

A New Automatic Method of Parkinson Disease Identification Using Complex-Valued Neural Network

Rashidah Funke Olanrewaju and Nur Syarafina Zahari

Department of Electrical and Computer Engineering, Faculty of Engineering, International Islamic University Malaysia, 50728 Kuala Lumpur

Email: frashidah@iium.edu.my, syarafina.zahari@gmail.com

Aibinu Abiodun Musa

Federal University of Technology, Minna, Nigeria

Email: maibinu@gmail.com

Abstract—A new automatic method of parkinson detection and classification using Complex Valued Neural Network (CVNN) is proposed in this paper. The proposed methodology used one of recently introduced dysphonia measure as part of its input data. The selected measures are those that are robust to many uncontrollable variations in individual and environments. The three selected dysphonia measures are converted from time domain to frequency domain by application of Discrete Fourier Transform (DFT) on the data. The frequency domain converted measures are fed to CVNN and the output of CVNN serves as input to the parkinson disease classifier for classification purpose. Result obtained by application of this technique on parkinson data resulted in classification performance of 96% accuracy.

Index Terms—complex backpropagation algorithm, Complex-Valued Data (CVD), Complex Valued Neural Network (CVNN), Fast Fourier Transform (FFT), parkinson disease (PD)

I. INTRODUCTION

Parkinson's disease (PD) is a chronic neurological progressive disorder caused by lack of the chemical dopamine in the brain. It is the second most regular neurodegenerative disorder after Alzheimer's disease, which affects the people regardless of their races [1]. PD occurs because of the degeneration of neurons in the brain's thalamic region [2].

Dopamine is a neurotransmitter that helps in the transmission of signals in the brain and other vital areas [3]. The oscillatory or involuntary movement in the body is the result of the dopamine degeneration. Fig. 1 shows the comparison of Dopamine levels in a normal and a Parkinson's patient. The dopamine levels in Parkinson's affected neuron are much smaller than the normal neuron.

PD symptoms are usually related to the movement. The common symptoms are "shakes" (tremor), muscle stiffness (rigidity), and slowness of movements

(bradykinesia) [2]. A person who has these symptoms usually will be diagnosed as PD. The next stages of PD is usually imbalance (postural instability) will occurs. Besides the motor symptoms, fatigues, depression, anxiety, slowness of thinking, difficulty concentrating, and visual hallucinations e.t.c. are symptoms of PD [2].

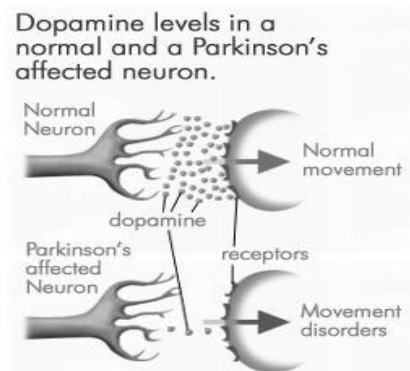


Figure1. Dopamine levels in a normal and a Parkinson's patient [4]

Up to today, there is still no cure or prevention for PD, and usually PD worsens gradually over time. However, this disease can be controlled with some treatment, especially in the early stage of the disease. Hence early detection is highly beneficial.

The common treatment given to the patient is based on restoring dopamine in the brain. Besides that, there is also deep brain stimulation (DBS) surgery that was operated to implant the medical device called a brain pacemaker, which sends electrical impulses to specific parts of the brain [5].

The main objective of the research in Parkinson's disease is to improve the diagnostic accuracy, and to find the best method to detect the disease in the early stage. It is very important to diagnose PD accurately since if the patient is misdiagnosed as healthy, his condition will worsens over time. If PD was diagnosed in the early stage, this disease can be controlled with the treatment. In an

effort to improve the diagnostic accuracy, the application of Complex Valued Neural Network (CVNN),

II. MATERIALS AND METHOD

The block diagram of the proposed automatic Parkinson detection is as shown in Fig. 2. It consist of a three stage cascade system, namely Data FFT, CVNN section and Parkinson disease classifier section.

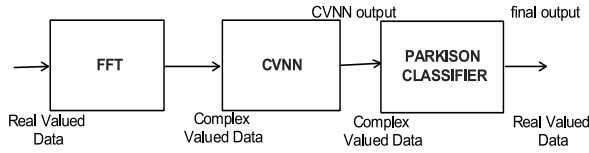


Figure2. Automatic Parkinson Detection Block Diagram

Fast Fourier Transform (FFT). Fourier transform is among the most widely used tools for transforming data sequences and functions from time domain to the frequency domain [6]. Discrete Fourier Transform, DFT is a method of calculating the frequency contents of a sampled signal. The signal can be from any source with a periodical or suspected periodical behavior. The One dimensional DFT of a signal $f(n)$ is a sequence defined over the interval from 0 to $N - 1$, the DFT $F(k)$, and $f(n)$ is defined over the same interval from 0 to $N - 1$ by:

$$F(k) = F\left(2\pi \frac{k}{n}\right) = \sum_{n=0}^{N-1} f(n) e^{-j2\pi \frac{kn}{N}} \quad (1)$$

where $k = 0, 1, 2, \dots, N-1$ are the discrete Fourier coefficients, N is the number of samples, $f(n)$ is the original signal in spatial domain. The corresponding inverse of the one dimensional DFT (IDFT) of $F(k)$ gives $f(n)$ sequence is defined as:

$$f(n) = \frac{1}{N} \sum_{k=0}^{N-1} F(k) e^{j2\pi \frac{kn}{N}} \quad (2)$$

FFT is a fast algorithm and methodology of implementing DFT. Since the number of complex multiplications and additions required to implement DFT equation is proportional to N^2 , the proper decomposition of eqn. (1) can make the number of multiplication and additions operation proportional to $N \log_2 N$. The reduction from N^2 to $N \log_2 N$ operations represents a significant computation effort. Therefore, FFT gives a computational advantage over direct DFT especially when N is relatively large. In this work, the FFT is applied on the data so as to convert the time domain signal to frequency domain for analysis and detection.

Complex Valued Neural Network (CVNN). CVNN is use to process complex valued data (CVD) such as in image with real and imaginary component [7]. CVNN is made up of Complex-Valued Feedforward (CVFF) known as the forward phase and a corresponding backward phase, Complex Back-Propagation (CBP) algorithm. The block diagram of CVFF and CBP is as shown in Fig. 3. CVNN has been studied and developed by authors in solving various problems [7]-[9]. The CVNN consists of an interconnection of Complex-Valued (CV) neurons and

complex valued synaptic weights. It processes information using a connectionist approach to computation in complex domain. CVNN starts with the forward phase by transmitting the complex input signals through the connection; each connection has an associated weight that improves the transmitted signal; each neuron transforms the received signals (sums the input multiplied by the connection weight)

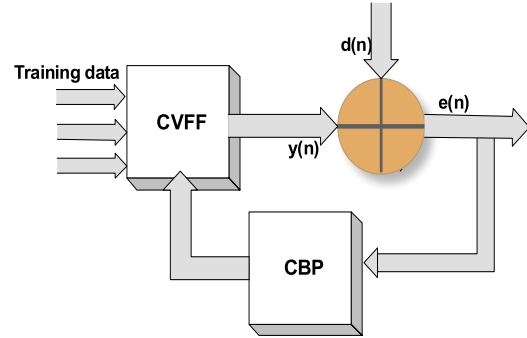


Figure3. complex valued feed forward (CVFF) and complex back-propagation (CBP) algorithm.

$$e(n) = [d(n)_R + id(n)_I] - [y(n)_R + iy(n)_I] \quad (3)$$

where $[d_R(n) + id_I(n)]$ is the target CVD and $[y_R(n) + iy_I(n)]$ is the output of the CVNN. The objective of CVNN training using CBP techniques is to finds a set of parameters that minimises the sum of the squared of error function, that is ;

$$E(n) = \frac{1}{2} \sum_{n=1}^L e(n) e^*(n) \quad (4)$$

where $e^*(n) = e_R(n) - ie_I(n)$ is the complex conjugate of the error function, L is the total number of neuron in the output layer. The complex network weight update is given by:

$$w(n+1) = w(n) + \Delta w(n+1) \quad (5)$$

but

$$\Delta w = -\eta \nabla_w E(n) \quad (6)$$

where η is the learning rate, is the gradient of the cost function and $w(n)$ is a complex weight function with Real (R) and Imaginary (I) parts.

Parkinson Classifier. The main objective of PD classifiers is to group the CVNN output into regions with same property or characteristics. The algorithm for this stage is called k-mean .The grouping is done by minimizing the sum of squares of distances between CVNN output and the corresponding cluster centroid. The algorithm produces tighter clusters than hierarchical clustering, especially if the clusters are globular, hence it is suitable for this work. Initial and New centroids is calculated by equation (7) and equation (8) respectively.

$$A_j(0) = \{mean(I) - sd_I\} \\ A_b(0) = \{mean(I) + sd_I\} \quad (7)$$

where (I) is the mean and sd_I the standard deviation of the CVNN output

$$\begin{aligned} A_j(n+1) &= \left\{ \frac{1}{A_j(n)} \mid \sum I_j \right\} \\ A_b(n+1) &= \left\{ \frac{1}{A_b(n)} \mid \sum I_b \right\} \end{aligned} \quad (8)$$

where I_b and I_j is the pixel of 2 clusters.

III. RESULTS AND DISCUSSION

The dataset used contains a range of biomedical voice measurements from 31 people, 23 with Parkinson's disease (PD), obtained from database [10]. The main aim of the data is to classify healthy people from those with PD and each instance in the final dataset contain 23 attributes. It was shown that filtering the 23 attributes leaves just 10 attributes that can be used for diagnosis. Subsequent analysis of the remaining 10 attributes leads to just 4 with desired properties for diagnosis. These 4 attributes are: Harmonic to Noise Ratio (HNR), Recurrence Period Density Entropy (RPDE), Detrended Fluctuation Analysis (DFA) and Pitch Period entropy (PPE). Out of these four properties, three (RPDE, D2, DFA) were selected as input data to the system. There are 6 recordings per patient, one row for some selected patient with and without PD were selected as the training set while the remaining patient serves as the validation data set.

The CVNN topology is configured with one hidden layer and the hidden layer neurons varies from 3-5, the diagram is as shown in Fig. 4.

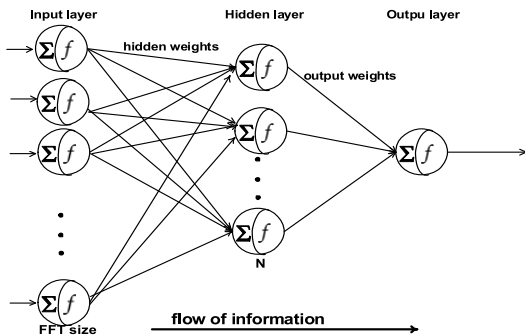


Figure4. CVNN topology.

Preprocess Block flow and classification. To obtain result of automatic diagnosis of PD, the following steps are involved :

- 1) **FFT Processing:** An N point FFT of each selected attribute is implemented in this stage as the input vector space.
- 2) **CVNN Training:** The Fourier transformed data is used as the input data to the CVNN while the target or classification signal is obtained from the dataset (column 17). FFT of the real values gives a complex value which were used for both training testing. 40% of the original data was use for training the network. After the network converged, the next 40% data were used as test data while the last 20% was also used for validation
- 3) **Test Data:** The trained CVNN is now fed with new set of data for classification purpose. The output is fed to the PD classifier

- 4) **PD Classifier:** The result of the test data of CVNN is fed to the classifier. The output of the classifier is "0+0i" for patient with PD while "1+0i" for healthy patient with no PD.

Evaluation Criteria. The performance of the algorithms were appraised by the following:

- True Positive(TP): If an input is positive P and the Network identifies and classified it as as positive, it is counted as a true positive.
- True Negative (TN): If an input is negative N and the Network identifies and classified it as negative , it is counted as true negative.
- False Positive (FP): the detection of Positive that was labeled as Negative.
- False Negative (FN): The detection of Negative thatwas labeled as Positive.
- The classifier was also evaluated in terms of Accuracy, Precision, True Positive Rate and False Positive Rate as follows:
 - 1) The accuracy of the classifier one of the most important measures in classification model. It is the degree of closeness of a measured or calculated quantity to its actual (true) value . Accuracy is defined as:

$$Accuracy (ACC) = \frac{TP + TN}{P + N} \quad (9)$$

- 2) Precision (PR) is a measure of ability of the classifier to detect the samemeasurement each time.

$$Precision (PR) = \frac{TP}{TP + FP} \quad (10)$$

- 3) True Positive Rate (TPR): The true positive rate (also called hit rate) of a classifier is estimated as rate of positives correctly classified and is given as;

$$True Positive Rate (TPR) = \frac{TP}{P} \quad (11)$$

- 4) False Positive Rate (FPR): The false positive rate (also called false alarm rate) of the classifier is defined as the ratio of total negatives incorrectly classified to total negatives.

$$False Positive Rate (FPR) = \frac{FP}{N} \quad (12)$$

Table I shows the result obtained using 4 and 3 hidden nodes with varying learning rate of 0.7 and 0.8. thne number of epoch for each hidden node runs for 1000 to 5000 with step of 1000. It was observed that for both 4 and 3 hidden nodes, only 3% of the result was misclassified,that is, false positive rate. Hence the total correctly classified subject is 97% for all the run

IV. CONCLUSION

In this paper, a new method of PD diagnosis have been presented. The method convert a real domain data to complex domain via Fourier transform technique. The transformed data was then used to train a CVNN system. Once the network is properly trained it was tested on some other cases that are even unknown to the system. The major contribution of this work is the level of accuracy

obtained while the second contribution of this work is the diagnosis of PD. innovative application of CVNN to real valued data for the

TABLE I. RESULT OF PD DETECTION

HN	Epoch.	LR	P	N	TP	TN	FP	FN	ACC	PR	TPR	FPR
4	5000	0.7	21	4	21	3	1.00	0	1.00	1.00	1.00	0.3
		0.8	21	4	21	3	1.00	0	1.00	1.00	1.00	0.3
		0.7	21	4	21	3	1.00	0	1.00	1.00	1.00	0.3
		0.8	21	4	21	3	1.00	0	1.00	1.00	1.00	0.3
	4000	0.7	21	4	21	3	1.00	0	1.00	1.00	1.00	0.3
		0.8	21	4	21	3	1.00	0	1.00	1.00	1.00	0.3
		0.7	21	4	21	3	1.00	0	1.00	1.00	1.00	0.3
		0.8	21	4	21	3	1.00	0	1.00	1.00	1.00	0.3
	3000	0.7	21	4	21	3	1.00	0	1.00	1.00	1.00	0.3
		0.8	21	4	21	3	1.00	0	1.00	1.00	1.00	0.3
		0.7	21	4	21	3	1.00	0	1.00	1.00	1.00	0.3
		0.8	21	4	21	3	1.00	0	1.00	1.00	1.00	0.3
	2000	0.7	21	4	21	3	1.00	0	1.00	1.00	1.00	0.3
		0.8	21	4	21	3	1.00	0	1.00	1.00	1.00	0.3
		0.7	21	4	21	3	1.00	0	1.00	1.00	1.00	0.3
		0.8	21	4	21	3	1.00	0	1.00	1.00	1.00	0.3
1000	0.7	21	4	21	3	1.00	0	1.00	1.00	1.00	0.3	
	0.8	21	4	21	3	1.00	0	1.00	1.00	1.00	0.3	
	0.7	21	4	21	3	1.00	0	1.00	1.00	1.00	0.3	
	0.8	21	4	21	3	1.00	0	1.00	1.00	1.00	0.3	
3	5000	0.7	21	4	21	3	1.00	0	1.00	1.00	1.00	0.3
		0.8	21	4	21	3	1.00	0	1.00	1.00	1.00	0.3
		0.7	21	4	21	3	1.00	0	1.00	1.00	1.00	0.3
		0.8	21	4	21	3	1.00	0	1.00	1.00	1.00	0.3
	4000	0.7	21	4	21	3	1.00	0	1.00	1.00	1.00	0.3
		0.8	21	4	21	3	1.00	0	1.00	1.00	1.00	0.3
		0.7	21	4	21	3	1.00	0	1.00	1.00	1.00	0.3
		0.8	21	4	21	3	1.00	0	1.00	1.00	1.00	0.3
	3000	0.7	21	4	21	3	1.00	0	1.00	1.00	1.00	0.3
		0.8	21	4	21	3	1.00	0	1.00	1.00	1.00	0.3
		0.7	21	4	21	3	1.00	0	1.00	1.00	1.00	0.3
		0.8	21	4	21	3	1.00	0	1.00	1.00	1.00	0.3
	2000	0.7	21	4	21	3	1.00	0	1.00	1.00	1.00	0.3
		0.8	21	4	21	3	1.00	0	1.00	1.00	1.00	0.3
		0.7	21	4	21	3	1.00	0	1.00	1.00	1.00	0.3
		0.8	21	4	21	3	1.00	0	1.00	1.00	1.00	0.3
1000	0.7	21	4	21	3	1.00	0	1.00	1.00	1.00	0.3	
	0.8	21	4	21	3	1.00	0	1.00	1.00	1.00	0.3	
	0.7	21	4	21	3	1.00	0	1.00	1.00	1.00	0.3	
	0.8	21	4	21	3	1.00	0	1.00	1.00	1.00	0.3	

REFERENCES

[1] L. S. Yang, S. D. Puvanarajah, and N. M. Ibrahim, "Parkinson's disease: Information for people living with Parkinson's," *Novartis Corporation (Malaysia) Sdn. Bhd. and Orient Europharma (M) Sdn. Bhd.*, 2011.

[2] R. Arvind, B. Karthik, N. Sriraam, and J. K. Kannan, "Automated detection of PD resting tremor using PSD with recurrent neural network classifier," in *Proc. 2010 International Conference on Advances in Recent Technologies in Communication and Computing (ARTCom)*, Kottayam, India, 2010, pp. 414-417.

[3] W. Dauer and S. Przedborski, "Parkinson's disease: mechanisms and models," *Neuron.*, vol. 39, no. 6, pp. 889-909, 2003.

[4] V. Giuliano. (June 30, 2012). A stem cell cure for Parkinson's disease—So close and yet so far away. [Online]. Available: <http://www.anti-agingfirewalls.com/2012/06/30/>

[5] B. Dovzhenok, C. Park, R. M. Worth, and L. L. Rubchinsky, "Failure of delayed feedback deep brain stimulation for intermittent pathological synchronization in Parkinson's disease," *PloS one*, vol. 8, no.3, pp. 1-10, 2013.

[6] J. Proakis and D. Manolakis, *Digital Signal Processing: Principles, Algorithms, and Applications*, 3rd ed. Prentice Hall New Jersey, 2004.

[7] R. F. Olanrewaju, O. O. Khalifa, A. H. H. Abdalla, A. A. Aburas, and A. M. Zeki, "Watermarking in safe region of frequency domain using complex-valued," in *Proc. IEEE Inter. Conf. on Computer and Communication Engineering (ICCCE)*, Kuala Lumpur, Malaysia, 2010, pp. 1-7.

[8] M. F. Amin and K. Murase, "Single-layered complex-valued neural network for real-valued classification problems," *Neurocomputing*, vol 72, no. 4-6, pp. 945-955, 2009.

[9] A. Aibinu, M. Salami, and A. Shafie, "Determination of complex-valued parametric model coefficients using artificial neural network technique," *Advances in Artificial Neural System*, pp. 1-11, 2010.

[10] UCI Machine Learning Repository: Parkinsons Data Set. (June 2008). [online]. Available: <http://archive.ics.uci.edu/ml/datasets/Parkinsons>