IJITKM Volume 7 • Number 1 • December 2013 pp. 27-30

Artificial Neural Network based classification of Neuro-Degenerative diseases using Gait features

Mandeep Singh [1], Mooninder Singh [2], Paramjeet [3]
[1], [2], [3] Department of Electrical & Instrumentation Engineering, Thapar University, Patiala, INDIA
E-mail: mandy_tiet@yahoo.com, mooninder@gmail.com, paramjeet.shahi@yahoo.com

Abstract
The neuro-degenerative diseases mainly affect the gait pattern. This paper focuses identification of neuro-degenerative diseases in three phases. First phase classifies normal and neuro-degenerative subjects. Second phase classify Parkinson and non-Parkinson subjects. Third phase classify Huntington and ALS subjects. Coefficient of Variation of left and right foot heel and toe strike intervals is taken as input vector to Artificial Neural Network (ANN) for these classifications. In phase 1, we obtained accuracy of 94 %. In phase 2, accuracy was 99.9 % and in phase 3, we obtained accuracy of 88 %.

Introduction

Neuro-degenerative disease occurs due to death of neurons in brain and spinal cord and results movement disturbances. Parkinson's disease (PD), Huntington's disease (HD) and Amyotrophic Lateral Sclerosis (ALS) are the three major diseases that come under neuro-degenerative diseases [1]. Gait disturbances are the main cause of disability and impairment for patients with neuro-degenerative diseases. The gait disturbances can be classified into two parts, the one is continuous and the other one is episodic. The episodic gait disturbances occur occasionally and very rarely. The main symptoms include festinating, start hesitation and freezing of gait. The continuous type gait disturbances are most commonly in patients. The age factor also contributes in neuro-degenerative diseases, as the age increases, the fall and impairment also progresses. Improper foot function resulting in abnormal walking is shown in figure 1.

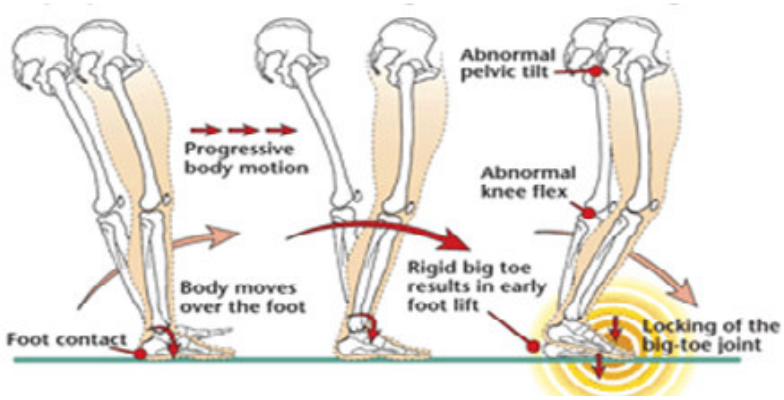

Figure 1: Improper foot function resulting in abnormal walking

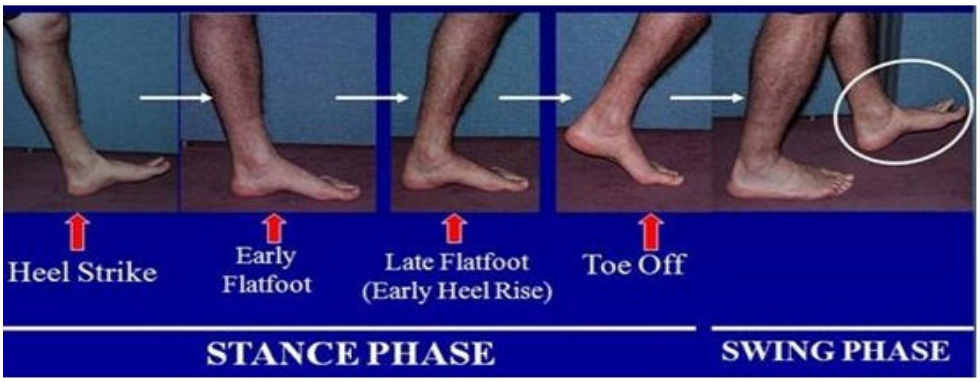

Figure 2: Phases of gait

The heel strike is defined as the heel first touches the ground and ends until the whole foot touches the ground [2]. The early flatfoot strike occurs, when the whole foot is on the ground. The late flatfoot stages ends when the heel lifts off the ground. The rise begins when the heel starts to leave the ground. The toe off phase occurs, when the toe leave the ground. 60% of the walking consists of stance phase. The Stance phase occurs when the whole foot is on the ground. Swing phase is basically defined as the one foot is on the ground and the other is in the air. The different gait phases of gait are shown in figure 2.

ARTIFICIAL NEURAL NETWORK

A neural network consists of hidden neurons arranged in layers. It is an interconnected group of artificial network which convert an input vector into some output. The basis network include nodes, called neurons and processing elements, which are connected together to form neural network. The work function refers to the inter–connections between the neurons in the different layers of system. Each neuron takes an input, applies a function to it and then passes the output to the next layer.

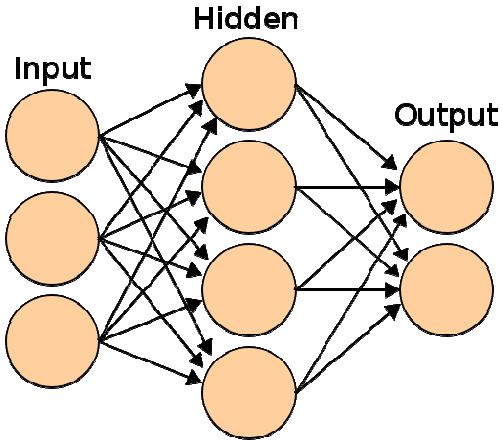

Figure 3: Artificial neural network architecture

Feed-forward Network

It is commonly used for prediction, pattern recognition etc. Feed forward Network is the one-way connection network from input layer to output layer. It includes feed-forward back propagation, cascade-backpropagation, and Perceptron networks. As shown in figure, it consists of input layer, hidden layer and output layer.

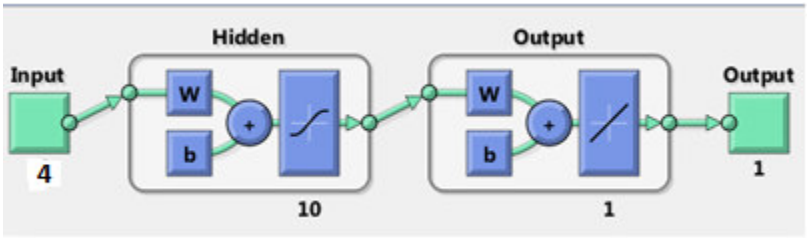

Figure 4: two layer feed- forward network

Data Collection

The Gait data for classification is collected from our previous work wherein the covariance of 13 subjects of healthy control, 13 subjects of PD, 13 subjects of HD and 13 subjects of ALS are computed [3]. The data is replicated here for ready reference in table 5-8. The correspond bar graph are shown in figure 5-8.

Methodology

The two-layer feed-forward back propagation Artificial Neural Network (ANN) is used for classification. It has one hidden layer with 10 neurons. Tan-Sigmoid function is used in hidden layer. The MATLAB Neural Network (nntool) opens the Network/Data Manager window, which is helpful to create, train and export the data. The collected data consists of two sets for the classification of normal and Neuro-degenerative subjects. The normal set contains 13 healthy control subjects whereas neuro-degenerative disease set contains 13 PD subjects, 13 HD

subjects and 13 ALS subjects. In our previous work it was seen that none of the four features, namely CV of left foot heel strike, Left foot toe strike, Right foot heel strike, Right foot toe strike interval is capable of classification on the basis of threshold, because of overlapping layer [3]. It is therefore essential to design some multi input classifier. Our proposed ANN has four inputs, namely CV of left foot heel strike, Left foot toe strike, Right foot heel strike, Right foot toe strike interval. We are proposing to have two-class classifier, and therefore the output layer will have only one neuron. The output will be 0 or 1 as per the case. We decided to classify the neuro-degenerative disease subjects and healthy control in three phases.

Phase 1

In first phase, we classify normal and neuro-degenerative disease. Since we have 13 normal subjects and 39 neuro-degenerative disease subjects, the input training data will have 52 samples. Each sample has 4 features, namely CV of left foot heel strike, CV of the left foot toe strike, similarly CV of the right foot heel strike and CV of the right foot toe strike interval. The target training data is given 0 for normal subjects and 1 for neuro-degenerative diseases.

The ANN gave classification accurately of 94%. If we frame a question "Is the person suffering from neuro-degenerative disease?" The answer may be yes or no. the confusion matrix is given in table 1.

Table 1: Confusion Matrix

	Predicted	
Actual	Yes (TP)	No (FN)
	No (FP)	Yes (TN)

We define:

Accuracy = (TP+TN) / (TP+TN+FP+FN)

Specificity= (No. of TN) / (No. of TN) + (No. of FP)

Sensitivity= (No. of TP) / (No. of TP + No. of FN)

TP= True Positive; TN= True Negative; FP= False Positive; FN= False Negative

Table 2: Confusion Matrix for phase 1

	Predicted	
Actual	36 (TP)	3 (FN)
	0 (FP)	13 (TN)

Accuracy = 94%; Sensitivity= 92%; Specificity= 100%

Phase 2

In second phase, we further classify neuro-degenerative diseases into Parkinson's disease and Non-Parkinson's disease. Since we have 13 normal subjects and 26 neuro-degenerative disease subjects, the input training data will have 39 samples. Each sample has 4 features, namely CV of left foot heel strike, CV of the left foot toe strike, similarly CV of the right foot heel strike and CV of the right foot toe strike interval. The target training data is given 0 for Parkinson's subjects and 1 for Non-Parkinson's subjects.

The ANN gave classification accurately of 100%. If we frame a question "Is the person suffering from Parkinson's disease?" The answer may be yes or no. the confusion matrix is given in table 3.

Table 3: Confusion Matrix for phase 2

	Predicted	
Actual	13 (TP)	0 (FN)
	0 (FP)	26 (TN)

Accuracy = 100%; Sensitivity= 100%; Specificity= 100%

Phase 3

In third phase, finally we classify neuro-degenerative diseases into Huntington's disease and ALS disease. Since we have 13 normal subjects and 13 neuro-degenerative disease subjects, the input training data will have 26 samples. Each sample has 4 features, namely CV of left foot heel strike, CV of the left foot toe strike, similarly CV of the

right foot heel strike and CV of the right foot toe strike interval. The target training data is given 0 for Huntington's subjects and 1 for ALS subjects.
The ANN gave classification accurately of 88%. If we frame a question "Is the person suffering from Huntington's disease?" The answer may be yes or no. the confusion matrix is given in table 4.

Table 4: Confusion Matrix for phase 3

	Predicted	
Actual	12 (TP)	1 (FN)
	2 (FP)	11(TN)

Accuracy = 88%; Sensitivity= 92%; Specificity= 84%

Table 5: CV of 13 PD subjects

Subjects	Left Heel	Left Toe	Right Heel	Right Toe
PARK1	0.070038	0.021344	0.029018	0.020928
PARK2	0.028801	0.031787	0.067669	0.026697
PARK3	0.063144	0.042653	0.035256	0.055042
PARK4	0.039457	0.027222	0.066766	0.021524
PARK5	0.301106	0.286624	0.051424	0.032498
PARK6	0.050278	0.039707	0.029469	0.03905
PARK7	0.09698	0.070059	0.119646	0.076914
PARK8	0.032059	0.030173	0.027168	0.038014
PARK9	0.053582	0.025893	0.367292	0.653307
PARL10	0.525637	0.472776	0.156842	0.156678
PARK11	0.083261	0.03026	0.028745	0.028342
PARK12	0.022464	0.087684	0.031348	0.027095
PARK13	0.029632	0.027679	0.033973	0.024128

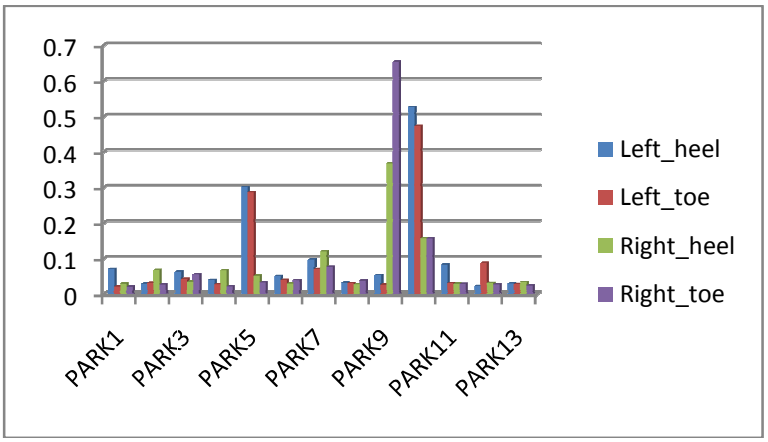

Figure 5: CV of PD

Table 6: CV of HD subjects

Subjects	Left heel	Left toe	Right heel	Right toe
HUNT1	0.05734	0.064892	0.07091	0.068975
HUNT2	0.098702	0.096021	0.098139	0.081684
HUNT3	0.094299	0.086311	0.104165	0.047279
HUNT4	0.064626	0.026839	0.037289	0.026319
HUNT5	0.040179	0.029596	0.065191	0.030287
HUNT6	0.107463	0.030763	0.049152	0.043331
HUNT7	0.039318	0.018978	0.039248	0.013578
HUNT8	0.041295	0.038312	0.052663	0.041429
HUNT9	0.036932	0.074962	0.033188	0.030259
HUNT10	0.073204	0.035551	0.261508	0.045279
HUNT11	0.072295	0.15502	0.074925	0.058226
HUNT12	0.035164	0.023276	0.034978	0.115548
HUNT13	0.039534	0.036478	0.058417	0.04118

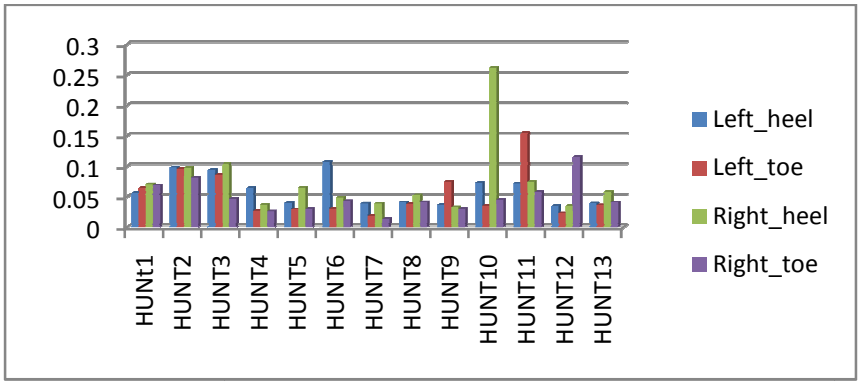

Figure 6: CV of HD subjects

Table 7: CV of ALS subjects

Subjects	Left heel	Left toe	Right heel	Right toe
ALS1	0.041411	0.027762	0.019919	0.02065
ALS2	0.049444	0.048	0.042323	0.046682
ALS3	0.057971	0.127942	0.153325	0.182501
ALS4	0.024044	0.033852	0.030648	0.05982
ALS5	0.060014	0.03748	0.205247	0.04527
ALS6	0.095806	0.082461	0.10109	0.177373
ALS7	0.013444	0.017996	0.01858	0.012898
ALS8	0.026808	0.015716	0.020486	0.023926
ALS9	0.014237	0.019693	0.018981	0.024232
ALS10	0.012002	0.015795	0.023072	0.012501
ALS11	0.034199	0.024395	0.120072	0.024292
ALS12	0.024762	0.026151	0.045355	0.028665

ALS13	0.051535	0.047871	0.049669	0.043397

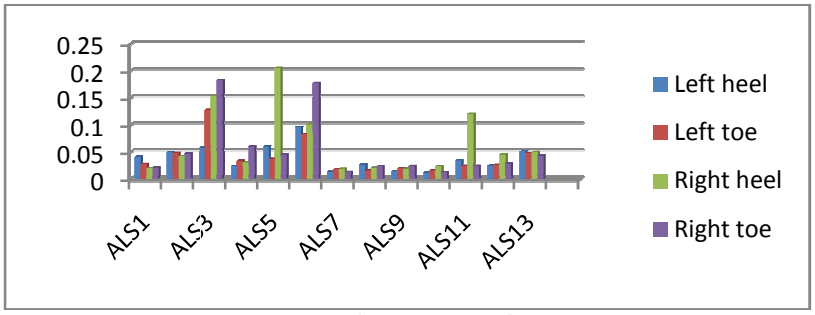

Figure 7: CV of ALS

Table 8: CV of healthy control

Subjects	Left heel	Left toe	Right Heel	Right toe
CONTROL1	0.01767	0.030575	0.019203	0.03
CONTROL2	0.014032	0.010834	0.009675	0.011616
CONTROL3	0.027747	0.022474	0.045674	0.014173
CONTROL4	0.021618	0.01644	0.020489	0.017795
CONTROL5	0.022141	0.022345	0.02474	0.024528
CONTROL6	0.044641	0.018917	0.02082	0.014187
CONTROL7	0.016078	0.019513	0.011888	0.017431
CONTROL8	0.147627	0.024434	0.038703	0.018457
CONTROL9	0.019699	0.016929	0.020913	0.023932
CONTROL10	0.012468	0.031141	0.067067	0.031865
CONTROL11	0.102323	0.020768	0.092558	0.027716
CONTROL12	0.033761	0.036911	0.06901	0.037517
CONTROL13	0.027179	0.024912	0.019366	0.018328

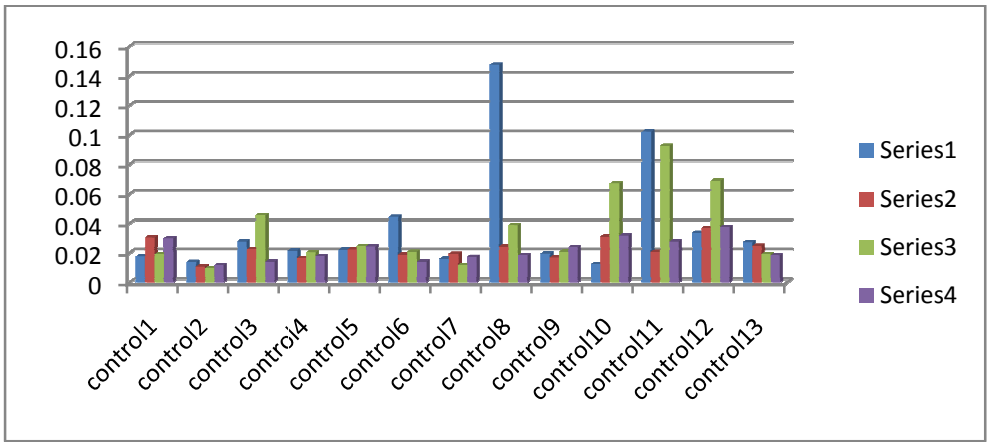

Figure 8: CV of Healthy control

Results

The comprehensive classification is given in table 9. As the accuracy is fairly high, the classification requires no more refinement.

Table 9: Comprehensive classification results

Class	Accuracy
Normal	94 %
Abnormal (PD, HD, ALS)	
Parkinson's	100%
Non-Parkinson's (HD, ALS)	
HD	88 %
ALS	

Conclusion and future scope

Thus we conclude that the four features extracted from the gait, namely CV of left foot heel strike, Left foot toe strike, Right foot heel strike, Right foot toe strike are sufficient for ANN based Classifier.

Classification was done in three phases. First phase includes normal and neuro-degenerative disease, second phase includes Parkinson's disease and non-Parkinson's disease and third phase includes HD and ALS. Multi-class classifier may also be designed. It classifies into single phase.

References

1. Mingjing Yang, Huiru Zheng, Haiying Wang, Sally McClean, "Feature Selection and Construction for the Discrimination of Neurodegenerative Diseases Based on Gait Analysis", *Pervasive Health*, pp. 1-7, Digital Object Identifier: 10.4108I1CST.PERVAS/VEHEALTH2009.6053
2. Mandeep Singh, Mooninder Singh, Paramjeet, "Neuro-degenerative disease diagnosis using human gait: a review, *"International Journal of Information Technology and Knowledge management"*, vol. 7, no.1, December 2013
3. Mandeep Singh, Mooninder Singh, Paramjeet, "Computation of heel and toe strikes using Computer Aided Techniques", *International Journal of Information Technology and Knowledge management",* vol. 7, no.1, December 2013