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Automated Classification of Autism Spectrum Disorders Gait Patterns Using Discriminant Analysis Based on Kinematic and Kinetic Gait Features

Che Zawiyah Che Hasan[1], Rozita Jailani[1], Nooritawati Md Tahir[1], Ihsan Mohd Yassin[1], Zairi Ismael Rizman[2]

[1]Faculty of Electrical Engineering, Universiti Teknologi MARA, Shah Alam, Selangor, Malaysia
[2]Faculty of Electrical Engineering, Universiti Teknologi MARA, Dungun, Terengganu, Malaysia

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ABSTRACT

Autism spectrum disorder (ASD) is a permanent neurodevelopmental disorder that can be recognised during the first few years of life and is further supported by the existence of gait impairments. Automated classification of ASD gait could provide assistance in diagnosis and ensure rapid quantitative clinical judgement. This study proposes an automated classification of ASD gait patterns based on kinematic and kinetic gait features with the application of machine learning approaches. Gait analysis of 24 ASD and 24 typical healthy children were recorded using a state-of-the-art three-dimensional (3D) motion analysis system and two force platforms during barefoot self-selected normal walking. Nine kinematic and sixteen kinetic gait features were statistically selected using the independent t-tests and Mann-Whitney U tests, which grouped into two types of datasets. Linear discriminant analysis (LDA) and quadratic discriminant analysis (QDA) were employed to perform the recognition task. Overall, the results of the proposed study suggest that LDA classifier with kinetic gait features as input predictors produces better classification performance with 82.50% of accuracy and lower misclassification rate.
KEYWORDS: Autism Spectrum Disorder (ASD), Linear Discriminant Analysis (LDA), Quadratic Discriminant Analysis (QDA), Gait Analysis, Gait Classification, Gait Features.

INTRODUCTION

Autism spectrum disorder (ASD) is a condition that can be characterised by a constant deficit in social communication, social interaction and the presence of restrictive and repetitive behaviour. It is a lifelong neurodevelopmental disorder that can be recognised during the early stage of the developmental period of a child. Other additional characteristics that support the diagnosis of ASD are the existence of motor deficits which include abnormal gait, clumsiness and irregular motor signs [1]. Abnormal gait is defined as an unusual style of walking from the normal walking pattern and this could cause deterioration in occupational and other substantial ranges of daily activities.

A number of studies have addressed various types of gait disturbance in children with ASD [2]-[6]. These studies had successfully documented abnormal gait features in individuals with ASD which could be beneficial for early diagnosis and better treatment planning for children with ASD [7]. Conventional methods of gait assessment are often time-consuming and highly dependent on the clinician judgement, which leads to subjective and qualitative evaluations. With the current advances in gait analysis technology, which not only allow new insights in understanding normal and pathological movement patterns but also provide prospects to develop an automated diagnosis of pathological disorders.

The use of machine learning classifiers for automated recognition of gait pattern deviations has grown enormously in the last decades. Artificial neural network (ANN) and support vector machines (SVM) have been employed for recognition and classification of Parkinson's disease [8], young-old gait patterns [9], cerebral palsy children [10] and patients with neurological disorders [11]. ANN was also successfully used for classification of gender in children [12] and post-stroke patients [13] based on their gait profile. More recent studies have applied linear discriminant analysis (LDA) to extract dominant features for discrimination of Parkinson's disease [14]. Most of the mentioned studies have used either basic gait measurements, kinematic, kinetic or combination of those features to be fed into machine classifiers.

Until now, the published literature dealing with automated classification on ASD gait patterns is, however scarce. Thus, this study proposes an automated classification of gait patterns of children with ASD based on kinematic and kinetic gait features. These features were first extracted using waveform analyses and parameterisation methods and then were selected using statistical techniques. Linear discriminant analysis (LDA) and quadratic discriminant analysis (QDA) were employed to model both input features and their classification performances with each input dataset were compared.

Corresponding Author: Rozita Jailani, Faculty of Electrical Engineering, Universiti Teknologi MARA, Shah Alam, Selangor, Malaysia, E-mail: rozita@ieee.org

This paper is organised as follows. The methodology of the proposed automatic gait classification will be elaborated in Methodology section. The obtained results will be presented and further discussed in Results and Discussions section. Finally, the summary of this study is presented in the Conclusion section.

METHODOLOGY

The methodology for the proposed gait classification system is illustrated in a block diagram as shown in Figure 1. It consists of four stages which include gait data acquisition, pre-processing and feature extraction, feature selection statistical procedures, and ends with gait classification using two types of discriminant analysis. Finally, the performance of each model using two types of data sets was evaluated.

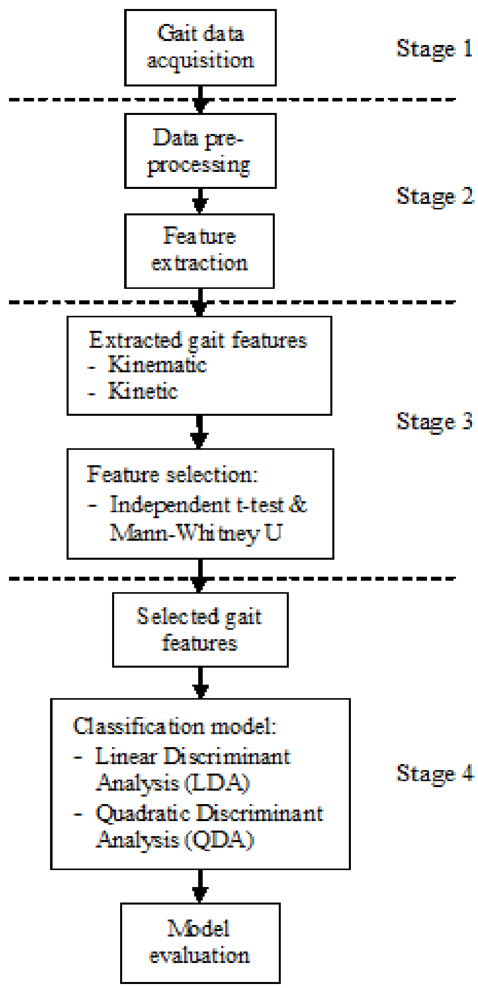

Figure 1: Block diagram of the proposed methodology

Gait Data Acquisition

Two groups of 24 children with ASD (18 male, 6 female) and 24 healthy children (12 male, 12 female) participated in the study. Participants were in the range of 4 to 12 years old. Table 1 shows a summary of the participants' characteristics.

Table 1: Characteristics of group participants

Characteristics	ASD	Control
Number of participants	24	24
Gender (Male:Female)	18:6	12:12
Age (years)	8.95(2.13)	9.67(1.88)
Height (m)	1.31(0.14)	1.27(0.13)
Body mass (kg)	32.71(15.24)	27.83(8.95)
Body Mass Index (BMI)	18.41(5.63)	16.78(2.66)

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

The children with ASD were recruited from the National Autism Society of Malaysia (NASOM) centre in Klang, Selangor, Malaysia and local community by approaching the parents via social media network. All ASD participants had been diagnosed with a mild category by qualified medical practitioners and were able to follow verbal instructions. The ASD participants were attended either by their parents or caretakers during the experiment. The typical healthy children were recruited from the families of faculty members and neighbourhoods nearby. All participants were able to walk independently without any assistive devices and had no medical history of lower extremity injuries. An informed consent form was obtained from the parent or guardian of the participants. The research procedures have been approved by the Research Ethics Committee of Universiti Teknologi MARA (UiTM), Shah Alam, Selangor.

The acquisition of gait data was performed at the Human Motion Gait Analysis laboratory at the UiTM Shah Alam using a state-of-the-art three dimensional (3D) motion analysis system. The system is equipped with an eight-camera (Vicon T-series) motion capture (Vicon Motion Systems Ltd., Oxford, United Kingdom) and two force plates (Advanced Mechanical Technology Inc., MA, USA). The 3D motion analysis system was used to record the movement of marker trajectories at 100 Hz and the force plates which were embedded in the middle of a 6.5-metre walkway were used to measure the 3D ground reaction forces (GRF) at 1000 Hz. A digital weight scale, measuring tape and a calliper was used to obtain anthropometric measurements of the participants.

Thirty-five spherical retroreflective markers bilaterally adhered onto the specific anatomical landmarks of the participants by the same investigator, using the full body Plug-in Gait model (Vicon) based on the Newington-Helen Hayes gait model [15-16]. After static calibration, participants were instructed to perform a straight barefoot walking along the walkway at their self-selected speed. Participants were allowed to perform several practice trials for familiarisation and then an average of five to ten walking trials were recorded from each participant. However, several ASD participants with small stride length and sensory issues had to perform more than twenty trials in order to achieve a valid walking trial with a single foot contact on each force plate as in Figure 2. Both force plates were calibrated at the beginning of each trial to reduce the effect of noise from surroundings.

Figure 2: A valid walking trial with a single foot contact on each force plate

Data Pre-Processing and Features Extraction

Pre-processing of walking trials involved the process of reviewing the entire trials obtained from each participant. However, due to several conditions such as sensory issues and small stride length of several ASD participants, only a single valid trial with a complete temporal-spatial, kinematic and kinetic measurements from each participant was chosen for further processing.

The marker trajectories were smoothed using the built-in Woltring generalised cross-validatory spline algorithm to minimise trajectory noise [17]. The 3D ground reaction forces (GRF) from the force plate were filtered using a second-order low-pass Butterworth filter with 30 Hz cut-off frequency and then down-sampled to match the kinematics of 3D joint angles data [18]. The 3D GRFs, together with the anthropometric measurements and accelerations data, then inputted into standard inverse dynamics approach to providing the resultant 3D joint moments and joint powers for the hip, knee, and ankle joints [19]. All data pre-processing were computed using the Vicon Nexus software (version 1.8.5, Vicon, Oxford, UK).

After pre-processing of the selected valid trials, then the kinematic and kinetic gait data from a single left limb gait cycle of the trial were chosen to represent each participant [20-21]. Furthermore, the children with ASD were found to demonstrate a typical interlimb movement during gait [22].

The gait cycle for every participant was normalised to the percentage of their stride duration. While the time component of the 3D GRFs was normalised to the percentage of stance phase time and the magnitude of GRF component was standardised to the percentage of participant's body weight. The joint moments was normalised to body weight. These normalisation steps were carried out in order to eliminate variations among the participants with different height, body mass and duration of the gait cycle and stance phase time [23-24].

In this study, 12-kinematic waveforms were calculated in the sagittal, frontal and transverse plane for pelvis, hip, knee, ankle and 12-kinetic waveforms were examined in 3D joint moments for hip, knee, ankle and joint powers for hip, knee and ankle. To group the data from the 48 participants, each waveform was normalised to 51-time points, one for every 2% of the gait cycle [25-26]. Then, the maximum and minimum value from all waveforms, and sagittal joint angle at hip, knee, and ankle during foot contact and toe off were extracted [5]. For the 3D GRFs in medial-lateral (x-axis), anterior-posterior (y-axis), and vertical (z-axis) directions, parameterization techniques were applied to each waveform to extract the instantaneous values of amplitude and its corresponding time of occurrence [27]-[29]. Both normalisation and gait feature extraction were computed in Microsoft Excel version 2013 (Microsoft Corp., USA).

Features Selection

Practically, all extracted gait features could be used as input data in the classification process. However, there were conditions that some features were irrelevant or unrelated to be used in the process and it sometimes could deteriorate the generalised performances of the classifiers. One of the suggested solutions to overcome this issue is by performing features selection so that only dominant features could be used to represent each group.

Features selection is also an important step in classification system in order to achieve good classification results especially if it deals with high dimensionality of data. By conducting this feature selection, the original high dimensional gait features could be reduced and only the significant features were selected as a dataset for classification stage. The gait features that were irrelevant were removed.

In this stage, a between-group test was employed to all extracted features to select the significant gait features that would possibly discriminate the gait patterns between both groups. For this purpose, two types of parametric and non-parametric statistical procedures were implemented. These tests were chosen for the ability to provide significant between-group differences for both kinematic and kinetic gait features [30]. Furthermore, the preliminary study had shown that there was no significant difference for basic temporal and spatial gait parameters between both groups.

Prior to analysis, each extracted gait features were explored for normality using the Shapiro-Wilk (SW) test [31]. The independent t-tests were used to compare the mean differences of gait features when data were normally distributed or parametric, and Mann-Whitney U tests for data that were non-parametric. The significant difference between the two groups was defined as $p < 0.05$.

Classification Model

Generally, classification is a machine learning technique used to categorise items in a collection to target classes or groups. In this study, the dominant kinematic and kinetic gait features that were selected from the feature selection stage were grouped into two types of data sets. These data sets were then used as input data to the machine classifiers. For this purpose, two types of discriminant analysis (DA), LDA and QDA were employed for classification purposes. DA is known as a simple classifier that is said to have low variance, mathematically robust, produces low error rates and accuracy as good as other complex classifiers [32-33].

DA algorithm assumes that different classes generate data based on different Gaussian distributions. To train a classifier, the fitting function evaluates the Gaussian distribution parameters for each class and then the created classifier finds the class with the smallest misclassification cost for predicting the classes of new data. For LDA, the model has the same covariance matrix but different means for each class. Meanwhile, for QDA, each class has different means and covariance matrixes. These two types of DA differ in the resultant discriminant function that is linear or quadratic. Further explanations on both classifiers were elucidated in [34-35].

This study employs a 10-fold cross validation method to test the generalisation ability of the classification method using various combinations of the testing and training data sets. These standard procedure has been used in a number of classification evaluations, particularly for data sets with small sample size [36]-[40].

In this method, the data set is randomly partitioned into 10 folds. A different fold of the data is used for testing, while the remaining nine folds are used as training data. 10-fold cross validation was iterated for ten times and the results from the folds are then averaged to produce the final result [41].

The performance of LDA and QDA classifiers with different input data of kinematic and kinetic data sets were measured using the accuracy and error rate based on the confusion matrix with two classes, ASD and normal. The accuracy is defined as the ratio of correctly classified cases to a total number of cases and error rate is the misclassification rate as given by Equation (1) and (2).

$$\text{Accuracy} = (TP+TN)/(\text{Total data}) \times 100\% \quad (1)$$

$$\text{Error rate} = (FP+FN)/(\text{Total data}) \quad (2)$$

In this study, true positive (TP) is the number of ASD cases correctly classified and true negative (TN) is the number of normal cases correctly classified. False positive (FP) is the number of normal cases incorrectly classified as ASD and false negative (FN) is the number of ASD cases incorrectly classified as normal.

RESULTS AND DISCUSSION

The developed features extraction, features selection, and the effectiveness of the proposed ASD gait patterns classification using LDA and QDA are elaborated in this section. Based on waveform analyses and parameterization techniques employed in features extraction stage, a total of 34 kinematic features and 44 kinetic features were extracted to represent the gait profiles of all participants.

Table 2 presents the kinematic and kinetic gait features selected using statistical feature selection techniques. The features with a p-value of less than 0.05 are assumed to provide great influence during the classification process. Based on the tabulated results, 9 joint angles at pelvis, hip, knee and ankle were found to be significant and these features represented kinematic dataset. Meanwhile, 5 joint moments, 4 joint powers and 7 from GRFs were clustered together as a kinetic dataset of 16 gait features.

Table 3 summarises the classification performance in terms of the accuracy and the error rate for LDA and QDA classifiers using kinematic and kinetic data sets selected using statistical feature selection techniques. Based on the two types of datasets as input features for both classifiers, the combination of the kinetic dataset and LDA classifier demonstrates a good performance for ASD gait classification with 82.50% of accuracy and lower misclassification rate of 0.175. Results also indicate that kinetic dataset is more discriminatory than the kinematic dataset. In other words, the ASD and normal groups differ mainly in the kinetic gait features. These results are expected since most of the gait deviations observed in ASD group is mostly signified by the kinetic gait features. Future studies should implement another type of feature selection techniques and other machine classifiers to optimise the classification accuracy.

Table 2: Kinematic and kinetic gait features selected using statistical feature selection techniques

Kinematic Gait Features (9)	Kinetic Gait Features (16)		
3D Joint Angles	3D Joint Moments	Joint Powers	**3D GRFs**
• Max pelvic tilt • Min pelvic obliquity • Hip flex foot contact • Max hip extension (stance) • Hip extension foot off • Knee flexion foot contact • Max knee abduction • Max ankle dorsiflexion (stance) • Max ankle plantarflexion (swing)	• Max knee adduction moment Y • Max knee rotation moment Z • Max ankle plantar flexor moment X • Max ankle moment Z • Min ankle moment Z	• Max hip power • Min hip power • Min knee power • Max eccentric ankle power	• Fx3 • Fy1 • Fy3 • Fz3 • Ty2 • Push-off rate • Peak ratio

Table 3: Classification accuracy and error rate for LDA and QDA classifiers using kinematic and kinetic data sets

Dataset	Classifier	Accuracy (%)	Error Rate
Kinematic	LDA	70.00	0.300
	QDA	80.00	0.200
Kinetic	LDA	82.50	0.175
	QDA	71.67	0.283

CONCLUSION

In this paper, discriminant analysis classifier for classifying gait patterns of children with ASD based on kinematic and kinetic gait features has been proposed. This study introduces statistical techniques for selecting dominant gait features from gait data obtained from a state-of-the-art 3D motion analysis system. In recognising gait impairments in children with ASD, two types of gait datasets had been discovered. Overall the results of this study suggest that LDA classifier with kinetic gait features as input predictors is more effective for categorising gait patterns of children with ASD. These potential findings would be beneficial for future applications in identifying gait abnormalities in individuals with ASD or other pathological gait patterns.

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