A Diagnosis Support System for Finger Tapping Movements Using Magnetic Sensors and Probabilistic Neural Networks

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Abstract — **This paper proposes a system to support diagnosis for quantitative evaluation of motility function based on finger tapping movements using probabilistic neural networks (PNNs). Finger tapping movements are measured using magnetic sensors and evaluated by computing 11 indices. These indices are standardized based on those of normal subjects, and are then input to PNNs to assess motility function. The subject's motor ability is probabilistically discriminated to determine whether it is normal or not using a classifier combined with the output of multiple PNNs based on bagging and entropy. This paper reports on evaluation and discrimination experiments performed on finger tapping movements in 33 PD patients and 32 normal elderly subjects. The results showed that the patients could be classified correctly in terms of their impairment status with a high degree of accuracy (average rate:** 93.1 ± 3.69 **%) using 12 LLGMNs, which was about 5% higher than the results obtained using a single LLGMN.**

Keywords — **Finger tapping movements, magnetic sensors, neural networks, pattern discrimination, diagnosis support**

I. Introduction

To identify neurological disorders such as Parkinson's disease (PD) and quantify motility function by measuring patients' physical movements, various assessment methods have been discussed, including tremor and reaction movements [1] and finger tapping movements [2]. In particular, finger tapping movements have already been widely investigated, and a method to analyze tapping rhythm as well as a method to quantify tapping amplification and velocity [3],[4] have been reported. However, the above evaluations have been performed only for basic analysis such as verification of the feature quantities of PD patients. To realize a diagnosis support system for use in the routine assessment of PD in clinical environments, the features of finger movement need to be extracted numerically for quantitative classification and evaluation.

The classification and evaluation of a subject's movement and symptom severity are equivalent to clustering on measured data distribution. So far, several nonlinear classification methods have been proposed by assuming probabilistic distribution of measured data, and probabilistic neural networks (PNNs) have recently attracted widespread attention [5]. However, the authors are unaware of any reports detailing the use of PNNs to classify motility disturbance.

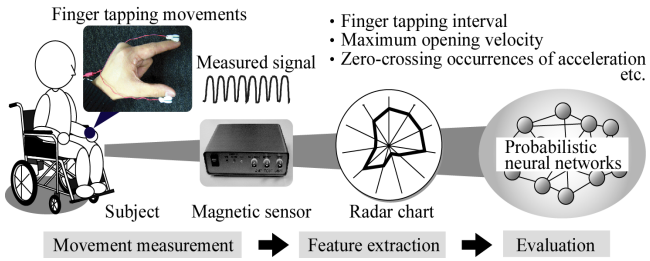

Fig. 1 Concept of the proposed diagnosis support system for finger tapping movements

In this paper, we propose a diagnosis support system employing multiple probabilistic neural networks. The system utilizes a magnetic sensor to measure finger tapping movement and extract its features (such as velocity and rhythm) based on medical knowledge, and then displays the feature indices for doctors' reference on a monitor. Further, the relationships between symptoms and movement features are embedded into the neural networks through learning, and can be used to evaluate motility function by combining outputs of multiple neural networks based on the ensemble learning method of bagging [6]. Since the outcomes of the neural networks indicate probabilities, doctors can intuitively understand the features of finger tapping movements and make quantitative evaluation from the indices or radar chart on the display.

II. Diagnosis Support System for Finger Tapping Movements

The diagnosis support system is shown in Fig. 1. The details of each process are explained in the subsections below.

A. Movement measurement [4]

The magnetic sensor developed by Kandori et al. [3] is utilized to measure finger tapping movements. This sensor

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can output a voltage corresponding to changes in distance between the detection coil and the oscillation coil by means of electromagnetic induction. First, the two coils are attached to the distal parts of the user's fingers, and finger tapping movements are measured. The distances between the two fingertips (the *fingertip distances*) are then obtained from the output voltage by a calibration model expressed as

$$d(t) = \alpha V^{-1/3}(t) - \varepsilon \,, \tag{1}$$

where $d(t)$ denotes the fingertip distance, $V(t)$ is the measured voltage of the sensors at a given time t, and α and ε are constants computed from calibration [4]. In the calibration process, α and ε are estimated using the linear least-square method for n values of measured output voltages and fingertip distances for each subject. Further, the velocity $v(t)$ and acceleration $a(t)$ can be calculated from the fingertip distance $d(t)$ using differentiation filters.

B. Feature extraction

This paper defines eleven indices for the evaluation of finger tapping movements as follows: (1) *total tapping distance*; (2) *average maximum amplitude of finger taps*; (3) *coefficient of variation* (*CV*) *of maximum amplitude*; (4) *average finger tapping interval*; (5) *CV of finger tapping interval*; (6) *average maximum opening velocity*; (7) *CV of maximum opening velocity*; (8) *average maximum closing velocity*; (9) *CV of maximum closing velocity*; (10) *average zero-crossing occurrences of acceleration*; and (11) *spectral variability of finger taps.*

First, the integration of the absolute value of velocity $v(t)$ through the measurement time is signified as the total tapping distance (Index 1). As feature quantities of the i^{th} tapping, the maximum and minimum amplitude points (dp_i, dq_i) between the interval [T_i, T_{i+1}] are calculated from the measured fingertip distance $d(t)$, and the average (Index 2) and CV (Index 3) of maximum amplitudes $ma_i = dp_i - dq_i$ are computed. Here, T_i (i = 1,2,…,I) is the instant of finger contact, and I is the number of contacts between fingertips. Further, the finger tapping interval It_i, which is the time interval between two consecutive contacts, is applied as $It_i = T_{i+1} - T_i$, and the positive and negative maximum velocity points are defined as the maximum opening velocity vo_i and the maximum closing velocity vc_i, respectively. The averages and CVs of the finger tapping interval, maximum opening velocity and maximum closing velocity are then computed from all the values of It_i, vo_i, and vc_i (Indices 4–9), respectively.

In addition, zc_i, which denotes the number of zero crossings of the acceleration waveform $a(t)$, is calculated from each interval between T_i and T_{i+1}, and the zero-crossing occurrences of acceleration zc_i are defined as the evaluation values of multimodal movements (Index 10). Finally, the time-series finger tapping interval It_i is resampled at f_a Hz by applying the linear interpolation method, and the power spectral density of the data is then estimated using the fast Fourier transform (FFT). The value of the integrated power spectrum from f_b to f_c Hz is defined as the spectral variability of finger taps (Index (11)).

The evaluation indices calculated for the subject are normalized based on the indices of normal subjects to enable comparison of the differences in movement. In this paper, the standard normally distributed variables x_j are converted to the mean and standard deviations of the tapping data from those of the normal subjects using Eq. 2.

$$x_j = (z_j - \mu_j)/\sigma_j \tag{2}$$

Here, j corresponds to the index number, z_j is the computed value in each index, and μ_j and σ_j describe the average and standard deviations of each index in the group of normal elderly subjects respectively. j = 1 represents the total tapping distance, j = 2,…, 9 signify the averages and CVs of maximum amplitude, finger tapping interval, maximum opening velocity and maximum closing velocity, and j = 10 and 11 denote the average zero-crossing occurrences of acceleration and the spectral variability of finger taps. Additionally, the input vector $\boldsymbol{x} = [x_1, x_2, ..., x_{11}]^{\mathrm{T}}$ is defined for the discrimination of finger tapping movements.

C. Evaluation using probabilistic neural network ensembles

The extracted features are discriminated to enable evaluation of motility function. In this paper, a log-linearized Gaussian mixture network (LLGMN) [5] is used as the PNN, and each index is evaluated using the ensemble learning method based on bagging [6] for the LLGMN.

LLGMN [5]*:* The LLGMN is based on the Gaussian mixture model (GMM) and the log-linear model of the probability density function (pdf), and the *a posteriori* probability is estimated based on the GMM by learning. By applying the log-linear model to a product of the mixture coefficient and the mixture component of the GMM, a semi-parametric model of the pdf is incorporated into a three-layer feed-forward PNN. Through learning, the LLGMN distinguishes movement patterns with individual differences, thereby enabling precise pattern recognition for bioelectric signals such as EMG and EEG [5].

Combination rules for LLGMNs: The combination strategy for multiple LLGMNs is shown in Fig. 2. This method consists of the C LLGMN classifiers, corresponding to the number of input vectors, $\boldsymbol{x}_1, \boldsymbol{x}_2, \ldots, \boldsymbol{x}_C$. Each LLGMN out-

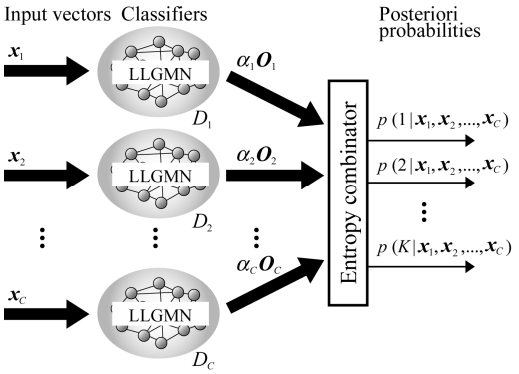

Fig. 2 Combination strategy for LLGMNs

puts the *a posteriori* probability of each learned class, which are then combined based on the ensemble learning method of bagging and entropy. First, each input vector $\boldsymbol{x}_c$ (c = 1,2,…,C) is input to the cth LLGMN, and the *a posteriori* probability vector $\boldsymbol{O}_c$ is calculated by the LLGMN. Here, $\boldsymbol{O}_c$ is defined by Eq. 3 using the *a posteriori* probability $p(k \mid \boldsymbol{x}_c)$ at given value $\boldsymbol{x}_c$:

$$\begin{aligned}\boldsymbol{O}_c &= \left[{}^{(3)}O_1, {}^{(3)}O_2, \ldots, {}^{(3)}O_K\right]^{\mathrm{T}} \\ &= \left[p(1 \mid \boldsymbol{x}_c), p(2 \mid \boldsymbol{x}_c), \ldots, p(K \mid \boldsymbol{x}_c)\right]^{\mathrm{T}}.\end{aligned} \tag{3}$$

The entropy combinator receives the output of each LLGMN weighted by coefficient α_c, and outputs the *a posteriori* probabilities of all classes. Each element of the entropy combinator's input vector $\boldsymbol{y}_c$ is given by

$$y_k(\boldsymbol{x}_c) = \alpha_c p(k \mid \boldsymbol{x}_c), \tag{4}$$

where coefficient α_c $(0 < \alpha_c < 1)$, which denotes the degree of effect of the cth LLGMN's output, is defined as

$$\begin{aligned}\alpha_c &= 1 - H(\boldsymbol{x}_c) \\ &= 1 + \frac{1}{\log K}\left(\sum_{k=1}^{K} p(k \mid \boldsymbol{x}_c) \log p(k \mid \boldsymbol{x}_c)\right).\end{aligned} \tag{5}$$

Here, $H(\boldsymbol{x}_c)$ signifies the entropy of the output of the LLGMN, and denotes the ambiguity of the *a posteriori* probabilities. When these probabilities are ambiguous, the entropy $H(\boldsymbol{x}_c)$ becomes large and α_c approaches 0.

In the entropy combinator, the *a posteriori* probabilities of all classes are calculated by

$$Y_k = p(k \mid \boldsymbol{x}_1, \boldsymbol{x}_2, \ldots, \boldsymbol{x}_C) = \frac{\sum_{c'=1}^{C} y_k(\boldsymbol{x}_c)}{\sum_{k'=1}^{K}\sum_{c'=1}^{C} y_{k'}(\boldsymbol{x}'_{c'})}. \tag{6}$$

In the above method, each pdf for input vector $\boldsymbol{x}_c$ can be estimated and combined, and the networks can be used to calculate the *a posteriori* probability of class k for any given measured data.

For the discrimination of measured data, the entropy of all classes defined by Eq. 7 is used:

$$E = -\sum_{k=1}^{K} Y_k \log Y_k. \tag{7}$$

If E is smaller than discrimination determination threshold value E_d, the class with the highest *a posteriori* probability becomes the result of discrimination. Otherwise, if E exceeds E_d, discrimination is suspended as an obscure class.

Evaluation of finger tapping movements: First, input vector $\boldsymbol{x}_c$ is created from measured finger tapping movements for their evaluation. $\boldsymbol{x}(t_{all}) \in \Re^{11}$ and $\boldsymbol{x}(t_d) \in \Re^{11}$, which are the feature vectors, are computed for the overall measurement time t_{all} and the time interval $[t_d^{st}, t_d^{ed}]$ respectively. Then, the jth elements $x_j(t_d)$ of $\boldsymbol{x}(t_d)$ (d = 1,2,…,D) are used to make the new vector, defined as $\boldsymbol{x}'_j = [x_j(t_1), x_j(t_2), \ldots, x_j(t_D)]^{\mathrm{T}} \in \Re^D$ (j = 1,2,…,11).

The system next measures the finger tapping movements of the patient and those of normal subjects. The feature vectors $\boldsymbol{x}'_j$ and $\boldsymbol{x}(t_{all})$ calculated from these movements are then input to each LLGMN as teacher vectors, and the LLGMNs are trained to estimate the *a posteriori* probabilities of each movement. Thus, the number of LLGMNs is C = 11+1 = 12. After training, the system can calculate similarities between patterns in the subject's movements and trained movements as *a posteriori* probabilities by inputting the newly measured vectors to the LLGMNs.

III. Experiments

A. Method

The subjects were 33 patients with PD (average age: 69.4 ± 8.1, male: 16, female: 17) and 32 normal elderly subjects (average age: 68.2 ± 5.0, male: 16, female: 16). Coils were attached to the distal parts of the thumb and index finger, and the magnetic sensor was calibrated using three calibration values of 20, 30 and 90 mm. The movement of each hand was measured for 60 s in compliance with instructions to move the fingers as far apart and as quickly as possible. The severities of PD in the patients were evaluated by a neuro-physician based on the finger tapping test of the Unified Parkinson's Disease Rating Scale (UPDRS). The calculated indices were standardized on the

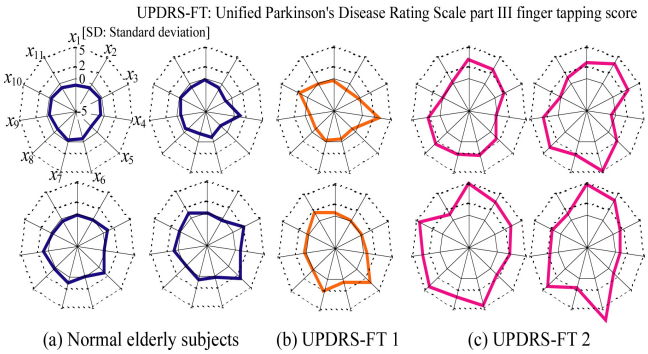

Fig. 3 Examples of radar chart representation of the results of the evaluated indices [4]

basis of the values obtained from the normal elderly subjects. The sampling frequency was 100 Hz. Each index was computed for the overall measurement time t_{all} = 60 and at four pre-specified time intervals of t_1 =[0,30], t_2 = [10,40], t_3 = [20,50] and t_4 = [30,60] and input to the LLGMNs. The measured finger tapping movements were then put into two classes in terms of whether they were normal or not; k = 1: normal elderly; k = 2: PD; K = 2. In addition, fifteen samples of each class were used as teacher vectors for learning.

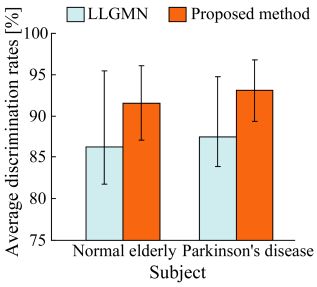

Fig. 4 Discrimination rates of finger tapping movements

B. Results

Radar chart representation of the results of the indices is shown in Fig. 3; (a) to (c) illustrate the charts for normal elderly subjects, PD patients with UPDRS-FT 1 and those with UPDRS-FT 2 respectively. The solid lines describe the average value of each index in the group of normal elderly subjects, and the dotted lines show double and quintuple the standard deviation (2SD, 5SD). The classification results of the finger tapping movements for all subjects are outlined in Fig. 4. This shows the mean values and standard deviations of the discrimination rates for 50 kinds of training set and for the test set, where the initial weight coefficients were changed randomly 10 times in each trial. The average discrimination rates of the normal elderly subjects using a single LLGMN with the proposed method were 86.2 ± 9.24% and 91.6 ± 4.51%, and those of the PD patients were 87.5 ± 7.25% and 93.1 ± 3.69% respectively. Further, each LLGMN's output $y_2(\boldsymbol{x}_c)$ (c = 1,2,…,12), which represents the *a posteriori* probability for PD patients, for all subjects is illustrated in Fig. 5. The subjects shown in this figure are the same as those in Fig. 3.

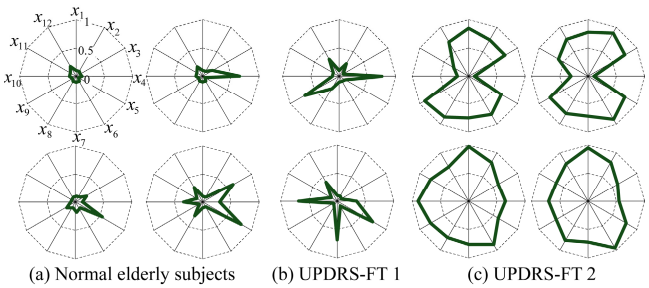

Fig. 5 *A posteriori* probabilities of Parkinson's disease in each index

C. Discussion

From the experimental results, plotting radar charts showing the indices of movements computed and standardized using the basic values obtained from normal elderly subjects revealed that data from normal elderly subjects lie near the average, while those in PD patients' charts become larger according to the severity of their condition. Further, the results of discrimination demonstrated that the patients could be classified correctly in terms of their impairment status using 12 LLGMNs with a degree of accuracy about 5% higher than results obtained using a single LLGMN. Moreover, representing the *a posteriori* probabilities as radar charts confirmed that the values for PD patients become large, and such charts enable quantitative evaluation and description of subjects' motility function. These results indicate that the proposed method is capable of detecting the disease and supporting PD diagnosis.

IV. Conclusions

This paper proposes a diagnosis support system that can quantitatively evaluate motility function for finger tapping movements. From the experiments performed, the finger tapping movements of PD patients were discriminated at a rate of 93.1±3.69%, demonstrating that the proposed system is effective in the support of diagnosis using finger movements. In future research, we plan to improve the proposed

method to enable diagnosis of the severity of the disease, as well as investigating the effects of aging with an increased number of subjects.

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