Automated Classification of Gait Abnormalities in Children with Autism Spectrum Disorders Based on Kinematic Data

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Abstract: - Autism spectrum disorders (ASD) are a permanent neurological disorder that can be recognized at the early stage of the developmental period and are recently associated with movement disturbances. The aim of this study was to classify gait abnormalities in children with ASD based on their respective three-dimensional (3D) kinematic data. The gait analysis of 30 ASD children and 30 normal healthy children was assessed using a state-of-the-art 3D motion analysis system during self-selected speed barefoot walking. Kinematic gait features from the sagittal, frontal and transverse joint angles waveforms at the pelvis, hip, knee, and ankle were extracted using time-series parameterization. Two statistical analysis techniques, namely the between-group tests (independent samples *t*-test and Mann-Whitney *U* test) and stepwise discriminant analysis (SWDA) were adopted as feature selector to select the dominant gait features that were then used for the purpose of training and testing of the artificial neural networks (ANN). The results indicate that the selected gait features using SWDA technique are more reliable for ASD gait classification with 91.7% accuracy, 93.3% sensitivity, and 90.0% specificity. These promising findings suggest that the kinematic gait features with the combination of SWDA feature selector and ANN classifier are potentially effective for the diagnosis of ASD gait patterns. Early detection of gait abnormalities could ensure rapid quantitative clinical decision and further facilitate for appropriate treatments to the ASD patients needing therapies.

Key-Words: - artificial neural network, autism spectrum disorders, gait classification, gait feature, kinematic, statistical analysis, stepwise discriminant analysis

1 Introduction

Autism spectrum disorders (ASD) are a lifelong neurodevelopmental disorder that can be identified in the early years of childhood. Children with ASD were found to demonstrate difficulties in their social communication, social interaction, and the presence of restricted and repetitive patterns of behavior [1]. Clinicians and researchers worldwide have reported increasing prevalence rates of ASD cases in many parts of the world [2].

Recently, researchers from various disciplines have identified movement and sensory disturbances as the focus symptoms of individuals with ASD [3]. Previous studies have reported a wide range of abnormal gait patterns in various aspects of gait parameters such as basic gait measurements, kinematic joint angles, and kinetic joint moments during walking in individuals with ASD [4]. Children with ASD were found to demonstrate several significant alterations on the ankle and hip joint kinematics and kinetics [5]. Gait abnormalities have become one of the characteristics to support the diagnosis of ASD [1]. An early identification of gait abnormalities in ASD children is crucial in order to facilitate appropriate treatments and rehabilitation programs for the ASD patients requiring therapies.

Nowadays, gait analysis is routinely used in clinical settings for the systematic study of the human walking patterns and also for the assessment of walking performance [6]. Gait can be assessed quantitatively to produce temporal-spatial, kinetic, and kinematic measurements that can be used for the examination of any deviation from the normal walking pattern.

The gait measurement using the state-of-the-art motion analysis system equipped in standard gait analysis laboratories allows new insights into the understanding of human gait patterns and promotes possibilities to develop an automated detection of gait abnormalities [7]. The current gait analysis provides a large amount of gait data that is time-consuming and difficult to interpret. It is well-known that an automatic system which is able to identify accurately impairments in gait patterns could provide support to clinicians in the diagnosis and to ensure rapid quantitative clinical decision.

Computational intelligence such as artificial neural networks (ANN) has been widely explored in analyzing gait and movement data [8]. Most studies in the gait research have employed ANN for distinguishing and recognizing numerous gait patterns including classification of healthy and pathological gait [9], automated diagnosis of gait patterns in certain gait conditions [10], distinguishing young and old gait patterns [11], and categorization of abnormal gait pattern in patients with Parkinson's disease [12] and post-stroke [13]. All these studies have proven that ANN has a greater potential to be used for automated classification of impairments in ASD gait patterns.

Apart from that, due to high dimensional data obtained from gait analysis, statistical feature selection techniques such as independent *t*-test [14], Mann-Whitney *U* [15], and stepwise method of discriminant analysis (SWDA) [13] are generally used to determine significant features for group separation. The independent *t*-test and Mann-Whitney *U* test (TMWU) are the types of between-group tests that have the ability to select significant features by identifying the mean scores of gait features across the two separate groups.

Meanwhile, SWDA was frequently utilized to determine the optimum set of input features for group membership prediction and to eliminate the least significant and unrelated features from the dataset [16]. Previous studies in gait analysis have validated that SWDA was able to identify specific individual features that best determined group placement [13].

It is globally well-known that far too little attention has been paid on the classification of ASD gait pattern. Thus, the aim of this study is to classify gait abnormalities in ASD children based on kinematic measurements with the utilization of ANN as pattern classifier. This study proposes two types of statistical feature selection techniques in selecting dominant kinematic gait features as input features to the ANN.

2 Methodology

The methodology for the proposed gait classification is depicted in a flowchart in Fig. 1. The proposed system consisted of four sequence stages of gait data acquisition, feature extraction, feature selection, and gait classification stage.

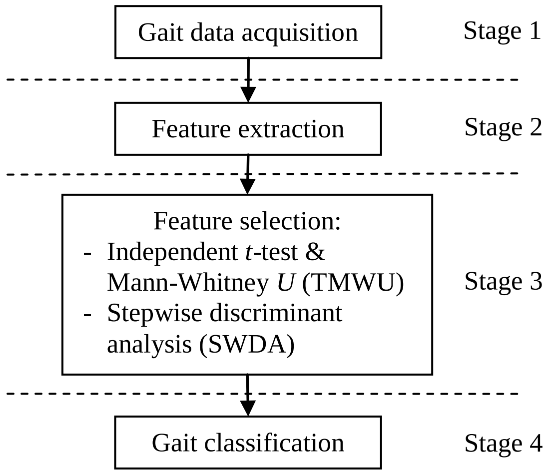

Fig. 1. Flowchart of the proposed ASD gait classification.

2.1 Participants

This study was ethically approved by the Research Ethics Committee of the Universiti Teknologi MARA (UiTM) Shah Alam, Selangor. The parent or guardian of each child signed an informed consent form prior to participation. Thirty children who had been previously diagnosed with the mild category of ASD and thirty normal healthy children participated in the study. All of them were under the age of 4 to 12 years old and were able to walk independently and had no medical history of lower extremity injuries.

Fourteen ASD participants were recruited from the National Autism Society of Malaysia (NASOM) center and sixteen were obtained from the local community by approaching their parents through the social media. The normal healthy children were employed from the nearby neighborhoods and the family members of the faculty employees and they served as the control group for the ASD participants. The demographic data of the participants from both groups are presented in Table 1.

Table 1. Demographic data of participants

Characteristics	ASD	Control
N (male:female)	30 (23:7)	30 (15:15)
Age (y)	8.63 (2.16)	9.52 (1.96)
Height (m)	1.29 (0.14)	1.27 (0.13)
Body mass (kg)	31.21 (14.20)	28.03 (10.57)

Data are given as total number and mean (standard deviation).

2.2 Gait Data Acquisition

The gait data acquisition was conducted in the Human Motion Gait Analysis laboratory at UiTM Shah Alam using a state-of-the-art three-dimensional (3D) motion analysis system by Vicon Motion Systems Ltd., Oxford, United Kingdom.

All participants were instructed to perform a straight self-selected speed barefoot walking along a 6.5-m walkway (Fig. 2) with 35 retroreflective spherical markers attached on the specific anatomical bony landmarks based on the full-body Plug-in Gait biomechanical model [17]. The 3D trajectories of the markers were recorded by an eight-camera Vicon T-series motion capture at 100 Hz. An average of ten walking trials was collected from each participant.

Fig. 2. A male participant during a gait motion capturing session.

2.3 Feature Extraction

Trials were excluded if the process of reviewing showed that participants intentionally extended or shortened their normal stride. Only genuine and valid trials were selected for further data analysis. The built-in Woltring generalized cross-validatory spline algorithm [18] was implemented to minimize noise from marker trajectories data. All data pre-processing was computed using the Vicon Nexus software version 1.8.5 (Vicon, Oxford, UK).

In order to evaluate changes in gait strategies as to ensure that those are dependable as possible, the kinematic data from each participant was computed in a single gait cycle from the selected valid trial [19]. The obtained gait features were then used to represent each participant walking pattern.

In this study, a total of 12-kinematic waveforms were assessed on the sagittal, frontal, and transverse plane at the pelvis, hip, knee, and ankle joints. Time-series parameterization [8] was performed to each waveform whereby the maximum and minimum values from all waveforms, and the sagittal joint angle at the hip, knee, and ankle during foot-contact and foot-off events were extracted as gait features.

2.4 Feature Selection

Two different statistical feature selection techniques namely between-group tests (TMWU) and stepwise discriminant analysis (SWDA) were evaluated in this study. These techniques have been successfully utilized in the selection of significant and dominant gait features in the previous studies [13]. All statistical features selections were performed using the IBM SPSS Statistics for Windows, version 21.0 (IBM Corp., Armonk, New York, USA).

Firstly before conducting between-group test, the extracted gait features were explored for normality using the Shapiro-Wilk (SW) test. The features were normally distributed if the SW outcome (p-value) was larger than or equal to 0.05. The normally distributed gait features were then analyzed for between-group differences by comparing the mean scores of each feature using the independent samples t-tests. For features that were not normally distributed, the between-group differences were examined using Mann-Whitney U tests. The statistically significant difference between the two groups for both tests was defined as $p < 0.05$. The gait features that significantly differentiate between both groups were selected as input features for classification stage.

Stepwise discriminant analysis (SWDA) is another statistical method that can be used to determine the best set of feature predictors that contribute significantly to the separation of ASD gait patterns from the controls [13]. This discrimination method revealed which gait features had the most discriminatory power to optimally separate the two groups [20].

In this study, the feature selection method was performed using the Wilks' lambda criterion with the setting criteria of F value to enter is at least 0.05 and F value to remove is less than 0.10 [21]. Features that fall within the range of F values are statistically significant for group discrimination. The significant gait features that were selected from the two statistical feature selection techniques were grouped into two datasets, namely Kinematic-TMWU and Kinematic-SWDA. These datasets were used as the input features to the classification stage.

2.5 ASD Gait Classification

Classification of ASD gait was carried out using ANN in MATLAB version R2015a (The MathWorks Inc., USA). The stage involved the process of training the ANN classifier to assign the correct target group with different input features. In this stage, ANN with three-layer feedforward network was employed to classify the gait patterns and also to evaluate the effectiveness of both selected kinematic gait datasets. The three layers of the network consisted of the input, hidden and output layers [9]. The number of neurons in the input layer was based on the number of input features in the feature selection stage, while the number of neurons in the output layer consisted of two neurons to represent the two-element target vectors, which are the ASD and control groups.

During network training, the three-layer ANN with weights adjusted using a scaled conjugate gradient backpropagation algorithm as the learning algorithm was used to train the relationship between gait features and the target classes. Apart from that, this ANN model was optimized by varying the number of hidden neurons and the initial weights. The performance of the ANN classifier was checked through the cross-entropy performance function. The generalization ability of the ANN model was evaluated using k-fold cross-validation technique.

2.6 Cross-validation and Performance Measures

Cross-validation method is a common approach in estimating the accuracy of machine learning classification [22]. Due to the small sample size of each group in the study, a 10-fold cross validation method was employed to assess the generalization ability of the classification using various combinations of testing and training datasets [23].

Each dataset was randomly partitioned into ten equal sized folds. Then, ten iterations of training and testing were executed so that for each number of iterations, nine folds were used for training, while the remaining one fold was used for testing. The estimated accuracy was the average accuracy for the ten folds [22].

The ANN classification performances with two different set of input features were evaluated based on accuracy, sensitivity, and specificity [24]. In this study, true positive (TP) is the number of ASD gait correctly classified as ASD and true negative (TN) is the number of normal gaits correctly classified as normal. False positive (FP) is the number of false ASD identification, which is, normal gait incorrectly classified as ASD and false negative (FN) is the number of false normal gait identification, which is, ASD gait incorrectly classified as normal.

Accuracy denotes overall identification accuracy for both ASD and normal gait patterns which are the ratio of correctly classified cases to total cases as described in (1). Sensitivity or true positive rate describes the ability of the ANN to correctly identify an ASD gait pattern as in (2), and specificity is the true negative rate that implies the ANN's ability in detecting normal gait pattern correctly as in (3).

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FN} + \text{TN} + \text{FP}} \times 100\% \quad (1)$$

$$\text{Sensitivity} = \frac{\text{TP}}{\text{TP} + \text{FN}} \times 100\% \quad (2)$$

$$\text{Specificity} = \frac{\text{TN}}{\text{TN} + \text{FP}} \times 100\% \quad (3)$$

3 Results and Discussion

In this section, the experimented results and discussions of the proposed method were presented. Based on the time-series parameterization techniques applied to the 12-kinematic waveforms, 34 raw kinematic gait features were extracted as gait patterns to indicate the gait summaries of all participants.

Table 2 presents the two gait dataset of the selected kinematic gait features using the TMWU and SWDA feature selection techniques. These datasets were used as input features to the ANN classification. For TMWU, significant between-group differences (p < .05) were found for nine kinematic gait features. The gait abnormalities were mostly observed on the sagittal joint angles at the hip, knee, and ankle which involved flexion and extension movement of the joints.

By applying the SWDA, the size of extracted dataset was significantly reduced. Thirty features were discarded due to unrelated and bad discriminant effects. The SWDA indicated that 4 of the 34 kinematic features were optimal and have a strong influence in group discrimination. The discriminant gait features with p < .000 were knee flexion during foot contact, maximum ankle plantarflexion during stance, maximum ankle adduction and maximum ankle abduction during the entire gait cycle.

Table 3 tabulates the ANN classification performance in terms of accuracy, sensitivity and specificity for the Kinematic-Raw, Kinematic-TMWU, and Kinematic-SWDA datasets. From Table 3, it is shown that the ANN trained with

Kinematic-SWDA dataset produced greater testing accuracy performance with 91.7% accuracy as compared to 90.0% for Kinematic-TMWU. For Kinematic-Raw dataset, the classification accuracy was 88.3%.

For comparison, the performance of ANN in classifying ASD gait patterns using different input dataset was presented using a clustered column chart as depicted in Fig. 3. It was observed that the Kinematic-SWDA achieved the highest sensitivity rate of 93.3% and specificity rate of 90.0%. This indicated that the ANN with four input features in the SWDA dataset has greater ability in recognizing ASD gait pattern. Additionally, the TMWU dataset with nine input features produced a perfect rate in identifying normal gait pattern but poor ability in the identification of ASD gait.

It was revealed that both feature selection techniques provided a different set of input features with a higher percentage of classification accuracy, however, the selected features using the SWDA approach showed relatively better performance in term of stability due to higher accuracy, sensitivity, and specificity. These results also underlined the importance of discarding unrelated features from the extracted gait dataset by performing statistical feature selection techniques in ensuring that classification performance could be enhanced.

Table 2. Gait dataset of selected kinematic gait features

Kinematic-TMWU
• Min. pelvic rotation – cycle • Max. hip extension – stance • Hip extension foot-off • Max. hip flexion – swing • Knee flexion foot-contact • Max. knee flexion – stance • Max. knee abduction - cycle • Max. ankle plantarflexion – swing • Max. ankle plantarflexion – stance
Kinematic-SWDA
• Knee flexion foot-contact • Max. ankle plantarflexion – stance • Max. ankle adduction – cycle • Max. ankle abduction – cycle

Table 3. ANN classification performance

Dataset	Acc (%)	Sens (%)	Spec (%)
Kinematic-Raw	88.3	86.7	90.0
Kinematic-TMWU	90.0	80.0	100.0
Kinematic-SWDA	91.7	93.3	90.0

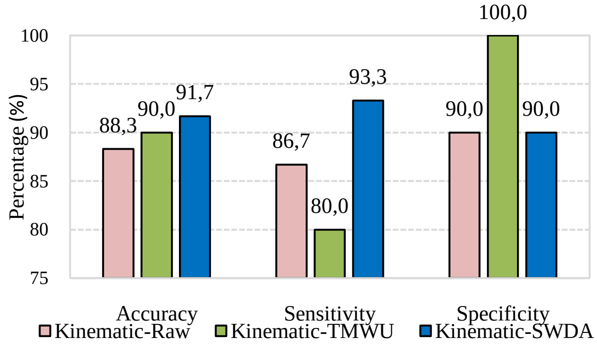

Fig. 3. The performance of ANN in classifying ASD gait patterns with different input dataset.

4 Conclusion

In conclusion, an automated classification of gait abnormalities in children with ASD based on kinematic data is presented. This study utilized two types of statistical feature selection techniques to select significant kinematic gait features that can be used as input features to the ANN classification stage. The outcomes of the study reaffirmed the importance of applying feature selection method prior to classification tasks to enhance the classifier performance and the possible method to achieve that was by conducting SWDA. The ANN trained with the Kinematic-SWDA dataset revealed a more stable classification performance with 91.7% accuracy, 93.3% sensitivity, and 90.0% specificity. This work can serve as an automated gait classification tool that may assist clinicians in the diagnosis and recognition of gait abnormalities in individuals with ASD or other neurological disorders that affect gait.

Acknowledgements

This study was supported by the Ministry of Higher Education (MOHE) Malaysia under the 2014 Federal Training (HLP) Scheme awarded to the main author. The research work was also funded by the MOHE through the Niche Research Grant Scheme (NRGS), project file: 600-RMI/NRGS 5/3 (8/2013). The authors would like to acknowledge all contributions especially the National Autism Society of Malaysia (NASOM), volunteered participants and their parents, colleagues, and staffs of the Human Motion Gait Analysis, Institute of Research Management and Innovation Unit (IRMI), UiTM Shah Alam, Selangor, Malaysia.

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