33rd Annual International Conference of the IEEE EMBS
Boston, Massachusetts USA, August 30 - September 3, 2011

Semi-Supervised Event Detection Using Higher Order Statistics for Multidimensional Time Series Accelerometer Data

Cheol-Hong Min and Ahmed H. Tewfik

Abstract— **In this study, we target to automatically detect stereotypical behavioral patterns (stereotypy) and self-injurious behaviors (SIB) of Autistic children which can lead to critical damages or wounds as they tend to repeatedly harm oneself. Our custom designed accelerometer based wearable sensors are placed at wrists, ankles and upper body to detect stereotypy and SIB. The analysis was done on four children diagnosed with ASD who showed repeated 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. Our 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 impossible to design a single algorithm to understand all events in natural setting. Therefore, a semi-supervised 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 paper, we show how the Higher Order Statistics (HOS) features can be used to design dictionaries and to detect novel events in a multichannel time series data. We explain our methods to detect novel events in a multidimensional time series data and combine the proposed semi-supervised learning method to improve the adaptability of the system while maintaining comparable detection accuracy as the supervised method. We, compare our results to the supervised methods that we have previously developed and show that although semi-supervised method do not achieve better performance compared to supervised methods, it can efficiently find new events and anomalies in multidimensional time series data with similar performance of the supervised method. We show that our proposed method achieves recall rate of 93.3% compared to 94.1% for the supervised method studied earlier.**

I. Introduction

There has been an increased awareness in Autism Spectrum Disorder as it is a development disorder that leads to many different cognitive impairment such as deficiencies in social interaction and communication [1]. The Centers for Disease Control (CDC) show that 1 in 150 births are diagnosed with autism with higher ratio for boys. It is estimated that 1 in 94 boys is 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 alone, it costs over $90 billion annually in the U.S. and it is estimated that the cost related to autism will increase to $200-400 billion in 10 years [2].

Since the cause is unknown, there is no real cure for Autism and diagnosis done based on questionnaires. But, recent studies show that early detection and intervention therapies are effective which may reduce the cognitive impairments and the stereotypical behaviors often observed in autistic children. Since, the diagnosis is based on observations which are subjective measurements, autism community has been seeking for an unbiased tool to quantify, automate or minimize various steps that would be beneficial to therapists, family and the patient himself.

Recently, there has been efforts to develop systems to detect autistic behaviors using accelerometers [3, 4, 5], which showed promising results but analysis was done on limited set of behavioral patterns which showed potential but lacked real world situations or focused more on assisting therapists. In this paper, we explore methods to target real world situations and also patient centered system to meet their immediate needs by detecting repetitive patterns and generating feedback for behavior modification. This feedback can be directly used by both caregivers and patients for developing behavior reversal programs.

The paper is organized as follows: In Section 2, we provide brief overview of our system. In section 3, we discuss the dictionary design method using HOS features and LPC model. Then, in section 4, we discuss experimental results obtained from autistic subjects. Finally, we discuss the outcome of the study and future studies.

II. Data Description

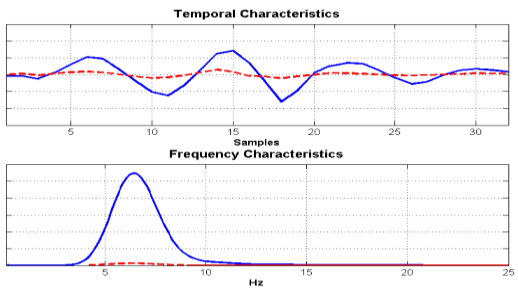
Our custom designed wearable wireless sensor system can be worn on wrists, chest, waist and ankles. This wearable sensor system is equipped with a 3-axis accelerometer, microcontroller and bluethooth module for wireless communication with the base station to transmit accelerometer data. Using the on board microcontroller, we 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 wearable system. For the behavior detection purposes, we do 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

This work was supported in part by the Medical Devices Center and Institute of Engineering in Medicine at the University of Minnesota – Twin Cities.

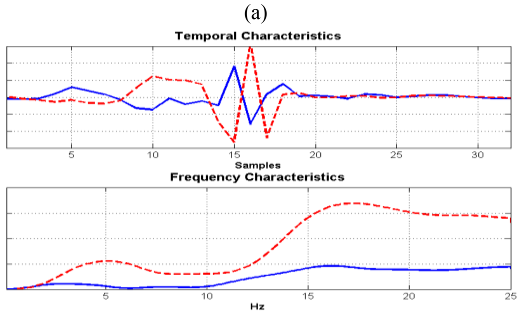
Cheol-Hong Min, is with the Department of Electrical and Computer Engineering at the University of Minnesota – Twin Cities, Minneapolis, MN 55455 USA (phone: 612-624-5285; fax: 612-625-4583; e-mail: cmin@umn.edu).

Ahmed H. Tewfik is with the Department of Electrical and Computer Engineering at the University of Texas – Austin, Austin, TX 78712-0240 USA (phone: 512-471-6170; fax: 512-471-3652; e-mail: tewfik@austin.utexas.edu).

978-1-4244-4122-8/11/$26.00 ©2011 IEEE



(a)



(b)

Fig. 1. Temporal and frequency characteristics of sample waveforms. (a) x and y axis data for the flapping event. (b) x and y axis data for the punching event.

the user interface shown in Fig 1.

For this particular study, we collected 4 types of accelerometer sensor data from 4 autistic children labeled as S1, S2, S3 and S4. Recorded data include self-stimulatory patterns and many other daily activities. Self-stimulatory patterns were hand flapping (F) and body rocking (R). Also, several SIB patterns such as punching one's own face (P) and hitting (H) one's laps were also recorded. These SIB patterns were used as novel events and we did not generate dictionary for SIB patterns. 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 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. Data was recorded from both in therapy and in home sessions.

III. AUTOMATIC CHARACTERIZATION AND DETECTION OF BEHAVIORAL PATTERNS

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 can be represented as below

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

where, n_0 is the event onset time, M is the number of sinusoids, a_m is the amplitude, ω_m is the frequency component of the signal and $v(n)$ is the additive noise. In natural setting, the event waveforms actually appear as a variation of the signal $x(n)$,

$$y(n) = \sum \alpha x(\beta n + \gamma) \tag{2}$$

where, the $x(n)$ are also stretched and translated using a function shown below, where α, β and γ represent scale, stretch and translation factors. 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.

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

A. 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 [6]. Higher Order Statistics have also found its application in number of signal processing applications. Especially in speech processing applications, it has found wide attention [7].

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

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

Skewness is the 3rd 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 μ and is defined as follows,

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

Kurtosis is the 4th moment in statistics and finds the peakness

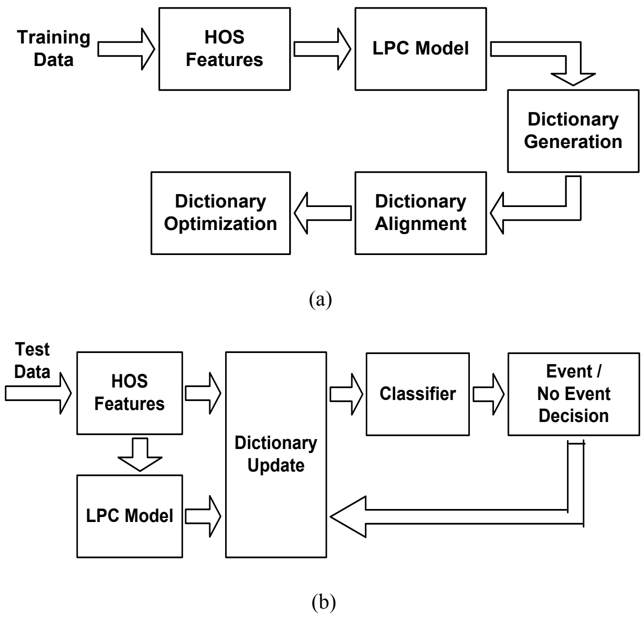


Fig. 2. (a) Schematic of the proposed training algorithm using HOS and LPC. (b) Schematic of the proposed testing algorithm using HOS and LPC.

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.

B. Linear Predictive Coding (LPC)

Linear Predictive Coding was largely used in speech and speaker independent word recognition system. In these studies, LPC parameters and LPC distance was used to measure similarity between the test signal and each of the training signals for classification purposes [6].

LPC uses a P-th order linear predictor that predicts current value using the past P samples of data,

$$y(n) = a_1 x(n-1) + a_2 x(n-2) + ... + a_p x(n-P) = \sum_{p=1}^{P} a_p x(n-p) \tag{5}$$

where *y(n)* is the prediction of *x(n)*, and *x(n-p)* is the *p-th* step previous sample, i.e. *p* is the order of the polynomial. LPC determines the coefficients of the predictor by finding the minimum error in the least square sense. LPC is an Autoregressive (AR) model, i.e. an all-pole model. As it is well known in filter design, angles and radius of the poles and zeros define characteristics filters. Similarly, pole locations as shown in the pole-zero planes show the frequency content in the windowed signal. Therefore, using the pole-zero planes, we are able to group similar patterns. We use Euclidean distance measure to define the proximity of the poles of the dictionary atoms to input signal and determine the signal as candidate of a predefined event. We use k-means algorithm to cluster pole locations and assign class labels for each cluster.

C. 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 [8, 9]. 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 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.

D. Dictionary Alignment and Optimization

Part of variability in the dictionary atoms and detection performance comes from the fact that the data is 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.

IV. RESULTS

The HOS features and LPC model based event detection method has great potential for continuous detection of the location and duration of the behavioral patterns. We have tested the proposed algorithm with data collected from 4 children with autism. Using the proposed method, we were able to detect the stereotypy and SIB with the accuracy shown in Table 1. We compared this result with our previous result using supervised method to generate initial dictionary in Table 2 [9]. We again focus on increasing the recall rate so that SIBs are not missed as it is more important to reduce true negatives then reducing false positives. On the average, we are able to detect the self stimulatory patterns with the average recall rate of 93.3% compared to 94.1% of the supervised method [9].

Table1. Classification results for flapping, rocking, punching and hitting using proposed learning method (recall rate).

	flapping	rocking	punching	Hitting
Subject 1	91%	95%	NA	NA
Subject 2	86%	96%	NA	NA
Subject 3	93%	NA	96%	NA
Subject 4	95%	NA	NA	95%

Table2. Classification results for flapping, rocking, punching and hitting using LPC based template matching method (recall rate).

	flapping	rocking	punching	hitting
Subject 1	94%	95%	NA	NA
Subject 2	89%	96%	NA	NA
Subject 3	95%	NA	96%	NA
Subject 4	96%	NA	NA	95%

V. 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 presented a method to characterize the stereotypical movements and dictionary design methods based on LPC and HOS features 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. The proposed algorithm shows comparable results over our previous reported results using supervised method for initial dictionary training. We believe time domain pattern matching performs better than the frequency based clustering approaches because of the variability such as length and frequency content in the behavioral patterns. Also, the proposed method is much faster than the previous method which uses ISI [8] allowing a step closer to real time implementation.

Although the semi-supervised method still needs improvement in its training stages, we have also shown that the system is able to learn similar patterns from training data and also able to update the dictionary with novel SIB patterns. The system's ability to isolate abnormal patterns enables monitoring of abnormal behaviors. It will to provide unbiased quantitative data and could be used with a treatment or intervention for behavior reversal therapy.

The next step is to develop unsupervised methods to characterize events from the initial training stages. This has potential in that the system could be fully adaptive to a patient's behaviors not only detecting novel events.

REFERENCES

[1] Center for Disease Control, http://www.cdc.gov/bcbddd/autism.

[2] Autism Society of America, http://www.autism-society.org.

[3] J. A. Kientz, G. R. Hayes, T. L. Westeyn, T. Starner and G. D. Abowd, "Pervasive Computing and Autism: Assisting caregivers of children with special needs", *IEEE Pervasive Computing Magazine*, Jan. 2007.

[4] M. S. Goodwin, S. S. Intille, W. F. Velicer and J. Groden, "Sensor enabled detection of stereotypical motor movements in persons with autism spectrum disorder", *Proc. of the 7th International conference on Interaction Design and Children*, Chicago, IL, USA, June 11-13, 2008, pp. 109-112.

[5] C.-H. Min, A. H. Tewfik, Y. Kim, and R. Menard, "Optimal sensor location for body sensor network to detect self-stimulatory behaviors of children with autism spectrum disorder", *31st Annual Int'l Conf. of the IEEE EMBS*, Minneapolis, MN, USA, Sep. 2-6, 2009, pp. 3489 – 3492.

[6] E. Nemer, R. Goubran, and S. Mahmoud, "Robust Voice Activity Detection Using Higher-Order Statistics in the LPC Residual Domain", *IEEE Transactions on Speech and Audio Processing*, vol. 9, no. 3, March 2001

[7] J. M. Mendel, "Tutorial on Higher-Order Statistics (Spectra) in Signal Processing and System Theory: Theoretical Results and Some Applications", Proceedings of the IEEE, vol. 79, no. 3, March 1991, pp. 278-305.

[8] C.-H. Min and A. H. Tewfik, "Novel Pattern Detection in Children with Autism Spectrum Disorder Using Iterative Subspace Identification", ICASSP 2010, Dallas, TX, USA, Mar. 15-19, 2010, pp.2266-2269.

[9] C.-H. Min and A. H. Tewfik, "Automatic Characterization and Detection of Behavioral Patterns Using Linear Predictive Coding of Accelerometer Sensor Data", *32nd Annual International Conference of the IEEE EMBS*, Buenos Aires, Argentina, Aug. 31-Sep. 4, 2010, pp. 220-223.