# Classification of autism children gait patterns using Neural Network and Support Vector Machine

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# Classification of Autism Children Gait Patterns using Neural Network and Support Vector Machine

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***Abstract*** **– In this study, we deemed further to evaluate the performance of Neural Network (NN) and Support Vector Machine (SVM) in classifying the gait patterns between autism and normal children. Firstly, temporal spatial, kinetic and kinematic gait parameters of forty four subjects namely thirty two normal subjects and twelve autism children are acquired. Next, these three category gait parameters acted as inputs to both classifiers. Results showed that fusion of temporal spatial and kinematic contributed the highest accuracy rate for NN classifier specifically 95% whilst SVM with polynomial as kernel, 95% accuracy rate is contributed by fusion of all gait parameters as inputs to the classifier. In addition, the classifiers performance is validated by computing both value of sensitivity and specificity. With SVM using polynomial as kernel, sensitivity attained is 100% indicated that the classifier's ability to perfectly discriminate normal subjects from autism subjects whilst 85% specificity showed that SVM is able to identify autism subjects as autism based on their gait patterns at 85% rate.**

***Index Terms*** **- Gait Analysis, Classification, Support Vector Machine, Neural Networks, Autism.**

## I. Introduction

Gait is the manner or style of walking. Clinical gait analysis has proven to be a great utility tool for medication and diagnosis for orthopedics to improve outcomes such as treatment [3], [11], & [12] and therapy [16] [24]. Research have shown that significant changes in individuals with disease in lower limbs of the body such as Parkinson's [11], cerebral palsy [19] and stroke [16] are more likely to have influences of pattern movement [13,17]. By examining abnormal gait of subjects to monitoring of deterioration of their gait is not an easy task. Thus, measurable temporal spatial, kinematic and kinetic gait parameters from multiple planes and segments should be analysed in advance either by video recording or signal of infrared markers attached to the subject.

On the other hand, autism is a heterogeneous disorder often involving a spectrum of motor symptom. Children with autism are found to have gait disturbances when compared with normal children namely their whole body limbs movement [2], [5] & [12]. It was proven from other researches findings that movement in autism subjects are due to the impact of external and internal effects such as the symmetry of movement [1], cerebellar involvement in motor symptoms[2],[4]&[6], clumsiness[5] and hypotonia [3]. It is indeed likely that a better understanding of gait classification based on a set of defined parameters of gait patterns into groups can differentiated from one another as normal or clinically healthy.

Conversely, in order to facilitate automated recognition of gait patterns, recent vast research activities in machine learning have shown and proven that neural network (NN) and Support Vector Machine (SVM) are vital for classification purposes. Numerous researches have underline NN are capable to characterise gait types can be attained from work by HH Manap et al [25], Muniz et al. [26] and Holzreiter SH et al. [27]. This is consistent too with previous studies that NN could distinguish three gait patterns of 83.3% as reported in [13] and the trained NN demonstrated unknown gait patterns into the right class at a success rate in the range of 75-95% and able to distinguish 'healthy' from 'pathological' gait patterns [27]. Furthermore, SVM is considered as a generalised linear classifier to deal with pattern recognition involving small sample, non-linear and high-dimension data [10].

As we know, SVM is a supervised learning method that is commonly used for classification [9], regression [28] and outlier detection [29]. Based on these literatures, SVM could distinguish the two gait patterns with 100% accuracy and overall accuracy obtained was 91.7% using basic, kinetic and kinematic gait data solely [9]. In addition, SVM with RBF kernel showed highest classification accuracy rate for gait pattern between normal and PD patients as discussed in [7]. Furthermore, SVM has also been applied for classifying normal and pathological gait patterns and demonstrated to be able to recognise and identify between young and elderly gait patterns [8] when trained with reduced number of selected features and appropriate kernel [10]. Considering all of these findings, hence NN and SVM are indeed suitable to be used in distinguishing gait patterns between different condition types of human. Thus, in this study, once again these two classifiers will be evaluated and validated with temporal spatial, kinematic and kinetic as input parameters in classifying abnormal gait pattern in autism children during normal walking.

## II. PROPOSED METHODOLOGY

This section discussed the proposed method to be implemented in this study. Firstly, twelve autism children ($n_1$=12) from National Autism Society of Malaysia (NASOM) participated in this research and have signed the consent form by their guardian. Also, thirty two normal developing children ($n_2$=32) children aged between 6 - 12 years voluntarily participated in this research and have signed the consent form too. These normal subjects are from UiTM staff's children or their friends. Note that definition of autism subjects in this study are based on mild severity autism thus excluding the toe-walkers' children. Additionally, all subjects had no known injuries or abnormalities that would affect their gait before signing the consent form approved by the UiTM Research Ethics Board. Mean age, height, weight of the two groups are as tabulated in Table 1:

Table 1: Mean height, weight & age value for each group

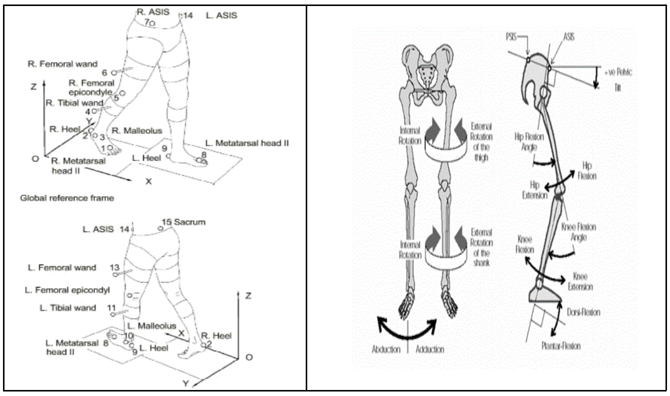
| Parameter | Autism | Normal |
|---|---|---|
| # of subjects (n) | 12 | 32 |
| Age (years) | 9.85 | 9.46 |
| Height (cm) | 135.22 | 127.02 |
| Weight (kg) | 36.29 | 28.91 |

Next, according to protocol stated by Helen Hayes (Davis) as in [17], sixteen passive reflective Plug-in-Gait (PIG) markers were fixed bilaterally to specific anatomical landmarks on the subject's lower limbs on the left side as shown in Figure 1a and similar positioning for the right side. To ensure that precise kinematics results are to be obtained, hence consistent and accurate method for marker placement and acquisition is indeed vital [3].

a) *Gait data acquisition*

Next, this section elaborated acquisition of gait data for both group. Firstly, participants are required to familiar with markers and the lab environment by several 'warm-up' trials of normal walking along the laboratory walkway. Gait acquisitions are performed when force plate was hit centrally between the two AMTI force plates during bare foot walking at a distance of approximately 8 meters. All participants in this study completed three gait trials with right foot chosen as initial/beginning of walking in order to establish baseline values. Marker trajectories and ground reaction force (GRF) are recorded respectively in order to compute three types of gait parameters namely temporal spatial, kinetic and kinematic features for each gait cycle. In addition, gait cycle is defined as two consecutive heel strikes of the same limb that can be subdivided into the stance phase and swing phase as demonstrated in Figure 2.

For normal subjects that walked at their preferred speed on a level surface, the stance phase can take approximately 62% of the complete gait cycle (100%). For each child, temporal spatial spent in left and right leg gait cycles was analysed for each gait cycle similar to method proposed in [14]. Recall that kinematic is the study of the positions, angles, velocities, and accelerations of body segments and joints during motion as shown in Figure 1b. Thus, hip, knee and ankle joint kinematics variables are temporally normalised to the gait cycle [7]. Moreover, a single stride was analysed by time-normalised as a percentage of the whole stride duration starting with initial contact or heel stride as shown in Figure 2. The single gait cycle that most closely approximated the individual mean of all gait cycles on these three measures was selected for further analysis [3].



(a) (b)

Figure 1: (a) Helen Hayes (Davis) Marker Placement Protocol [17] and (b) Kinematic variable definitions [30]

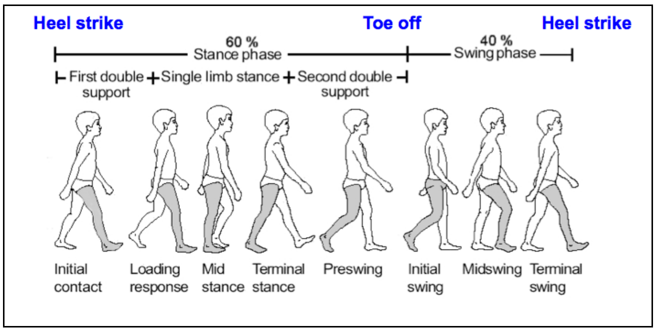



Figure 2: Phases in a normal gait cycle [30]

Furthermore, normal distribution of data was confirmed by using the Kolmogorov–Smirnov Normality test that demonstrated the parameters are normally distributed. This is done via *t*-test for both normal and autism children [16]. Significance for all statistical tests was established at $p < 0.05$. To evaluate the effectiveness of each features, two mode of classification are employed namely NN and SVM classifier. Firstly, basic gait features as well as kinetic and kinematic gait features are evaluated solely. Then, fusion of features will be done along with significant features based on statistical analysis conducted.

*b) Neural Network (NN) and Support Vector Machine (SVM) as Classifier*

It is well known that feed forward multi layer perceptron NN normally consists of three adjacent layers; the input, hidden and output layers [13]. In our experiments, a fully connected feed-forward neural network is used to evaluate the efficiency of the pattern classification from the extracted gait features where a three-layer NN with weights adjusted using Sigmoid Conjugate Gradient as the training algorithm with maximum 1000 epochs is trained to learn the relationship between the input gait features and the respective subject that is categorised as either 'Normal' or 'Autism'. In addition, 10 fold cross-validation technique is used due to the small sample size [23, 24].

Further, SVM with different kernel functions and different values of parameter C are tested to determine the optimal parameters for classification of autism subjects based on the gait patterns. The three common kernel functions for the SVM namely the linear kernel, polynomial kernel and radial basis function (RBF) kernel are used in this study. In order to enhance the performance of the SVM, parameter C with the range of values of 1, 101 and 102 is applied too in order to be able to evaluate the impact of the implementation of different kernel functions and different range of parameter as well as classifier performance.

## III. Experimental analysis, Results and Discussion

In this section results attained will be elaborated and discussed. As stated earlier, the aim of this research is to classify 3D joint gait during normal walking between autistic children's compared to normal children in identifying differences in gait parameters using two different classifiers. For that reason, these three parameters and group parameters are combined as ANN and SVM inputs. Firstly, the *t*-test is conducted based on all twenty one gait features extracted in describing temporal spatial, kinetic and kinematic features of the gait patterns and results obtained is as shown in Table 2. Based on the statistical analysis done as shown in Table 2, it was found that seven features from kinematic parameter are indeed significant in categorising between gait patterns as either 'Normal' or 'Autism'. The parameters are:

- three joint angle of the hip;
- three knee angle and
- one dorsiflexion ankle;

Subsequently, as for classifiers performance measure via accuracy (Acc), sensitivity (Sens) and specificity (Spec), Table 3 depicted the classification performance using NN and SVM. It was found that with NN as classifier, results attained showed that combined gait features of temporal spatial and kinematic attained highest classification rate that is 95%. Next, it was observed that using all seven significant features as identified via statistical analysis has contributed as the second highest accuracy specifically 93.44%. Hence, this initial findings proven that weaken dorsiflexion is one the possible cause of altered gait patterns or deviation and can be considered for comparison between normal and autism due to lack of control of the dorsiflexion and swinging their limbs that further contributed to shorter percentage of gait cycle. This finding may be important in terms of treatment planning for children with autism since it is possible that one of the functions of the treatment focus is in improving the control and strength of the dorsiflexion.

In addition, performance measure among the three kernels of SVM is reported too. In general, results showed that combining all three categories of gait parameters showed improved performance as compared to one category of gait parameter. The highest accuracy (Acc) was at 95.8% when all twenty one features of all three categories namely temporal spatial, kinetic and kinematic gait parameters are used as SVM inputs with Polynomial as kernel. As for sensitivity (Sens), results showed an excellent rate of 100% whilst specificity (Spec) is at 85%. This result validated that SVM classifier with polynomial as kernel perfectly discriminated normal subjects as "Normal' and capable to identify as high as 85% autism subject as 'Autism'.

Table 2: Gait parameter t-test result across groups

| Gait parameter | Mean and standard deviation: Normal children | Autism children | T test result: P value |
|---|---|---|---|
| Stride time (s) | 1.04(±0.09) | 1.04(±0.17) | 0.98 |
| Cadence (steps/min) | 116.37(±10.54) | 117.98(±18.55) | 0.71 |
| Step length (m) | 0.56(±0.12) | 0.55(±0.09) | 0.83 |
| Walking speed(m/s) | 1.03(±0.17) | 1.06(±0.19) | 0.58 |
| Maximum vertical loading response ($Fz_1$) force | 114.85(±15.52) | 113.98(±16.37) | 0.87 |
| Maximum vertical mid stance ($Fz_2$) force | 77.33(±7.87) | 72.67(±15.58) | 0.187 |
| Maximum vertical terminal stance ($Fz_3$) force | 110.25(±8.06) | 104.69(±8.88) | 0.051 |
| Maximum horizontal mid stance ($Fy_1$) force | -20.63(±5.26) | -20.93(±5.60) | 0.868 |
| Maximum horizontal terminal stance ($Fy_2$) force | 21.96(±3.89) | 22.39(±4.13) | 0.748 |
| Hip angle at heel strike angle | 30.51(±10.13) | 39.01(±11.94) | **0.021*** |
| Hip angle at toe off angle | -7.68(±9.31) | 1.08(±13.69) | **0.018*** |
| Maximum hip flexion angle | 34.23(±9.21) | 39.71(±11.79) | 0.107 |
| Maximum hip extension angle | -11.15(±8.82) | -2.67(±12.98) | **0.015*** |
| Knee angle at heel strike angle | 5.58(±7.37) | 11.79(±9.66) | **0.026*** |
| Knee angle at toe off angle | 32.38(±8.02) | 35.32(±10.88) | 0.327 |
| Maximum knee flexion angle | 58.83(±14.32) | 37.10(±9.82) | **$1.58e^{-05}$*** |
| Maximum knee extension angle | 3.26(±6.44) | 9.29(±8.44) | **0.014*** |
| Ankle angle at heel strike angle | -0.01(±6.46) | 1.75(±7.01) | 0.433 |
| Ankle angle at toe off angle | -9.46(±7.18) | -7.50(±7.07) | 0.420 |
| Maximum ankle plantarflexion angle | 17.59(±6.24) | 20.11(±4.14) | 0.201 |
| Maximum ankle dorsiflexion | -17.41(±7.26) | -9.74(±7.84) | **0.004*** |

Table 3: Performance Measure using NN and SVM as classifier in classifying autism gait pattern

| Gait features | Neural Network | | | Support Vector Machine | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | Linear | | | Polynomial | | | RBF | | |
| | *Acc* | *Sens* | *Spec* | *Acc* | *Sens* | *Spec* | *Acc* | *Sens* | *Spec* | *Acc* | *Sens* | *Spec* |
| **Temporal spatial** | 80.31 | 72.86 | 78.57 | 67.0 | 69.2 | 60.0 | 72.5 | 78.3 | 55.0 | 73.2 | 77.5 | 60.0 |
| **Kinetic** | 82.19 | 71.43 | 74.29 | 72.2 | 81.7 | 55.0 | 74.3 | 79.2 | 60.0 | 78.2 | 92.5 | 40.0 |
| **Kinematic** | 84.69 | 81.43 | 81.43 | 91.0 | 86.7 | 100.0 | 93.8 | 90.8 | 100.0 | 89.7 | 88.3 | 95.0 |
| **Temporal spatial ∩ Kinetic** | 85.00 | 77.14 | 81.43 | 70.3 | 70.0 | 75.0 | 64.7 | 67.5 | 55.0 | 76.5 | 81.7 | 70.0 |
| **Temporal spatial ∩ Kinematic** | **95.00** | **75.71** | **85.71** | 86.5 | 88.3 | 85.0 | 91.8 | 97.5 | 75.0 | 94.1 | 96.7 | 90.0 |
| **Kinetic ∩ Kinematic** | 90.00 | 75.71 | 90.00 | 87.0 | 91.7 | 70.0 | 89.5 | 95.0 | 70.0 | 93.5 | 95.0 | 90.0 |
| **Temporal spatial ∩ Kinetic ∩ Kinematic** | 87.19 | 84.29 | 84.29 | 88.2 | 91.7 | 80.0 | **95.8** | **100.0** | **85.0** | 86.2 | 94.2 | 65.0 |
| ***Significant features via Statistical Analysis** | 93.44 | 77.14 | 84.29 | 95.5 | 96.7 | 95.0 | 90.0 | 96.7 | 70.0 | 93.0 | 90.8 | 100.0 |

Hence, SVM is able to discriminate perfectly gait patterns of normal subjects from autism subjects. On the other hand, classification with SVM also showed that kinematic gait parameters demonstrated lower accuracy specifically 93.8% but perfect specificity along with sensitivity of 90.8%. This indicated that using kinematic gait features, the SVM classifier with polynomial kernel once again is able to discriminate perfectly autism subject as "Autism' based on their gait patterns. As for SVM with RBF kernel, accuracy was highest at 94.1% with basic and kinematic gait parameters as inputs. However, the accuracy rate reduced to 93.5% with kinetic and kinematic parameters as inputs. Also, classification accuracy of SVM with linear and RBF kernel performed poorly with temporal spatial features as inputs with attained accuracy rate of 67.0% and 73.2% respectively.

As can be seen in the Table 3 too, classification performance using linear kernel is second highest at 95.5% along with specificity of 96.7% and sensitivity of 95% with significant features attained based on statistical analysis. Recall that these significant features comprised of all seven kinematics features as listed earlier. Conversely, the classifier performance is at 91% and is the second highest accuracy using kinematic gait parameters.

## IV. Conclusion

In conclusion, a method is proposed in classifying gait features between autism children and normal children. Both SVM and NN are capable to distinguish gait patterns between autism children and normal children. Firstly, each category of gait parameter specifically temporal spatial, kinetic and kinematic gait parameters are evaluated solely using these two classifiers. Next, fusion or combination amongst these three categories of gait parameters is conducted. This is done in order to evaluate and verify either each gait category solely or combination within these three categories contributed to highest accuracy rate. Hence results revealed that combination of all three category namely temporal spatial, kinetic and kinematic parameters contributed to highest accuracy that is 95% with SVM as classifier based on polynomial kernel. Future work will focus on implementation of feature selection algorithms and further investigate if this could increase the accuracy before suggesting for possible intervention procedures.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