Use of statistical approaches and artificial neural networks to identify gait deviations in children with autism spectrum disorder

Che Zawiyah Che Hasan, Rozita Jailani, and Nooritawati Md Tahir

***Abstract*—**Automated differentiation of ASD gait from normal gait patterns is important for early diagnosis as well as ensuring rapid quantitative clinical decision and appropriate treatment planning. This study explores the use of statistical feature selection approaches and artificial neural networks (ANN) for automated identification of gait deviations in children with ASD, on the basis of dominant gait features derived from the three-dimensional (3D) joint kinematic data. The gait data from 30 ASD children and 30 normal healthy children were measured 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 feature selection techniques, namely the between-group tests (independent samples t-test and Mann-Whitney U test) and the stepwise discriminant analysis (SWDA) were adopted as feature selector to select the meaningful gait features that were then used to train the ANN. The 10-fold cross-validation test 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. The findings of the current study demonstrate that kinematic gait features with the combination of SWDA feature selector and ANN classifier would serve as a potential tool for early diagnosis of gait deviations in children with ASD as well as provide support to clinicians and therapists for making objective, accurate, and rapid clinical decisions that lead to the appropriate targeted treatments.

***Keywords*—**Artificial neural network, gait classification, gait feature, stepwise discriminant analysis.

I. INTRODUCTION

AUTISM spectrum disorder (ASD) is the name refer to a group of neurodevelopmental disorders that affects the cognitive function and diminishes the quality of life of an individual. It is a severe and lifelong impairment, which can be identified in the early years of childhood. Recently ASD has become the most rapidly increasing neurodevelopmental disorder worldwide [1]. ASD is one of the most prevalent forms of developmental disabilities, with current estimates of prevalence is one in 68 children and it is 4.5 times more common among boys than among girls [2].

According to the fifth edition of the Diagnostic and Statistical Manual of Mental Disorders (DSM-5), children with ASD are recognized by persistent deficits in social communication and social interaction, in addition to the presence of restricted, repetitive behavior patterns, interests, or activities. Additional symptoms that support the diagnosis of ASD are the existence of movement and motor disturbances such as irregular motor signs, clumsiness as well as abnormal gait [3]. Earlier detection of these symptoms creates better opportunities for children with ASD to benefit more fully from early intervention or treatment programs [4]. It has been suggested that motor skills need to be considered and incorporated in early intervention programs [5].

Clinicians and researchers from various disciplines have identified movement and sensory disturbances as the focus symptoms of individuals with ASD [6]. 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 [7]. Children with ASD were found to demonstrate a variety of significant alterations on the ankle and hip joint kinematics and kinetics [8]. Our recent study has also reported significant gait deviations in the 3D ground reaction forces of children with ASD which particularly related to the difficulties in supporting their body weight as well as exhibiting gait instability during the stance phase of gait [9]. Several significant ground reaction forces gait features can potentially be used in the identification of ASD gait [10]. An early identification of these aspects of gait deviations 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 [11]. Gait can

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be assessed quantitatively to produce temporal-spatial, kinetic joint moments and joint powers, ground reaction forces, and kinematic joint angles that can be used for the examination of any deviation from the normal walking pattern [12].

Gait measurement using the state-of-the-art motion analysis system equipped with a 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 [13]. Current gait analysis provides a large amount of gait data that is time-consuming and difficult to interpret. It is well-known that an automated 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 [14].

Computational intelligence such as artificial neural networks (ANN) has been widely explored in analyzing gait and movement data [15], [16]. Previous studies in gait research have successfully employed ANN for distinguishing and recognizing numerous gait patterns including classification of healthy and pathological gait [17], automated diagnosis of gait patterns in certain gait conditions [18], distinguishing young and old gait patterns [19], and categorization of abnormal gait pattern in patients with Parkinson's disease [20] and post-stroke [21]. 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 the high-dimensional data obtained from gait analysis, statistical feature selection techniques such as independent *t*-test [22], Mann-Whitney *U* [23], and stepwise method of discriminant analysis (SWDA) [21] 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 [24]. Previous studies in gait analysis have validated that SWDA was able to identify specific individual features that best determined group placement [21].

It is globally well-known that far too little attention has been paid on the automated identification of ASD gait pattern. Thus, the aim of this study is to explore the use of statistical feature selection approaches and artificial neural networks for automated identification of gait deviations in children with ASD, on the basis of selected gait features derived from the 3D joint kinematic data. Two statistical feature selection approaches are proposed in order to select the dominant features as the inputs for the ANN classification.

II. Methodology

The methodology for the proposed gait classification is illustrated 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.

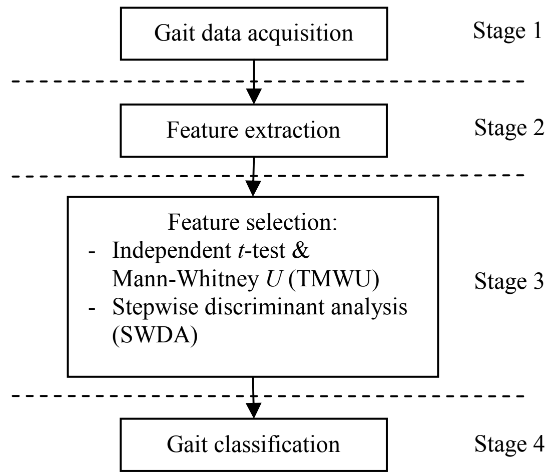

Fig. 1. Flowchart of the proposed ASD gait classification.

A. Subjects

Thirty children who had been previously diagnosed with the mild category of ASD and thirty normal healthy children were voluntarily recruited to participate 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 subjects were recruited from the National Autism Society of Malaysia (NASOM) center and 16 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 subjects. The demographic data of ASD and control subjects are summarized in Table 1. 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.

Table 1. Demographic data of ASD and control subjects.

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).

B. Gait Data Acquisition

Kinematic data were acquired using an eight-camera (Vicon MX T-Series) motion capture system (Vicon Motion Systems Ltd., Oxford, United Kingdom). Thirty-five retroreflective spherical passive markers were attached on the specific anatomical bony landmarks in accordance with the full-body Plug-in Gait biomechanical model [25]. The movement or trajectories of the markers in 3D directions were recorded by the Vicon cameras at 100 Hz. The recording procedures were conducted in the Human Motion Gait Analysis laboratory at the UiTM Shah Alam.

Each subject was instructed to perform a straight self-selected speed barefoot walking along a 6.5-meter walkway (Fig. 2). An average of ten walking trials was collected from each subject. A single valid trial, with complete kinematic measurements was chosen from each subject for further processing. Trials were excluded if the process of reviewing showed that subjects intentionally extended or shortened their normal stride. The built-in Woltring generalized cross-validatory spline algorithm was implemented to minimize noise from marker trajectories data [26]. The data pre-processing were computed using the Vicon Nexus software version 1.8.5 (Vicon, Oxford, UK).

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

C. *Feature Extraction*

Feature extraction is a process of identifying valid, useful, and understandable patterns of gait data and to reduce the dimensionality of the time-series data generated from the gait measurements [15]. The most common approach is by applying time-series parameterization whereby the meaningful features were extracted from the time-series waveforms [15].

In order to evaluate changes in gait strategies as to ensure that those are dependable as possible, the kinematic data from each subject was computed in a single gait cycle from the selected valid trial [27]. The obtained gait features were then used to represent each subject 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 [15] was performed to each kinematic waveform. The maximum and the minimum values were extracted from all waveforms. Joint angles for the sagittal plane at the hip, knee, and ankle were computed during the foot-contact and foot-off events.

D. *Feature Selection*

Feature selection is an essential stage in performing a pattern classification system in order to achieve good generalization performance. Only relevant features were selected from this stage and irrelevant features were removed. 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 [21]. 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 [21]. This discrimination method revealed which gait features had the most discriminatory power to optimally separate the two groups [28].

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 [29]. 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.

E. *ASD Gait Classification*

In this stage, ANN with a three-layer feedforward network was employed to differentiate the ASD gait from normal gait patterns and also to evaluate the effectiveness of statistical feature selection techniques. This process involved the training of the ANN classifier to assign the correct target group with different input features. The three layers network consist of the input, hidden, and output layers [17]. 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 the input gait features and the target groups. This learning algorithm is good for training pattern recognition networks with fast performance and small memory requirement [30].

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. Further, the generalization ability of the ANN model was evaluated using 10-fold cross-validation technique. The classification of ASD gait was developed using MATLAB version R2015a (The MathWorks Inc., USA).

F. Cross-validation and Performance Measures

Cross-validation method is a common approach in estimating the accuracy of machine learning classification [31]. 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 [32].

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 [31].

The ANN classification performances with two different set of input features were evaluated based on accuracy, sensitivity, and specificity [33]. 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).

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

$$\text{Sensitivity} = \frac{\text{TP}}{\text{TP} + \text{FN}} \times 100\% \tag{2}$$

$$\text{Specificity} = \frac{\text{TN}}{\text{TN} + \text{FP}} \times 100\% \tag{3}$$

III. 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 of the sagittal, frontal, and transverse plane at the pelvis, hip, knee, and ankle joints, 34 raw kinematic gait features were extracted as possible gait features to indicate the gait profiles of the subjects.

From the feature selection stage, two subsets of kinematic gait features were selected out of the total extracted features. Table 2 presents the two subsets of selected kinematic gait features using the TMWU and SWDA feature selection techniques. These datasets were used as input features to the ANN classification. For Kinematic-TMWU, significant between-group differences ($p < 0.05$) 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 movements of the joints.

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

Overall accuracy, sensitivity, and specificity results for ASD and normal gait pattern classification based on the three sets of kinematic input features are summarized in Table 3. Accuracy was at best 91.7% when Kinematic-SWDA with four gait features were used as the inputs to the ANN classifier. In general, gait features selected using the SWDA approach showed better performance compared to TMWU and with less number of input features.

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 also 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

Kinematic-TMWU
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

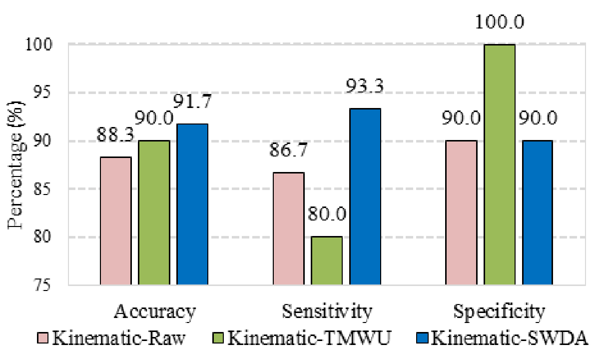

Fig. 3. The performance of ANN in classifying ASD gait patterns with different input dataset.

IV. Conclusion

In this study, an automated identification of gait deviations in children with ASD based on statistical feature selection approaches and ANN was explored. By using the 3D joint kinematic data, this work proposed a set of four dominant gait features which can successfully differentiate ASD and normal gaits. This study utilized two statistical feature selection approaches to select dominant kinematic gait features that can be used as input features to the ANN classification stage. The best classification performance was achieved from the dominant gait features selected using the SWDA approach. The ANN trained with the Kinematic-SWDA dataset revealed a more reliable classification performance with 91.7% accuracy, 93.3% sensitivity, and 90.0% specificity. The outcomes of the study reaffirmed the importance of applying feature selection technique prior to classification tasks to enhance the classification performance. Overall, it is believed that the proposed statistical feature selection and ANN approaches have greater potential to be applied as a diagnostic tool that may assist clinicians in the automated identification and recognition of ASD gait deviations.

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