Diagnosing Parkinson's Disease Using Movement Signal Mapping by Neural Network and Classifier Modulation

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Parkinson's disease is a growing and chronic movement disorder, and its diagnosis is difficult especially at the initial stages. In this paper, movement characteristics extracted by a computer using multilayer back propagation neural network mapping are converted to the symptoms of this disease. Then, modulation of three classifiers of C4.5, *k*-nearest neighbors, and support vector machine with majority voting are applied to support experts in diagnosing the disease. The purpose of this study is to choose appropriate characteristics and increase the accuracy of the diagnosis. Experiments were performed to demonstrate the improvement of Parkinson's disease diagnosis using this method.

Keywords: BP neural network, Diagnosing Parkinson's disease.

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I. Introduction

Parkinson's disease is the second most destructive disease of the neurons after Alzheimer's disease. A person suffering from Parkinson's disease will lose her/his physical ability gradually, and it will get worse if there is no healthcare or a suitable solution. This disease occurs in all races and spreads in one to two individuals per thousand people. Its spread increases with age [1]. It has been estimated that about 40% of people with this disease may not be diagnosed.

Unfortunately, Parkinson's disease has no certain treatment despite scientific research and studies, but early diagnosis can accelerate treatment procedures and help millions suffering from this disease around the world. Diagnosing Parkinson's disease in its early stages can assist greatly in synthesizing more effective drugs and improving the life of patients with this disease. As previously mentioned, Parkinson's disease creates movement disorders. Thus, in this paper, symptoms of this disease are extracted and presented by recording movement information of individuals while using computers, and then by mapping neural networks based on this movement information. The proposed method can help the diagnosis of this disease. Although many machine learning techniques are suggested for diagnosing this disease, these techniques use audio data, clinical data, and so on for diagnosis. Data related to the movement information of individuals collectable by computer with low cost are used in this paper, and neural network mapping is used for diagnosing.

The remainder of this paper is organized as follows: Some related literatures are studied and compared in Section II. The proposed method for extracting the symptoms of Parkinson's disease from movement information is described in Section III. Empirical results are presented in Section IV, and the conclusion and final remarks are presented in Section V.

II. Literature Review

Rustempasic and Can [2] suggested an automated machine learning method and diagnosed Parkinson's disease using speech data from a person's voice. The authors applied *C*-means phase clustering and pattern recognition to distinguish between healthy individuals and those suffering from Parkinson's disease.

Chen and others [3] suggested an effective diagnosis system based on fuzzy KNN (FKNN) to diagnose Parkinson's disease. Empirical results showed that the FKNN method performed much better than methods based on a support vector machine (SVM) (and other methods in related works). The best classification accuracy obtained from the FKNN was by a 10-fold method, which can create a reliable diagnosis model for diagnosing Parkinson's disease. Lan and Shih [4] presented a method based on pedestrian dead reckoning to record characteristics of patients' walking (for example, gait length, gait frequency, and movement speed) using smartphones.

The authors of this paper achieved early diagnosis of Parkinson's disease by identifying variations in a patient's walking using a simple binary classifier of a support vector machine. Singh and Samavedham [5] extracted some features from magnetic resonance image processing using a self-organizing map, and also selected excellent characteristics using the Fisher-discriminant ratio statistic technique. The author uses a least-squares SVM classifier to diagnose patients at the early stages of the disease.

Chen and others [6] applied several feature-selecting methods: maximum relevance minimum redundancy (mRMR), relief information gain, and t-test. They also used two machine learning techniques—extreme learning machine (ELM) and kernel ELM (KELM)—to diagnose Parkinson's disease. They obtained the highest accuracy with the least characteristics by a combined method of mRMR-KELM. Tomar and others [7] suggested a system to diagnose Parkinson's disease using a least squares twin SVM classifier and particle swarm optimization (PSO) feature selection method, which achieved the highest accuracy compared with other techniques.

Clayton and others [8] obtained a new dataset by processing the handwriting of the individuals and extracting its feature using a low-cost device and an applied Bayesian network classification, optimum-path forest, and an SVM to diagnose. Bouchikhi and others [9] employed a Relief-F feature selection algorithm to increase efficiency and decrease features from 22 to 10 features having high dependence, and also used an SVM to diagnose Parkinson's disease. Sharma and Gupta [10] extracted characteristics related to voice signals using PRAAT software, and selected 15 features out of 23 in which their noise was removed.

The authors of this paper used artificial neural network (ANN) and SVM classifiers to diagnose Parkinson's disease. Sharma and Giri [11] employed three types of KNN, multilayer neural network (MLP), and SVM classifiers to diagnose Parkinson's disease. Can [12] achieved the highest accuracy in diagnosing Parkinson's disease by reinforcing a parallel distributed neural network with two hidden layers through filtering with back propagation (BP) along with majority voting. Shahbakhi and others [13] extracted 14 features from recorded voice signals and introduced a genetic algorithm and SVM classifier to classify individuals as healthy and patients suffering from Parkinson's disease.

Farhad and Peyman [14] suggested an MLP with a back-propagation learning algorithm and radial basis function and an ANN to diagnose Parkinson's disease (to distinguish between treatment variables of the sample (N = 195) suffering from Parkinson's disease and those who were healthy). Navid and Saheb [15] introduced a new model based on combining PSO algorithm and Bayesian network classifier to diagnose Parkinson's disease. Daliri [16] proposed an approach for the diagnosis of neurodegenerative diseases based on gait dynamics. His proposed method uses information from a time series of stride intervals, swing intervals, stance intervals, and double support intervals of stride-to-stride measures of footfall contact times using force-sensitive resistors. Different features were extracted from these time series, and the best of them were selected for the diagnosis.

Khorasani and Daliri [17] used a hidden Markov model (HMM) with Gaussian mixtures to separate patients with Parkinson's disease from healthy subjects. They obtained an accuracy of 90.3% using a hidden Markov model classifier. In another paper, Khorasani and others [18] used a factorial hidden Markov model (FHMM) to distinguish ALS patients from healthy subjects with proper preprocessing by removing unwanted artifacts from the raw stride interval times and then extracting meaningful features from these data. The results of this classification accuracy evaluated using the leave-one-out cross-validation algorithm showed that the FHMM method provides better recognition of ALS and healthy subjects compared to standard HMM.

III. Proposed Method

In general, in the proposed method, movement characteristics of individuals were saved on the computer, and then symptoms of the disease were extracted by mapping multilayer BP neural networks on these movement characteristics. In addition, C4.5, KNN, and SVM classifiers and their modulations were used to diagnose this disease as a majority vote.

A flowchart of the proposed Parkinson's disease diagnosis is presented in Fig. 1, and each stage is described in more detail in the following sections.

1. Extracting Characteristics and Describing Database

In this stage, first the movement characteristics are extracted, and then datasets related to these characteristics are described.

A. Extracting Characteristics

Movement characteristics were extracted by a computer using Fitts' Law software [19]. This set included 14 movement characteristics and three features (age, sex, and experience of working with a computer), which will be explained in Section B [20], [21].

B. Describing Database

A database of individuals referring to the brain and nerve clinic of Ghaem Hospital, Mashhad, was used to provide a standard dataset for implementing the system, performing experiments, and obtaining results.

The proposed method was performed with completely different data and slight changes. All data in this set have the following conditions:

- Male and female
- Minimum of 26 years old and maximum of 81 years old.

Dataset consists of 17 characteristics and a class label as the feature of that class. Each feature is described briefly in Tables 1 and 2.

Symptoms of Parkinson's disease extracted by neural network mapping are presented in Table 3 and are fully explained in Section III-3.

2. Data Preprocessing

Necessary preprocessing of data needed for characteristics selection are presented in this section and are completely explained in the following parts.

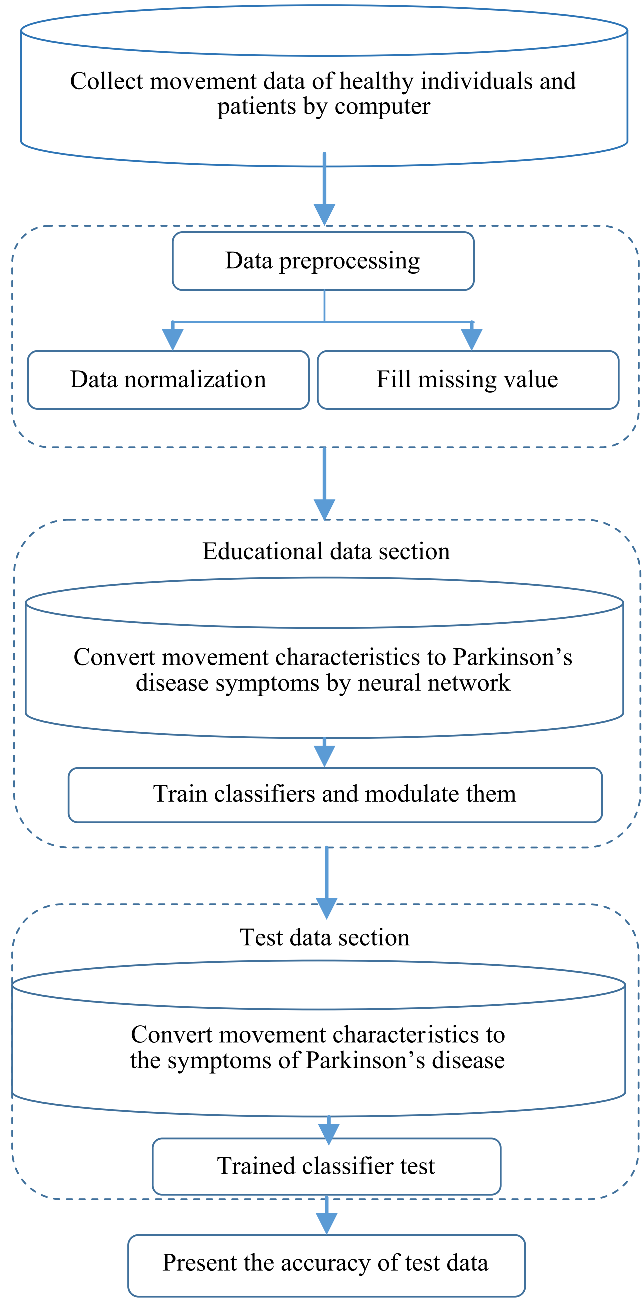

Fig. 1. Chart of proposed method.

A. Estimating Missing Values

Missing values are those values lost from records of databases, especially medical databases, owing to different reasons such as noncooperation of patients and their conditions (labs, repetitive relocation of datasets) that affect the result and quality of the paper. In this paper, values are lost nonrandomly owing to lack of experience with computers and inadequate education levels.

Different methods such as mathematical methods and machine learning methods are used to estimate missing

Table 1. Dataset related to movement characteristics using computer.

No	Feature	Description	No	Feature	Description
1	PT (ms)	Pointing time (ms)	10	ME	Movement error
2	ST (ms)	Selection time (ms)	11	MO	Movement offset
3	MT (ms)	Movement time (ms)	12	Count delete	Number times of pressure delete button keyboard
4	ER	Error rate (%)	13	Count backspace	Number times of pressure backspace button keyboard
5	TRE	Target re-entries	14	Type time (s)	Time typing a sample sentence (s)
6	TAC	Task axis crossings	15	Gender	
7	MDC	Movement direction changes	16	Age	
8	ODC	Orthogonal direction changes	17	Computer expertise	
9	MV	Movement variability			

values. The machine learning technique of KNN is used in this paper to estimate missing values.

B. Data Normalization

As values obtained from movement information are in a wide numeric range, data are normalized using the following formula to convert values to a narrower numeric range and improve efficiency [6]:

$$x' = \frac{x - \min_x}{\max_x - \min_x}. \tag{4}$$

3. Mapping Neural Network on Movement Characteristics and BP Algorithm

The method of converting movement characteristics of individuals to the symptoms of Parkinson's disease is described below.

A. Converting Movement Characteristics to Symptoms of Parkinson's Disease Using BP Neural Network

In this paper, an MLP neural network with BP learning algorithm is used for diagnosis.

The network is a two-layer neural network, as shown in Fig. 2, consisting of 17 movement characteristics as input, a hidden layer with 30 neurons, and an output layer including 7 features of this disease. These are used to map movement characteristics to the symptoms of this disease.

B. BP Algorithm

The performance of the BP algorithm is as follows:

- Put weight in small random values
- Perform the following steps for all patterns
  - Perform direct calculations. Calculate all *Net*s and *O*s for all layers
  - Perform return path calculations. Start from output layer:

$$\delta_i^L = \frac{\partial E_p}{\partial net_i^L} = -2f'(net_i^L)(d_{pi} - O_i^L). \tag{5}$$

Then, for previous layers until the first layer:

$$\delta_i^l = \frac{\partial E_p}{\partial net_i^l} = f'(net_i^l) \sum_{j=1}^{nl+1} \delta_j^{l+1} w_{ji}^{l+1}, l = L-1, \ldots, 1. \tag{6}$$

The error derivative in relation to weights is

$$\frac{\partial E_p}{\partial w_{ij}^l} = \delta_i^l \cdot O_j^{l-1}, \tag{7}$$

  - Calculate the sum of derivatives

$$\frac{\partial E}{\partial w_{ij}^l} = \frac{\partial E}{\partial w_{ij}^l} + \frac{1}{P}\frac{\partial E_p}{\partial w_{ij}^l}. \tag{8}$$

- Adjust the weights (one gradient step)

$$w_{ij}^l = w_{ij}^l - \mu \frac{\partial E}{\partial w_{ij}^l}. \tag{9}$$

- Return to step two if stop conditions are not met.

4. Classification Method

A complete list of applied classifications in this paper is as follows:

- SVM
- KNN
- Decision tree (C4.5)

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Table 2. Brief description of several features [20].

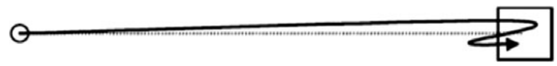
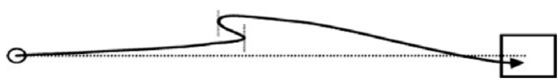
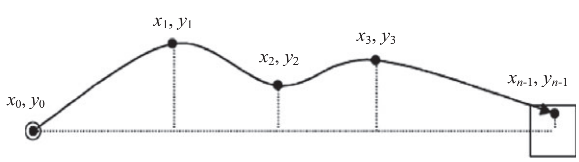
	Target reentry (TRE): If the cursor enters a target region, leaves, and reenters the target region, then a TRE has occurred.
	Task axis crossing (TAC): The task axis is defined as the straight line from the start point to the target center. A TAC occurs when the cursor crosses this line.
	Movement direction change (MDC): A MDC occurs when the tangent to the cursor path is parallel to the task axis, measured as a standard deviation.
	Orthogonal direction change (ODC): An ODC occurs when the tangent to the cursor path is perpendicular to the task axis.
	Movement variability (MV): Represents the extent to which the sample cursor points lie in a straight line along an axis parallel to the task axis. MV is computed as the standard deviation in the distances of the sample points from the mean: $$\mathrm{MV} = \sqrt{\frac{\sum (y_i - \bar{y})^2}{n-1}}. \quad (1)$$ y_i is the distance from a sample point to the task axis, $\bar{y}$ is the mean distance of the sample points to the task axis, and n is the number of sample points.
Movement error (ME): The mean of the absolute distances of the cursor sample points from the task axis, irrespective of whether the points are above or below the axis. $$\mathrm{ME} = \frac{\sum \lvert y_i \rvert}{n}. \quad (2)$$	
Movement offset (MO): The overall mean distances of the cursor sample points from the task axis. Unlike movement error, this measure is not independent of whether the points are above or below the axis. $$\mathrm{MO} = \bar{y}. \quad (3)$$	
Selection time: The amount of time it takes for the target user choices.	Pointing time: The amount of time it takes for the user to point the mouse pointer on purpose.
Movement time: The amount of time it takes for the user until the target is reached and clicked on.	
Error rate: The number of times a user clicks outside of the target.	

Table 3. Symptoms of Parkinson's disease [22], [23].

No.	Symptoms
1	Tremor
2	Bradykinesia
3	Rigidity
4	Constipation
5	Skeletal pain
6	Depression
7	Sleep disturbance

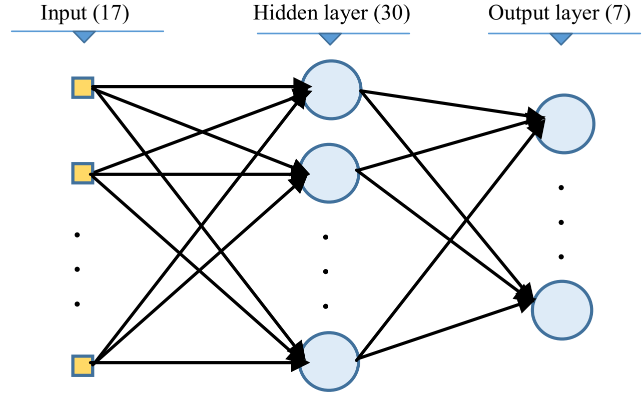


Fig. 2. Two-layer neural network structure.

IV. Empirical Results

Applied data in this paper include 91 persons with 17 characteristics from which 50 were Parkinson's disease patient and 41 were healthy. This is shown in Fig. 3.

This dataset is divided into two randomly, from which 43% are considered as a training dataset. The symptoms of Parkinson's disease are also included in this part to train neural networks and classifiers; and 75% of the data are attributed to testing neural network and classifiers, which are obtained by mapping neural networks of disease symptoms to test classifiers.

Figure 4 shows neural network mapping in which weight variation is decreasing compared with previous values. This shows the convergence of weights (by hidden layer) in neural networks to convert movement characteristics to disease symptoms.

In this experiment, the number of neurons in the hidden layer changed from 20 to 100, and the maximum number of repetitions of a neural network changed from 1,000 to 6,000. The best value of the hidden layer neurons of the neural network, and the best maximum number of iterations to update the weights, were set to 30 and 2,000, respectively.

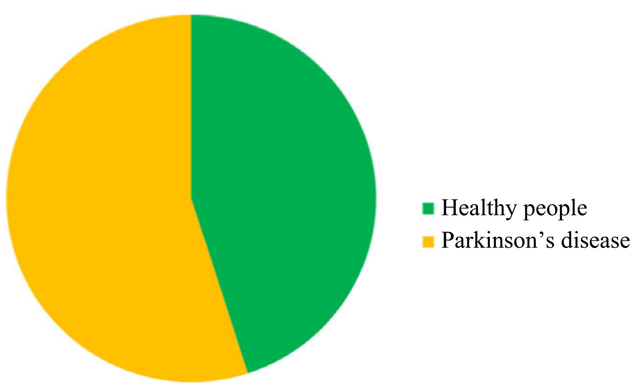


Fig. 3. Collected dataset.

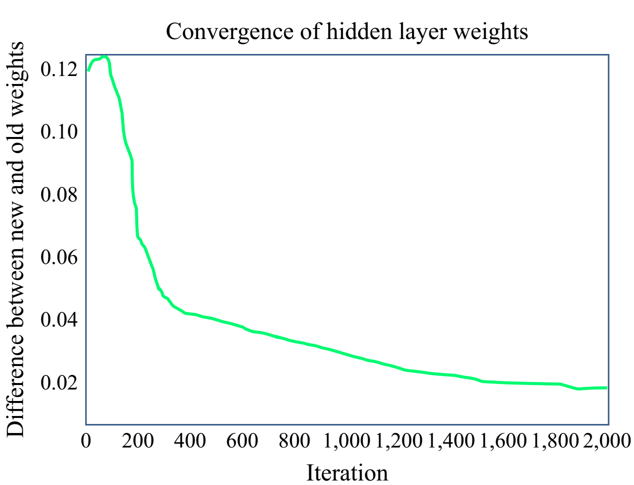


Fig. 4. Mapping neural network.

The efficiency of applied classification can be compared using an accuracy parameter:

$$Accuracy\ (\%) = \frac{TP + TN}{TP + FP + TN + FN}.$$

C4.5, KNN, and SVM classifiers and their majority voting are applied in the education section and are tested in data test section. The results obtained from the collected data of this method are presented in Tables 4 and 5, before and after neural network mapping.

According to the results in Tables 4 and 5, the proposed method has shown better performance after neural network mapping and classifier modulation. Also, KNN and majority voting classifiers of the proposed diagnosis system have constantly better efficiency than C4.5 and SVM.

Table 4. Obtained accuracy before mapping neural network.

Classifier	SVM	KNN	C4.5	MV
Accuracy (%)	62	64	60	**70**

Table 5. Obtained accuracy after mapping neural network.

Classifier		SVM	KNN	C4.5	MV
Accuracy (%)	$N = 10$	66	70	66	**70**
	$N = 7$	68	70	68	**70**
	$N = 5$	72	72	68	**72**
	$\mathbf{N = 3}$	78	78	76	**78**

V. Conclusion

As there is no experimental or radiologic method for diagnosing Parkinson's disease, diagnosis is only performed by a physician based on signs and symptoms derived from examination. In this paper, a system based on majority voting of classifiers and mapping a neural network on a movement dataset was presented to diagnose Parkinson's disease. In this system, movement data are converted to Parkinson's disease symptoms. Obtained results show the effective performance of the neural network and classifier modulation on this set.

The proposed model will help physicians to diagnose more easily, quickly, and effectively, and then provide different treatment options for individual patients. An early diagnosis may enable physicians to provide medical care at an earlier stage.

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