TYPICALLY DEVELOPED ADULTS AND ADULTS WITH AUTISM SPECTRUM DISORDER CLASSIFICATION USING CENTRE OF PRESSURE MEASUREMENTS

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ABSTRACT

Autism spectrum disorders (ASD) are neurodevelopmental disorders which affect a persons ability to interact with the world around him/her. Emerging studies have shown abnormal postural control in people with ASD. The aim of this study was to enable the classification of adults with ASD and typically developed (TD) adults based on force plate measurements of centre of pressure. Nineteen typical adults and eleven adults diagnosed with ASD primarily high functioning autism or Asperger's syndrome participated in this study. A correlation-based feature selection algorithm was used to evaluate the quality of the attributes and the results have achieved up to 0.976 classification accuracy.

***Index Terms*—** Autism spectrum disorder, classification, correlation-based feature selection, frequency analysis

1. INTRODUCTION

Autism spectrum disorders (ASD) are neurodevelopmental disorders of complex origin; they are characterised by significant difficulties in communication, social interaction, repetitive interests and behaviours [1]. ASDs include autism, Aspergers syndrome and pervasive developmental disorder not otherwise specified [2]. A South Korean study (n=55,266) estimated the population prevalence of ASDs to be 2.64% [3] whereas in United States, the prevalence rate for ASDs has been reported as 0.91% [4]. The prevalence rate for ASD has increased over the years and the lifetime cost of raising a child with ASD is currently between USD $1.4 million to $2.4 million [5]. This results in enormous financial and personal costs to both families and communities.

Whilst impairments in communication and social interaction are the core symptoms for ASDs, emerging studies have reported abnormal postural control for individuals with the disorders [6]. Poor control affects physical functioning by reducing the ability to perform activities of daily living and potentially impacts on the psychosocial functioning of individuals [7]. Thus, if individuals with ASD have impaired postural control, this could lead to significant motor and social difficulties [8]. In order to evaluate the postural stability of a human subject, centre of pressure (COP) measures derived from a force platform during quiet standing are used in both clinical and research settings [9]. The COP trajectory data is usually characterised spatially in the anterior-posterior (AP) and medial-lateral (ML) directions. The COP data can further be analysed in time domain, frequency domain or hybrid of both domains [10, 11]. Studies using COP range in AP direction and ML direction, for sway area and sway velocity have shown that children with ASD have a different pattern in postural control as compared with TD children [12, 13]. Moreover, poor postural control persisted into adulthood with ASD [8, 14].

The aim of this study was to classify TD adults and adults diagnosed with high functioning ASD primarily or Aspergers Syndrome based on COP measurements during quiet standing. Top data mining tools such as decision tree [15], naïve Bayes [16], support vector machine [17], K-nearest neighbour [18] as reference in [15] and random forest [19], multilayer perceptron neural network [20] and Bayesian network [21] were used for classification. In addition, correlation-based feature selection [22] algorithm was used to evaluate the worthiness of the COP features. The area under receiver operating characteristic (AUC) results have revealed up to 0.976 accuracy from 20 seconds with 50% overlapping dataset.

2. METHODS

2.1. Participants

Recruitment was through advertising in social media and snowball sampling. Nineteen TD adults aged between 19 and 35 (Mean 23.5 $\pm$ 5.05) and eleven adults diagnosed with high function autism or Aspergers Syndrome aged between 19 to 40 (Mean 23.58 $\pm$ 7.9) participated in this experiment. Each participant provided their written informed consent prior to participation. The study was approved by the Curtin University Human Research Ethics Committee (Approval No: PT250/2013).

Table 1. Datasets with various sample size and duration

Sampling period	TD group samples	ASD group samples	Total
5	437	253	690
10	209	121	330
20	95	55	150

Table 2. The distribution of feature vectors

Notation	Feature Set	No. of Features
A	Time-domain	28
B	Frequency-domain	14
C	Time and frequency domain	42

2.2. Data Acquisition

Centre of pressure data was obtained using AMTI AccuGait portable force platform (Advanced Mechanical Technology, Watertown MA, USA). Data was recorded using in-house custom made program written under LabView (National Instruments Corporation, Austin TX, USA), and was sampled at 100Hz.

2.3. Experimental Protocol

Potential candidates were familiarized with the procedure, completed a questionnaire assessing inclusion and exclusion criteria and were provided with the opportunity to ask any questions prior to participation. Once the written informed consent was completed and it was verified that the participants met the criteria, the height and weight of the participants was then measured. Participants attended a single session where they undertook a set of experimental trials in quiet standing. This paper reports on the baseline assessment of quiet standing which occurred at the start of the session.

The participants task was to stand on a force plate at a set distance of 1.5 meters from a white wall with a black horizontal line running at a height of 165cm from the floor. Movement of the COP with respect to AP and ML directions were calculated using force and moment data extracted while the participants stood on the portable force platform (Advanced Mechanical Technology, Watertown MA, USA). The recording was taken over 60 seconds with vision available for each participant.

2.4. Data Processing, Parameters Settings and Analysis

Subsequent processing were done using Matlab 2014a (Mathworks Inc, Natick MA, USA) and Weka [23]. Of the thirty two adults who participated in this study, two adults (one TD adult and one adult with ASD) were excluded due to hardware issues. Since the recording was over 60 seconds, the sample size was expanded by generating more samples with shorter duration and 50% overlap. Thus, there were 5 second, 10 second and 20 second sampling duration datasets with 50% overlap. The 40 second and 60 second sampling durations were ignored due to small sample size for classification. The details of datasets are shown in Table 1.

Descriptive measures (in both time and frequency domains) of each COP duration were calculated in anterior-posterior (AP) direction and medial-lateral (ML) direction. Resultant distance (RD) which denoted as the vector distance from the mean COP point was also calculated for the measurements. The COP measurements include time domain measures such as mean distance (RD, AP, ML), resultant sway path, sway path (AP, ML), standard deviation (AP, ML, RD), amplitude of COP displacement (AP, ML), resultant mean velocity, mean velocity (AP, ML), total excursion (COP, AP, ML), max distance, area (95% of COP data, 95% confidence circle area, 95% confidence ellipse area), sway area, mean frequency (COP, AP, ML), fractal dimension (planar dimension, confidence circle, confidence ellipse) and frequency domain measures such as total power, mean power frequency, peak frequency, power frequency (50%, 95%), centroid frequency and frequency dispersion. For the details of the time and frequency domain measures can refer to Prieto et al. [10]. The frequency domain measures were calculated from range 0.15 Hz to 5.0 Hz as in references [10, 11]. The power spectral density of AP and ML direction was computed using Welchs periodogram technique by dividing the data into 7 segments with 50% overlap. The distribution of the feature vectors is shown in Table 2.

Top data mining tools such as decision tree, naïve Bayes, support vector machine and k-nearest neighbour as recommended by Wu et al. [15] and few additions such as random forest, multilayered perceptron neural network and Bayesian network were used for comparison and classification in this paper. Brief explanation and parameters settings of the algorithms were written below.

Decision tree decided the target class of a new sample based on selected features from available data using the concept of information entropy. The nodes of the tree were the attributes, each branch of the tree represented a possible decision and the end nodes or leaves were the classes. Pruning was used to avoid overfit the training data. Next is the random forest, it worked by constructing multiple decision tree on various sub-samples of the datasets and output the class that appeared most often or mean predictions of the decision trees. In the experiment, the random forest consisted of 100 trees with each tree considered 6 random COP measurements. The third classifier was the naïve Bayes classifier which based on Bayes theorem with strong independent assumptions between features. The forth is the multilayered perceptron neural network, a non-linear feed-forward network model which mapped a set of inputs x onto a set of outputs y using multi weights connections. The network was trained by updating the weight and bias value using gradient descent. One hidden layer was used in this paper, and the number of hidden neurons was calculated based on the number of features plus the number of class divided by two. The learning rate was set to 0.3, the momentum was set to 0.2 in each weight updating and the number of epoch for each training time was set to 500. There was a validation set which used to terminate the training when the validation set error got worse 20 times in a row. Bayes network was a probabilistic graphical model for reasoning under uncertainty, where the nodes represented discrete or continuous variables and the links represented the relationships between them. The initial count of the values, alpha was set as 0.5 and estimated directly from the data. Hill-climbing algorithm was used to search for the structure of the Bayesian Network. Support vector machine was used to discriminate a set of high-dimension features using one or sets of hyperplanes that gave the largest minimum distance to separates all data points among classes. Sequential minimal optimization was used to train the support vector machine and polynomial kernel was selected to perform non-linear classification on high dimensional samples to a higher dimensional space. Lastly, K-nearest neighbour was an instance-based learning algorithm that stored all available data points and classified the new data points based on similarity measure such as distance. There was no distance weighting for the setting and Euclidean distance was used to search for the nearest neighbour.

In order to evaluate the performance of the algorithms, a 10-fold cross validation was used to assess how accurately a model performed in practise. Unlike precision and recall which depended on particular threshold, the area under receiver operating characteristic (AUC) was determined by plotting true positive rate versus the false positive rate in various threshold value. Thus, AUC was emphasized to measure the performance because it did not depend on any threshold. In addition, correlation-based feature selection was used to evaluate the worthiness among the subsets of features which were highly correlated with the classes while having low inter-correlation among each other [22]. The space of feature subset was searched using a greedy hill-climbing algorithm. Furthermore, the features were selected based on 10-fold cross validation. In this paper, only those features that appeared in 5 fold or greater were considered.

3. RESULTS AND DISCUSSIONS

In this section, the AUC results from 5, 10 and 20 seconds sampling period datasets using decision tree, random forest, naïve Bayes, multilayered perceptron neural network, Bayesian network, support vector machine and K-nearest neighbour were presented. The results were classified on time-domain features (feature set A), frequency-domain features (feature set B) and both time and frequency-domain features (feature set C). The AUC results from 5, 10 and 20 seconds sampling period datasets are shown in Table 3, 4 and 5.

Table 3. AUC classification results on 5 seconds sampling period dataset

Classifier	**Feature Set**		
	A	B	C
Decision Tree	0.788	0.580	0.771
Random Forest	0.831	0.809	0.848
Naïve Bayes	0.808	0.687	0.804
Multilayer Perceptron	0.827	0.760	0.823
Bayesian Network	0.826	0.748	0.826
Support Vector Machine	0.745	0.621	0.772
K-Nearest Neighbour	0.727	0.623	0.726

Table 4. AUC classification results on 10 seconds sampling period dataset

Classifier	**Feature Set**		
	A	B	C
Decision Tree	0.819	0.604	0.850
Random Forest	0.916	0.872	0.927
Naïve Bayes	0.837	0.751	0.855
Multilayer Perceptron	0.876	0.808	0.935
Bayesian Network	0.872	0.716	0.882
Support Vector Machine	0.777	0.747	0.830
K-Nearest Neighbour	0.792	0.665	0.830

From the observation of the tables (Table 3, 4 and 5), the AUC results in feature set A have shown greater results compare to the ones in feature set B, suggesting that time-domain features are more significant than frequency-domain features. Subsequently, the AUC results resulting from the combination of both time and frequency domain features (feature set C) in 5 seconds sampling period datasets have reported not much significant compare to the AUC results classified using only the time-domain features. However, the AUC results computed from feature set C in 10 and 20 seconds sampling datasets have shown greater results compare to feature set A or feature set B, thus suggest a minimum of 10 seconds

Table 5. AUC classification results on 20 seconds sampling period dataset

Classifier	**Feature Set**		
	A	B	C
Decision Tree	0.844	0.711	0.868
Random Forest	0.961	0.894	0.973
Naïve Bayes	0.881	0.696	0.918
Multilayer Perceptron	0.924	0.856	0.974
Bayesian Network	0.826	0.748	0.826
Support Vector Machine	0.745	0.621	0.772
K-Nearest Neighbour	0.727	0.623	0.726

Table 6. Correlation-based features on 20 seconds sampling period dataset

Feature Set	Correlation-based Features
A^*	Resultant mean velocity, sway area, fractal dimensions (confidence ellipse), 95% confidence ellipse area, total excursion, mean velocity (AP,ML)
B^*	Total power (AP,ML), 50% of power spectrum (AP,ML)
C^*	Resultant mean velocity, sway area, fractal dimensions (confidence ellipse), 95% confidence ellipse area, total excursion, mean velocity (AP,ML), 50% of power spectrum (AP,ML)

Table 7. AUC classification results on 20 seconds sampling period dataset from correlation-based features

Classifier	Feature Set		
	A^*	B^*	C^*
Decision Tree	0.866	0.635	0.927
Random Forest	0.970	0.847	0.976
Naïve Bayes	0.952	0.837	0.972
Multilayer Perceptron	0.943	0.860	0.962
Bayesian Network	0.949	0.639	0.949
Support Vector Machine	0.824	0.619	0.866
K-Nearest Neighbour	0.863	0.755	0.909

sampling period is required to pick up useful information in frequency-domain. Among the datasets, multilayered perceptron neural network and random forest are the best performed classifiers to discriminate between TD adults and adults with ASD with up to 0.974 AUC in former classifier and 0.973 AUC at the latter classifier.

Correlation-based feature selection was used to compute the worthiness of the features among the feature set. In the next experiment, the feature extraction algorithm was used on the 20 seconds sampling period dataset as the dataset had reported the highest AUC results among the three datasets. The selected features are presented in Table 6 and the AUC results are presented in Table 7.

In Table 6, feature set A^* denotes as features selected from time domain, feature set B^* denotes as features selected from frequency domain and feature set C^* denotes as features selected from both time and frequency domains. 7 features are selected in feature set A^*, 4 features are selected in feature set B^* and 9 features are selected from feature set C^*. All the features in feature set C^* appear to be in feature set A^* and feature set B^* except total power in AP or ML. The reason is because the total power feature is having low correlation (total power AP appear in 2 fold and total power ML appear in 3 fold), thus were not selected.

The AUC results from the selected correlation-based features on 20 seconds sampling period dataset were presented in Table 7. The results in feature set A^* from various classifier have shown up to 0.97 AUC. Even though the highest results from Feature set B^* were lower as compare to Feature Set A^*, the table had reported better AUC results using selected features from both domains (feature set C^*). Random Forest is the best performed classifier with 0.97 AUC in feature set A^* and 0.976 AUC in feature set C^* whereas Multilayer Perceptron has the best AUC result in selected frequency domain with 0.86 AUC result. The AUC results from Nave Bayes are close to those performed by random forest and multilayer perceptron neural network, suggesting that these three classifiers are suitable to classify TD adults and adult with ASD.

The findings of this study were consistent with previous reported findings regarding the selected features describing COP. Specifically the findings support larger mean velocity with children with ASD [17, 18] and greater sway area [10]. Even though the supporting studies here were mostly children, there were studies reported postural control was underdeveloped with children with ASD and never achieved adult levels [21]. Thus, deficient postural control persisted into adulthood with ASD [13]. This study had reported that frequency domain COP features such as 50% of power spectrum in AP or ML are important in distinguishing adults with autism from typically developed adults. Furthermore, the AUC result of this work is higher than a recent diagnostic algorithm which reported 0.89 AUC [24]. It would be valuable to include frequency domain COP measurements in future research in postural control in autism. Moreover, since the preliminary classification performance were more than 0.90 AUC (considered as excellent), there was no subsequent attempt at fine tuning the parameters of individual classifier to achieve further improvement.

4. CONCLUSION

Resultant mean velocity, mean velocity in AP and ML, 95% of confidence ellipse area, sway area, total excursion, fractal dimensions confidence ellipse and 50% of power spectrum in combination discriminate adults with ASD and TD adults. With a sampling period of 20 seconds, random forest managed to achieve 0.976 AUC. Future research is required to extend the classification of COP features to develop a potential screening tool for ASD in childhood.

5. REFERENCES

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