Linear Discriminant Analysis in Classifying Walking Gait of Autistic Children

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Abstract — **The aim of this research is to investigate the effectiveness between Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA) along with neural network (NN) in classifying the gait of autistic children as compared to control group. Twelve autistic children and thirty two normal children participated in this study. Firstly the walking gait of these two groups are acquired using VICON Motion Analysis System to extract the three dimensional (3D) gait features that comprised of 21 gait features namely five features from basic temporal spatial, five features represented the kinetic parameters and twelve features from kinematic. Further, PCA and LDA are utilized as feature extraction in determining the significant features among these gait features. With NN as classifier, results showed that LDA as feature extraction outperform PCA for classification of autism versus normal children namely kinematic gait patterns attained 98.44% accuracy followed by basic temporal spatial gait features with accuracy of 87.5%.**

Keywords - Gait Classification, Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA), Autism, Neural network (NN).

I. Introduction

Recently, researchers have raised interest in investigating and exploring gait abnormalities for autism children that suggested early identification due to these abnormalities. Additionally, numerous researches have highlighted that gait has advantages in medical diagnostics as well as in monitoring the progress of treatment outcomes [3, 4, 5]. Recall that autism is defined as a developmental disability that significantly affects verbal or nonverbal communication and in general social interaction too [1, 2]. Symptoms often associated with autism are engaging in repetitive activities and stereotyped movements that sometimes cause depression and resistance to environmental changes. Despite the importance of early detection, the neuro-behavioral autism is still not well understood namely the motor symptoms [3, 17].

The study of gait abnormality can be defined as a deviation from the normal. Individuals diagnosed with autism are correlated with differences in gait and relationship in movement patterns can be categorized as a sign of this syndrome [9]. As discussed by M. Nobile et al. [8], this study examined the manner of walking by a younger group of children with autism suggested that the variables of gait associated with the neurobiology of autism may be useful for the clinical definition of disorder. Hence, children with autism have displayed stance position longer due to differing percentage total gait cycle and has trend in reducing velocity [3]. P. Teitelbaum et al. [4] found that movement of autism children involving the arm and leg on the right side of the body were relatively asymmetry during their normal walking. Another application of classification of gait in children with autism is to assist in diagnosis, clinical decision-making and communication [5, 6, 9]. Considering all of these evidences, parameter gait pattern in autism children is indeed vital to identify the abnormal gait based on finding that cerebellar involvement in the motor symptom [6, 21]. Due to insufficient reporting and low level of methodological quality of studies using machine learning construction methods, automated recognition of gait pattern from respective measures changes by a machine classifier is expected to offer many advantages [23, 31, 33] This is achievable using computer-aided tools that can support and assist pediatricians in their diagnosis and this is an important effort in the early detection of this population [10]. It would be interesting to apply automated gait classification subsequently develop new robust algorithms.

In order to extract associative features from gait data without any prior information, Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA) are the two technique used for dimensionality reduction. PCA and LDA are also used as feature extraction [11, 26]. Feature extraction means transforming the existing features into a lower- dimensional space which is useful for feature reduction to avoid redundancy due to high-dimensional data Previous researches have established that PCA technique is used to identify kinematic gait pattern by obtaining the differences in the knee flexion angle, knee adduction moment and the knee flexion moment for knee osteoarthritis as database [18]. LDA also known as a Fisher Discriminant Analysis is used to extract features for body gait recognition[38], face recognition [29] and has been used to

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improve the recognition of human faces images performance [13, 37].

On the other hand, artificial neural network (ANN) is utilized as classification in medical diagnostic decision for numerous biomedical signal analyses [14, 15, 16 and 32]. ANNs offered advantage for characterizing gait types [23, 24, & 25]. For instance as reported in [19], the trained NN is used to distinguish 'healthy' from 'pathological' gait patterns demonstrated that it can assign previously unknown gait patterns at an achievement rate in the range of 75% - 95% .

Thus, this study is conducted to investigate, analyse and explore further the significant features amongst the twenty-one gait parameters namely temporal–spatial, kinematic and kinetic in sagittal plane in classifying the gait pattern between normal versus autistic children. Further, PCA and LDA are used as feature extraction with neural network (NN) as classifier. The accuracy of both feature extraction and classifier will be assessed and cross-compared, and advantages and limitations of each technique will be discussed. Twenty one gait features describing the basic, kinetic and kinematic aspects of gait data are as listed in Table 1.

II. MATERIALS AND METHOD

This section will discuss in detail the proposed method as well as the database used in this study. Figure 1 depicted the method used in classifying the gait pattern of autistic versus normal children along with PCA and LDA as feature extraction and NN as classifier.

A. Subjects

Twelve autistic children (n=12) aged between 4 to 12 years from The National Autism Society of Malaysia (NASOM) participated in the study (mean age = 9.85 years; mean height = 135.22 cm; mean weight = 36.29 kg). As for normal/control group, thirty-two typically developing children (n=32) children aged between 6 to 12 years participated (mean age = 9.46 years; mean height = 127.02 cm; mean weight = 28.91 kg.) The control group was matched to the autism group based on age, weight, height and gender. However, for this study the children involved in the experiments were not matched based on IQ criterion. Parental consent and child assent were obtained prior to each child's participation in the study. It was assumed that there is no association between child's developmental delay and motor tasks with IQ level [9]. Ethical approval from the university's Research Ethics Board has been granted to conduct this study. Further participant characteristics are as detailed in Table 2.

TABLE 1: GAIT PARAMETERS EXTRACTED DURING EXPERIMENTAL ANALYSIS

Basic Temporal Spatial Features (4) • Stride time s) • Cadence (steps/min) • Step length (m) • Walking speed(m/s)
Kinetic Features (5) • Maximum vertical loading response (F_{z1}) • Maximum vertical mid stance (F_{z2}) • Maximum vertical terminal stance (F_{z3}) • Maximum horizontal mid stance (F_{y1}) • Maximum horizontal terminal stance (F_{y2}) Kinematic Features (12) • Hip angle at heel strike • Hip angle at toe off • Maximum hip flexion • Maximum hip extension • Knee angle at heel strike • Knee angle at toe off • Maximum knee flexion • Maximum knee extension • Ankle angle at heel strike • Ankle angle at toe off • Maximum ankle plantarflexion • Maximum ankle dorsiflexion

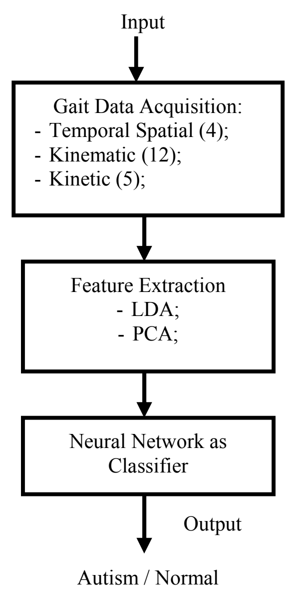

Fig 1: Overview of the proposed method for gait recognition of autistic children

Furthermore, a one-way ANOVA is used to test for significant differences ($P<0.05$) in height, weight, and age between the autism and normal/control groups. No significant differences were found in all three parameters specifically:

- Height [$F(1,42) = 0.038$, $p = 0.85$];
- weight [$F(1,42) = 3.42$, $p = 0.07$];
- age [$F(1,42) = 3.43$, $p = 0.07$];

TABLE 2: CHARACTERISTICS FOR EACH GROUP				
Parameter	*Normal (32 subjects)*		*Autism (12 subjects)*	
	Mean	SD	Mean	SD
Age(years)	9.46	1.79	9.85	2.55
Height(cm)	127.07	12.37	135.22	14.71
Weight(kg)	28.91	10.85	36.29	14.07
Gender	14 male & 18 female		8 male & 4 female	

While there is no significant between-group difference, it should be noted that normal distribution of the data was verified too. In this study, we consider the characteristics of the normal/control group to approximate those of the autism group.

B. Gait data acquisition

Data Acquisition was done at the university Human Motion Laboratory. The laboratory incorporates a Vicon Nexus® Motion Capturing System (Oxford Metrics, United Kingdom). All subjects were evaluated instrumentally using an eight optical cameras motion capture system with up to 16 Megapixels resolution with synchronized to a sampling frequency of 1000 Hz that can be used to measure the three-dimensional (3D) trajectories, forces and moments of a subjects walking gait. In addition, two force plates (AMTI) and two camera video (BTS, Italy) are synchronized with the system for video recording. The timing of these force events is used to estimate the gait temporal-spatial parameters of the subject. Furthermore three force components along the axes of an orthogonal of x, y, z-coordinate system are the horizontal components consist of F_x, F_y with the vertical force component as F_z. However, only horizontal (F_y) and vertical (F_z) of the ground reaction force (GRF) are considered as kinetic features in this study [23].

C. Feature Extraction

C–i. Principal Component Analysis (PCA)

Principal Component Analysis (PCA) is a linear dimensionality reduction technique that seeks the most important information in the data [26, 27]. PCA represented the data in less number of components to show the highest possible discrimination [33, 36]. The maximal amount of variance in the original variables is corresponding to the top eigenvalue provides the basis vector for the direction of highest variability.

C–ii. Linear Discriminant Analysis (LDA)

Linear Discriminant Analysis (LDA) is used to project the data onto a lower-dimensional vector and provides highest possible discrimination between different classes [39].The technique is usually applied in the pre-processing step for pattern-classification[37] and machine learning applications to avoid overfitting [31]. LDA achieves maximum discrimination that helps to classify the data accurately. In order to find a good discrimination of these classes a measure of separation is to be defined. This process involves the following steps:
Step 1: Compute the scatter matrices (between-class ,S_i and within-class scatter matrix, S_B).

$$S_i = \sum_{x \in D_i}^{n} (x - m_i)(x - m_i)^T \quad (1)$$

$$S_B = \sum_{i=1}^{c} N_i (m_i - m)(m_i - m)^T \quad (2)$$

m is the overall mean, and m_i and N_i are the sample mean and sizes of the respective classes.
Step 2: Compute the eigenvectors $(e_1, e_2, \ldots, e_d)$ and corresponding eigenvalues $(\lambda_1, \lambda_2, \ldots, \lambda_d)$ for the scatter matrices.
Step 3: Sort the eigenvectors by decreasing eigenvalues and choose k eigenvectors with the largest eigenvalues to form a $d \times k$- dimensional matrix W (where every column represents an eigenvector). $d \times k$ eigenvector matrix transforms the samples onto the new subspace. Finally, the projection matrix is computed as,

$$Y = X \times W \quad (3)$$

(where X is an $n \times d$ dimensional matrix; the i_{th} row represents the i_{th} sample, and Y is the transformed $n \times k$ dimensional matrix with the n samples projected into the new subspace). Here the variance is calculated as percentage of maximum discrimination since linear combination required largest mean difference between classes [28] . Since variance of the data measure separation between projections for each classes, the larger variance is better expected separation implies the gap between classes is high [29] .

D. Neural network (NN) classifier

In this study, a feed-forward neural network [23, 30, 34] is used to evaluate the efficiency of the pattern classification from the extracted gait features. The structure of multilayer feed forward network comprised of a three-layer NN with one hidden layer with weights adjusted using Sigmoid Conjugate Gradient as the training algorithm [35]. 1000 epochs was trained to learn the relationship between input gait features and the respective subject category as either normal or autism children. The input layer consists of n nodes corresponding to the number of features using a hidden layer of maximum 210 neurons and an output layer of 2 neurons corresponding to the two classes, autism and normal children. The hidden layer processes and transmits the input information to the output layer. The choice of neurons in the hidden layer is by trial and error method [30]. The correct classification or misclassification is assessed as accuracy of classification. Sensitivity and specificity are also used as performance measure [14, 18]. Random sub-sampling cross validation selects data points for the sets of training, test and validation is used in order to prevent the model from over fitting.

III. Experimental Results and Discussion

All twenty one gait parameters that represent the basic temporal spatial, kinetic and kinematic gait parameters for 12 autism and 32 normal subjects constitutes the database to generate the eigenvalues based on PCA. From the PCA results, applying KG rule suggested retaining all eigenvalues > 1 [33] resulting the principal components (PCs) attained as tabulated in Table 3.

As shown in Table 3, temporal spatial has one PC > 1 whilst kinetic has five PCs and kinematic has 11 PCs. To support the PCs generated using PCA, these data are projected and compared with the two groups to be classified namely normal and autistic children as illustrated in the scatter plot shown in Figure 2. It is observed that the scatter plots of the PCs revealed the ability of the first two PCs in discriminating the gait features of both groups as either 'Normal' or 'Autism'. The scatter plot represents the new feature subspace that constructed via PCA. It is observed that for kinematic parameters, the PC1 and PC2 separated the two groups of children well as compared to basic temporal spatial and kinetic parameters and these two categories of gait parameters provide less valuable information.

There were some differences in performance between the two types of features extraction when applied to individual gait data parameters. As observed in Table 4, superior classification results were found in kinematic gait parameter which attained the highest accuracy of 98.44% using LDA followed by PCA with accuracy of 95.63%. The two classes can only be fully separated by the scatter plots of kinematic gait parameters as in Figure 2 and Figure 3. On the other hand, the best linear separator is possible to separate completely the classes with a linear decision boundary that showed good separation of these two groups of children. As for basic temporal spatial gait parameters, once again LDA outperformed PCA with 87.5% classification rate. Conversely, kinetic gait parameters are suitable to be used as features to classify the children as either 'Normal' or 'Autism' using original kinetic data. This is because the original data offered highest accuracy rate namely 82.19% as compared to 78.44% using PCA and 79.06% using LDA. The figure also highlights that for these gait parameters used, the overall performance of the classifier deteriorated with kinetic features. Next, we will analyse the scatter plot representing the new feature subspace that constructed via LDA as in Figure 3. Similar to PCA technique, once again it is observed that for kinematic parameters, the first linear discriminant 'LD1' separated the two groups of children extremely well as compared to basic temporal spatial and kinetic parameters.

TABLE 3: THE SIGNIFICANT EIGENVALUES OR PCS USING THE KG RULE FOR ALL THREE GAIT PARAMETER CATEGORY.

PC	Temporal Spatial	Kinetic	Kinematic
1	166.14	298.99	556.97
2	0.02	78.24	277.18
3	0.01	64.43	123.91
4	0.00	19.18	58.79
5		8.06	37.76
6			28.26
7			22.13
8			10.65
9			4.78
10			3.71
11			1.79
12			0.67

In order to test the effect of features selection on classification performance, the gait features acted as inputs to the MLPNN classifier. The classification results attained is as tabulated in Table 4.

TABLE 4: CLASSIFICATION RESULTS OF LDA AND PCA AS COMPARED TO ORIGINAL GAIT FEATURES WITH NN AS CLASSIFIER

Gait Features	Category	Accuracy	Sensitivity	Specificity
Basic Temporal Spatial	Original	80.31	72.86	78.57
	PCA	83.75	80.00	84.29
	LDA	**87.50**	71.43	80.00
Kinetic	Original	**82.19**	71.43	74.29
	PCA	78.44	75.71	77.14
	LDA	79.06	70.00	75.71
Kinematic	Original	84.69	81.43	81.43
	PCA	95.63	80.00	98.57
	LDA	**98.44**	**94.29**	**97.14**

Additionally, the computed rate for sensitivity and specificity resemble the NN classifier performance. Sensitivity represented the ability of NN classifier to recognise autism gait pattern as 'Autism 'while specificity resembled correctly classify normal/control children gait pattern as 'Normal'. Hence as illustrated in Table 3, with LDA as feature extraction and kinematic gait parameters as the feature inputs, it is proven that LDA outperformed PCA and original gait data as well with 94.29% sensitivity and specificity of 97.14%. It appears that not all gait features are good contributors to separation between the two groups because it was found that (Fig. 3 and Fig 4) with only kinematic features it is possible to achieve greater accuracy than temporal and kinetic features.

IV. Conclusion

As a conclusion, this study evaluated the performance of LDA and PCA as feature extraction with basic temporal spatial, kinetic and kinematic as gait parameters and classification via neural network. It was founds via the scatter plots that LDA is the most significant approach to discriminate these two group of children as normal or autism based on the good separation as visualized by the scatter plots.These findings are supported by the classification rate that once again shows LDA the attained highest classification rate with kinematic data as inputs to the NN classifier. Identification of gait pattern differences between autistic children could help in understanding age-related changes associated with the performance of the movement deviations of abnormal gait. Further work includes utilizing statistical analysis and Bayesian classifier in classifying the gait parameters of these two groups of children.

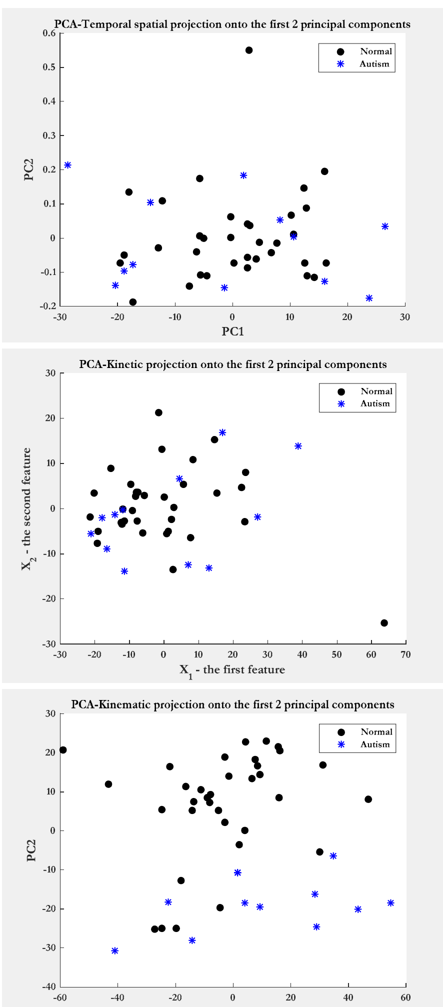

Fig 2: PCA -Gait parameters projection onto the first 2 principal components (PCs) for temporal spatial (top), kinetic (middle) and kinematic (bottom)

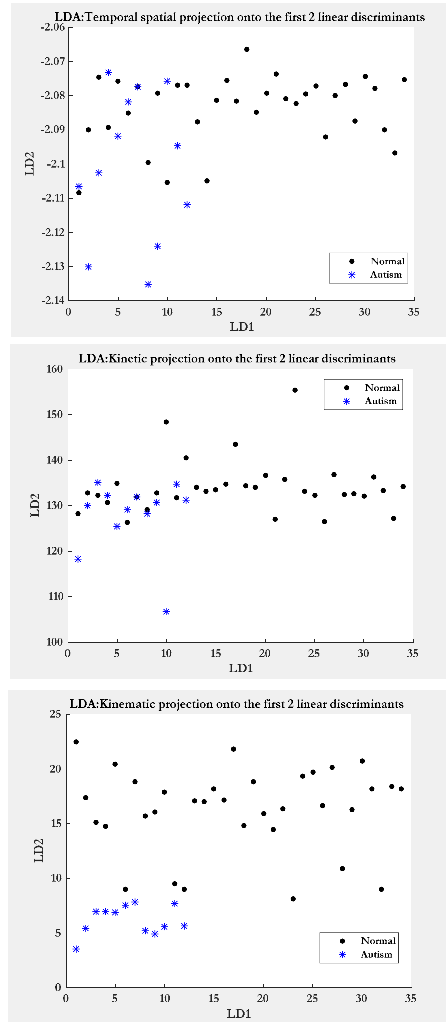

Fig 3: LDA -Gait parameters projection onto the first 2 linear discriminants (LDs) for temporal spatial (top), kinetic (middle) and kinematic (bottom)

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