitive patterns and generating feedback. This feedback can be directly used by both caregivers and patients for developing behavior reversal programs and helping them to be more socially agreeable.

The paper is organized as follows: In Section 2 and 3, we provide details of our system and data acquisition strategy. In section 4, we discuss the feature extraction and the classification strategy. Then, in section 5, we discuss experimental results obtained from autistic subjects. Finally, we discuss the outcome of the study and future studies.

II. Data Acquisition

Our system consists of 2 sensor systems. The first sensor system is based on multiple wearable sensor systems that could be deployed to various parts of the body. Target location depends on what events we are interested in detecting. They could be wrists, arms, neck, torso, legs, or ankles which can provide detailed movements of the body parts. We have developed a wearable sensor system equipped with a 3 axis accelerometer, microcontroller and Bluethooth module for wireless communication with the base station.

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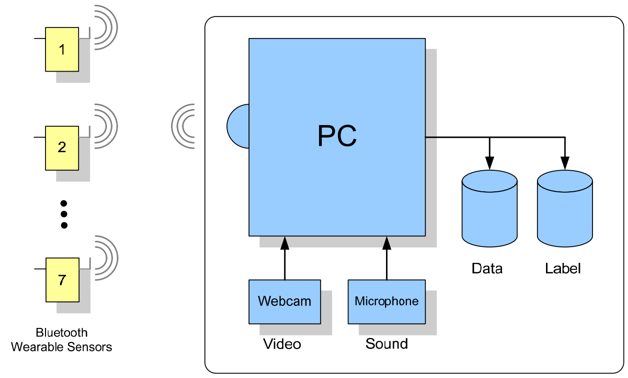
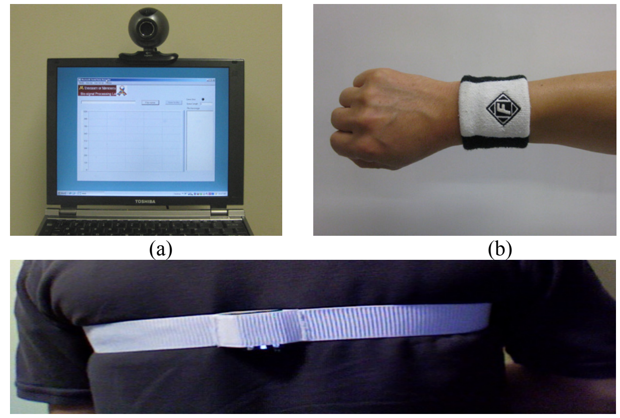


Fig. 1. Proposed data acquisition platform that combines 2 different sensor platforms which are wearable wireless sensors and static audio/video sensors.



(a) (b) (c)

Fig. 2. (a) Data recording system (b) Wearable wireless sensor kit enclosed in a wrist band. (c) Wearable body sensor strapped to upper body.

Using the microcontroller, we can sample and quantize the analog accelerometer output at high sampling rate (up to several kHz). 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.

Data from wearable sensors alone are not sufficient to understand the behavioral patterns of people with autism. 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. For the behavior detection, we do not require high sampling rate. Therefore, the accelerometer signal is sampled at 50Hz and transferred to the PC via Bluetooth module in real-time, while video records 30 fps and audio at 22kHz.

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 is currently being modified to provide automatically labeled video clips that are associated with the behaviors being detected. Once the behavioral patterns are detected by the sensors, then the system automatically records a buffered video stream which could be set to record, for example, 5 minutes before and after the detection of the behavioral patterns. This will allow the behavior and video clip to be synchronized with respect to time and event. Then, doctors and therapists can randomly access only the events they prefer to view reducing the burden of video analysis.

III. DATA DESCRIPTION

We underwent a University of Minnesota's Institutional Review Board (IRB) approval before enrolling autistic children to participate in the study. For this particular study, we collected 2 types of accelerometer sensor data from 2 autistic children labeled as S1 and S2. Recorded data include 2 self stimulatory patterns and many other daily activities. Self-stimulatory patterns were Hand Flapping (F) and Body Rocking (R). Our subjects S1 and S2 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 the behavior intervention therapy needed to be flexible in order to be patient specific. This is consistent with studies in the literature. 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. We were able to observe that the self-stimulatory repetitive behavioral patterns were different from their every day 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).

From subject S1, we recorded hand flapping and rocking. Other activities recorded in the home were activities such as reading, studying, walking, sitting down, standing up, playing video games, etc. From subject S2, we also recorded hand flapping events and rocking patterns. Other activity patterns such as playing board games, playing with toys, eating, walking, lying down and many more were recorded from S2. In the following sections, we analyze data from S1 and S2 and compare the detection accuracy.

IV. DATA ANALYSIS

With the data collected, we proceed to perform analysis and look for traits that show self-stimulatory repetitive behavioral patterns from accelerometer readings. Our automatic data recording system will rely on having an accurate event detection system. Therefore, in this section, we describe the detection of the self stimulatory events from the accelerometer data recorded.

A few examples of accelerometer data segments from self stimulatory behaviors are shown in figure 3. The frequency and speed of the arm movement contribute to different frequency characteristics and associated band powers in the frequency domain while the different position of the arms generate different DC values in the accelerometer data in time domain. Thus, we are able to understand and distinguish different arm positions and involved activities.

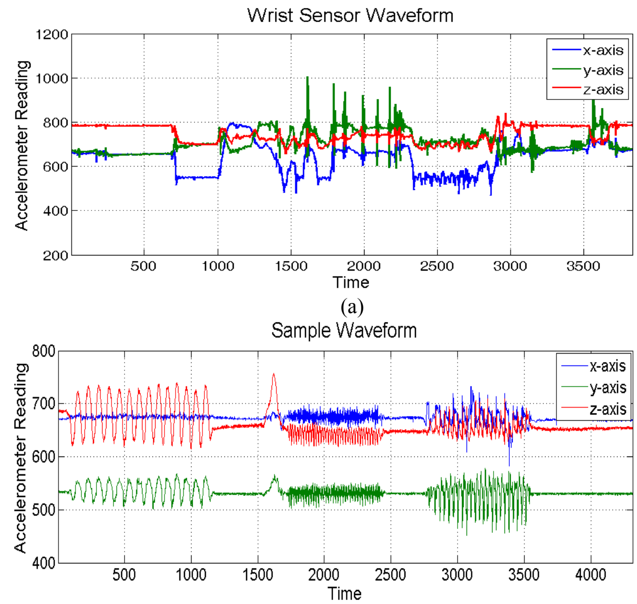
In order to detect repetitive events, researchers extract features from both time and frequency domains which have shown to provide good distinguishing characteristics for acceleration based sensors [4]. For each axis data, features are extracted for each 64 sample window and shifted with 50% overlap. Time domain features used are mean, rms and number of zero crossings. A discrete Fourier transform was performed to extract frequency domain features on the same 64 sample windows and are divided into 5 frequency bands taking into consideration the frequency content of the acquired accelerometer data. We thus have feature vectors that exploit 3 time domain features and 5 frequency domain features per axis in each window. Therefore, features we have 9 features from time-domain and 15 features from frequency domain for each 64 sample window.

A. Processing Wrist Sensor Data

In order to detect hand flapping events, sensors were worn on the wrists of autistic patients. As shown in Fig. 3, flapping events produced high frequencies along the y-axis while the x-axis data showed almost no information. This information was distinctive with other daily patterns shown by the subject. We thus used all 24 features extracted from both time and frequency domains. The extracted features from the training set were used to generate a dictionary for flapping events (D_f). Another training set which includes data from other daily activities were used to generate non-flapping dictionary (D_{nf}). Both the flapping and non-flapping data were segmented by generating a series of frames. A frame, denoted as *"y"*, is a data segment with 64 samples with 50% overlap. The window used was a Hanning window and a 128-point DFT was used. For each source, the K-SVD algorithm was used [5]. K-SVD solves the following equation,

$$\min_{\Phi,X}\{\| Y - \Phi X \|_F^2\} \; s.t. \; \forall_i \; \| x_i \|_0 \le T_0, \qquad (1)$$

where T_0 is the constraint on the allowed non-zero element and Φ is the dictionary. Solution is obtained, first by sparse coding and then sequentially updating the dictionary by using SVD operations. We then use the Orthogonal Matching



(b)

Fig. 3. Typical recordings obtained from 3 channel (x, y, z axis) sensor. (a) Hand flapping accelerometer readings from a wrist worn sensor (b) From left to right; Rocking, standing, flapping and walking activity accelerometer readings from a body worn sensor.

Pursuit (OMP) algorithm [6] to find a representation of activity *y,* from the augmented dictionary, $D = [D_f \mid D_{nf}]$, such that,

$$y = [D_f \mid D_{nf}][\, \vec{x}_f \mid \vec{x}_{nf}]^T + \varepsilon. \qquad (2)$$

We decide *"y"* as "flapping", if $\| D_f \vec{x}_f \|_2 > \| D_{nf} \vec{x}_{nf} \|_2$. 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.

B. Processing Body Sensor Data

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 15 features from frequency domain. 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 (D_r) and non-rocking training set (D_{nr}). We also used a 64 sample window with a 128-pt DFT for the body sensor data. We then used the same approach as above, to classify the observed patterns as rocking or non-rocking.

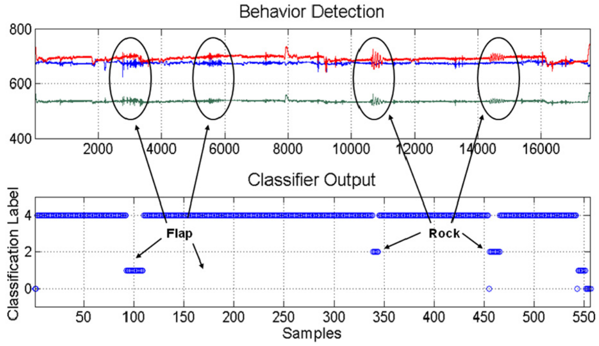


Fig.4. Detection of flapping and rocking results using a single body sensor. Encircled areas denote locations where flapping and rocking have occurred and lower figure shows the classifier output with a missed flapping.

V. RESULTS

The extracted features showed a good separation in time-frequency feature domain which has great potential for continuous detection of the location and duration of the self-stimulatory behaviors. We have recorded over 10 hours of annotated data from 2 children with autism with 99 and 124 flapping events, respectively for S1 and S2. We also acquired 40 and 96 rocking events from them. From the analysis of this data we were able to detect the self stimulatory patterns with the accuracy shown in Table 1. On the average, we are able to detect the self stimulatory patterns with the average of 92.7% (sensitivity). Authors in [3] 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.

We have also 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 2, flapping detection rate for both S1 and S2 decreased 6% compared to that of the wrist sensor. But, when flapping was detected from a 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 5 FPs and 15 FPs for flapping respectively and no FPs 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 at this time 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.

VI. CONCLUSION AND FUTURE WORK

In this paper we presented new methods and overall system architecture to continuously recognize the activities 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 used sparse signal representation methods to test the proof of concept and currently are exploring other classification methods. The number of sensor systems can be extended to other parts of the body such as legs to detect other behavioral patterns such as leg shaking. We will continue our studies to find optimal locations for sensor placement for self stimulatory behavior detection.

We are currently in the process of enrolling more patients and also studying the fusion of audio and accelerometer data 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 using a single body sensor for both rocking and flapping. Using the results from this study, our contribution was; 1) provided an unbiased objective measure to detect amount of self-stimulatory behavior one exhibited and 2) provided a study results on the sensor placement and associated detection rate to find optimal sensor location. We believe that using the combination of different sensor modalities properly positioned in right location combined with audio/video recordings may lessen the burden of the therapists and provide us with information on what triggers the self-stimulatory patterns for the autistic children.

Table1. Classification accuracy using separate wrist and body sensors.

Events	Flapping (wrist)	Rocking (body)
Subject 1	89%	95%
Subject 2	84%	96%

Table2. Classification accuracy using single body sensor on the back

Events	Flapping (body)	Rocking (body)
Subject 1	83%	95%
Subject 2	78%	96%

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