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Identifying People with Parkinson's Disease using Foot Pressure Data

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Abstract

In this paper, we propose a method to distinguish healthy people from those suffering from Parkinson's disease using foot pressure data, Fast Fourier Transform (FFT), and Principal Component Analysis (PCA). We applied an FFT based on the Hamming method to extract frequency ranges of pressure data from the left and right feet of subjects. We used PCA to reduce the dimensions of features generated by FFT. A neural Network with Weighted Fuzzy Membership functions (NEWFM) was used to distinguish healthy subjects from those with Parkinson's disease. Our method yielded accuracy, specificity, and sensitivity values of 75.90%, 61.41%, and 81.09%, respectively.

Keywords: FFT, Gait, NEWFM, Parkinson's Disease, PCA

1. Introduction

Parkinson's disease is a representative degenerative brain disease caused by a lack of dopamine, a neurotransmitter secreted in the substantia nigra, a region of the midbrain. Clinical symptoms of the disease include resting tremors, rigidity, bradykinesia, postural instability, etc. Analyses of figure motion[3] and foot pressure[4,8] have been used for the diagnosis of Parkinson's disease based on bradykinesia. Some of these involved statistical methods to distinguish healthy subjects from those diagnosed with Parkinson's disease based on foot pressure[4,8]. References [4,8] have no general rules. Thus, there may be different classification results from their point of view.

In this study, we report the results of an experiment to distinguish healthy subjects from those diagnosed with Parkinson's disease based on foot pressure data using neural Networks with Weighted Fuzzy Membership functions (NEWFM)[5,6]. In order to extract the features to use as input to NEWFM, we collected foot pressure data from the left and right feet of our subjects in the first stage. In the second stage, we divided the frequency ranges of the pressure data from both feet obtained in the first stage into bandwidths using a Fast Fourier Transform (FFT) based on the Hamming method. In the third stage, between one and 15 dimensions were extracted from the bandwidths generated in the second stage using Principal Component Analysis (PCA). In the fourth stage, 15 types of data items were entered from one to 15 dimensions, such as one dimension, one to two dimensions, one to three dimensions, and so on. In the fifth and final stage, we used from one to 15 dimensions as inputs to NEWFM and obtained the accuracy measure of each entry. The highest accuracy was obtained when one to eight dimensions were used as input to NEWFM. We proposed eight fuzzy membership functions in order to interpret the eight features used in this study[5,6].

2. Experimental Data and Preprocessing

2.1 Experimental Data

For our experiment, we used experimental data provided by PhysioBank. The data were collected from 93 subjects diagnosed with Parkinson's and 73 healthy subjects using sensors attached to the subjects' soles, eight on each foot. We collected 92 items of experimental data from the 73

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healthy subjects and 214 items of experimental data from the 93 subjects diagnosed with Parkinson's. Approximately two minutes' worth of continuous data were saved in the individual experimental data. The frequency of the saved experimental group data was 100 Hz.

As shown in Table 1, data collected at any given time required 19 inputs. We used the sum of the 18th input and the 19th input for the experiment. The experimental group data shown in Table 2 were extracted from the sum of the 18th and the 19th input, and were composed of 2,048 sums of the two inputs. For the experiment, we allocated 210 data items from healthy subjects and 487 data items from those with Parkinson's disease to each of the training and the testing set, as shown in Table 2.

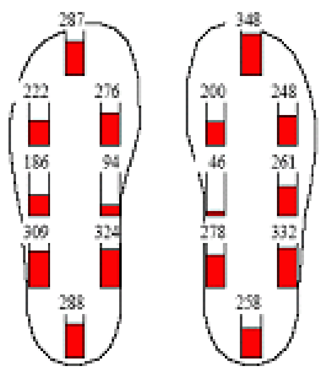

Figure 1. Pressure data collected through the sensors on the sole.

Table 1. Explanation of measured data

Input Order	Explanation
The first input	Time
The second till the ninth input	8 data items collected from the sensors on the left sole shown in Figure 1
The 10th to the 17th input	8 data items collected from the sensors on the right sole shown in Figure 1
The 18th input	The entire input data collected from the left sole
The 19th input	The entire input data collected from the right sole

Table 2. The experimental groups used for the identification of subjects with Parkinson's disease

Class	Training Set	Test Set	Total Number
Parkinson's disease	487	487	974
Healthy people	210	210	420
Total Number	697	697	1394

2.2 Fast Fourier Transform

The Fast Fourier Transform (FFT) was developed as an algorithm to rapidly generate a Discrete Fourier Transform (DFT). FFT was developed to reduce the number of calculations required for DFT, and quickly generates DFT by eliminating repetitive calculations in DFT equations. FFT can be divided into algorithms that separate the time and the frequency regions. We carried out a Hamming method-based FFT to decompose the 2,048 data items, which constituted the groups shown in Table 2, into 1,024 frequency regions.

2.3 Principal Component Analysis

The objective of Principal Component Analysis (PCA) is to describe the entire change using m principal components by means of the first-order combination of p given (measured) parameters, and to rank the components in order of their contribution to the explanation of the change. In this study, we extracted from one to 15 components using PCA from the 1,024 features generated by FFT.

3. Neural Network with Weighted Fuzzy Membership Function (NEWFM)

A neural Network with Weighted Fuzzy Membership function (NEWFM) is a supervised classification neuro-fuzzy system that uses the Bounded Sum of Weighted Fuzzy Membership functions (BSWFMs)[5,6]. The structure of a NEWFM, shown in Figure 2, consists of three layers: input, hyperbox, and the class layer. An hth input pattern can be recorded as $I_h = \{A_h = (a_1, a_2, \dots, a_n), class\}$, where

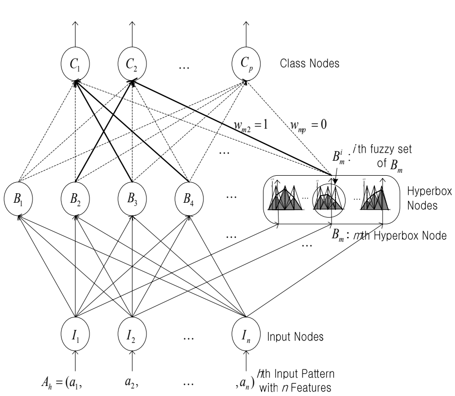

Figure 2. Structure of NEWFM.

class is the result of the classification and A_h is a set of n features of an input pattern. One to 15 dimensions generated by the PCA were used as input in this study, as shown in Figure 2. The hyperbox layer consists of m hyperbox nodes. Each hyperbox node B_l, which is to be connected to a class node, contains n BSWFMs for n input nodes. The output layer is composed of p class nodes. Each class node is connected to one or more hyperbox nodes. An hth input pattern can be recorded as $I_h = \{A_h = (a_1, a_2, \ldots, a_n), class\}$, where *class* is the result of the classification and A_h is a set of n features of an input pattern.

The connection weight between hyperbox node B_l and class node C_i is represented by w_{li}, which was initially set to 0. From the first input pattern I_h, w_{li} was set to 1 by the winner hyperbox node B_l and class i in I_h. C_i should have one or more connections to hyperbox nodes, whereas B_l is limited to only one connection to a corresponding class node. B_l can be learned only when it is a winner for input I_h, with class i and $w_{li} = 1$.

As shown in Figure 3, the weight and the center of each membership function were adjusted during the learning process, e.g., W_1, W_2, and W_3 moved down, v_1 and v_2 moved toward a_i, and v_3 stayed in the same location. Following learning, each of n fuzzy sets in the hyperbox node B_l contained three "weighted fuzzy membership functions" (WFMs, the membership functions in gray in Figure 4). The "bounded sum" (an operation on the fuzzy set) of WFMs (BSWFM) in the ith fuzzy set of $B_l^i(x)$, denoted as $\mu_b^i(x)$ (bold line in Figure 4), was defined by:

$$\mu_b^i(x) = \sum_{j=1}^{3} B_l^i\left(\mu_j(x)\right) \quad (1)$$

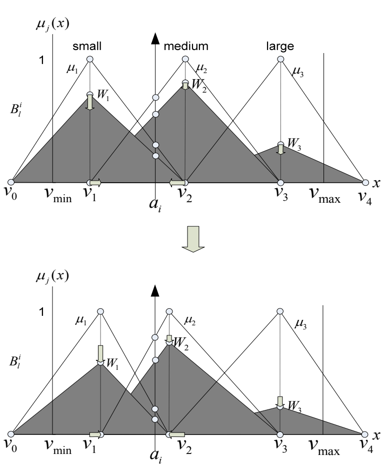

Figure 3. Before and after the *Adjust*(B_l) operation.

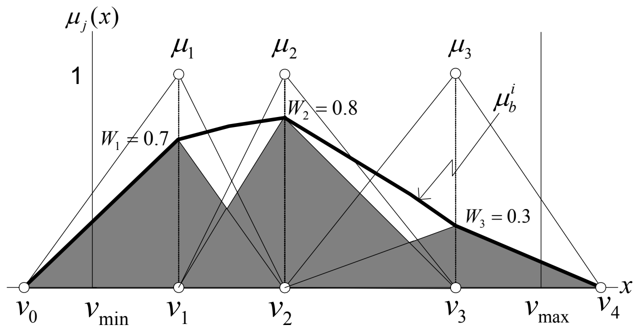

Figure 4. Example of bounded sum of 3 weighted fuzzy membership functions (BSWFM, bold line).

4. Experimental Result

We applied a Hamming method-based FFT to extract 1,024 features for each frequency region from the 2,048 foot pressure data items. One to 15 dimensions were extracted from the extracted features using PCA. The dimensions were then used as input to a NEWFM to distinguish subjects with Parkinson's disease from healthy subjects.

Figure 5 shows examples of fuzzy membership functions, with the one to eight dimensions recording

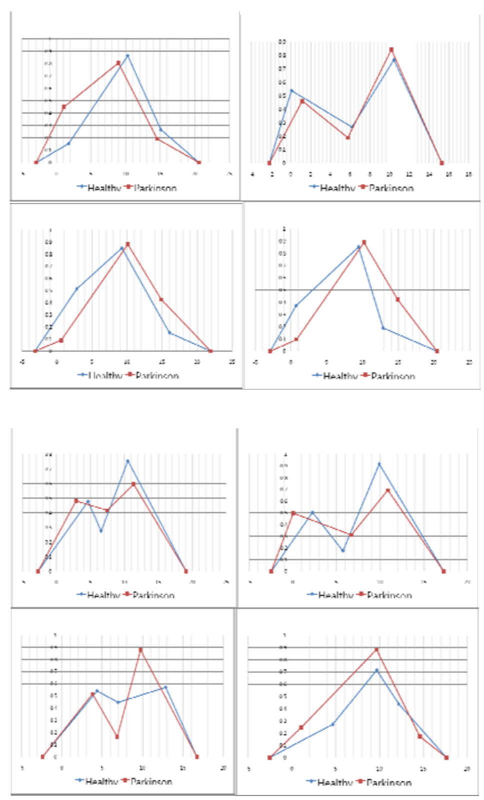

Figure 5. Examples of the BSWFM of the 8 features.

the highest accuracy among the one to 15 dimensions extracted by PCA. These represent the BSWFM described in [5]. Using these, the difference in foot pressure between healthy subjects and those with Parkinson's was visualized and accordingly analyzed with respect to eight dimensions.

In Equation (2) below, TP (true positive) indicates cases where subjects with Parkinson's were correctly identified based on foot pressure data, TN (True Negative) indicates cases where healthy subjects were correctly identified, FP (False Positive) denotes cases where subjects with Parkinson's were incorrectly identified as healthy subjects, and FN (false negative) denotes cases where healthy subjects were incorrectly identified as subjects with Parkinson's using foot pressure data. The performance of Back Propagation (BP)[7] and that of NEWFM are compared in Tables 3, 4, 5, and 6. Tables 3 and 4 show the confusion matrix of the classification results of BP and NEWFM, respectively. Tables 5 and 6 show the accuracies, specificities, and sensitivities obtained using BP and NEWFM, respectively, and defined in Equation (2):

$$Sensitive\ y = \frac{TP}{TP+FN} \times 100$$

$$Sensitive\ y = \frac{TN}{TN+FN} \times 100 \qquad (2)$$

$$Accuracy = \frac{TP+TN}{TP+FN+TN+FP} \times 100$$

Table 3. Confusion Matrix of Classification Results Using BP

Foot pressure of subjects with Parkinson's disease	**TP**	**FN**
	364	123
Foot pressure of healthy subject	FP	TN
	95	115

Table 4. Confusion Matrix of Classification Results Using NEWFM

Foot pressure of subjects with Parkinson's disease	**TP**	**FN**
	416	71
Foot pressure of healthy subjects	FP	TN
	97	113

Table 5. Classification results using BP

Epochs	Number of Hidden Nodes	Accuracy	Specificity	Sensitivity
5000	4	63.99	62.86	64.48
	6	64.85	61.90	66.12
	8	66.66	57.62	70.43
	10	66.28	58.57	69.61
10000	4	65.14	55.24	69.40
	6	68.58	58.57	72.90
	8	**68.72**	**54.76**	**74.74**
	10	66.71	50.48	73.72
15000	4	66.28	53.33	71.87
	6	68.58	59.05	72.69
	8	66.14	51.90	72.28
	10	66.57	48.57	74.33

Table 6. Classification results using NEWFM

	Accuracy	Specificity	Sensitivity
Performance (%)	75.90	61.41	81.09

5. Conclusion

In this study, we proposed a method to identify people with Parkinson's disease by applying a Hamming method-based FFT to foot pressure data. We extracted 1,024 features for each frequency region, and then reduced them to eight dimensions using PCA. The reduced data were then used as input to NEWFM, which was used to distinguish healthy subjects from those with Parkinson's disease. Using our method, a system to distinguish healthy people from those with Parkinson's disease can be developed by measuring and processing foot pressure data in real time.

6. Acknowledgment

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