A Feature Extraction of the EEG Using the Factor Analysis and the Neocognitron

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Abstract: It is known that an EEG is characterized by the unique and personal characteristics of an individual. Little research has been done to take into account these personal characteristics when analyzing EEG signals. Often the EEG has frequency components which can describe most of the significant characteristics. These combinations are often unique like individual human beings and yet they have an underlying basic characteristics as well. We think that these combinations are the personal characteristics frequency components of the EEG. In this seminar, the EEG analysis method by using the Genetic Algorithms (GA), Factor Analysis (FA), and the Neural Networks (NN) is proposed. The GA is used for selecting the personal characteristic frequency components. The FA is used for extracting the characteristics data of the EEG. The NN is used for estimating the characteristics data of the EEG. Finally, in order to show the effectiveness of the proposed method, classifying the EEG pattern is carried out via computer simulations. The EEG pattern is evaluated under 4 conditions: listening to Rock music, Schmaltzy Japanese ballad music, Healing music, and Classical music. The results, when personal characteristics frequency components are NOT used, gave over 80 % accuracy versus a 95 % accuracy when personal characteristics frequency components are used. This result of our experiment shows the effectiveness of the proposed method.

Keywords: electroencephalogram, factor analysis, neo-cognitron

1. Introduction

Recently in the world, the research of the electroencephalogram (EEG) interface is done, because it has the possibility of becoming an interface that can be operated without special knowledge and technology, and the action for the operation is not needed by using the EEG. The EEG is activities of electric potential inside the brain recorded from the top of the scalp. The EEG is a time series signal to change by the internal factor, which is human's thinking and conditions, or the outside stimulus those are the light and sound [1]-[4]. Moreover, the EEG is including much noise, having large data dimension, intertwining more than one factor intricately, and different according to measurement points. Therefore, taking account of these, we must think the EEG analysis method and the measurement points of the EEG.

In this paper, taking account of the EEG interface, we propose the method. The proposed method is focused on three points of the following. First of all, taking account of the EEG interface, the EEG is analyzed by the information of one measurement point [4],[5]. Second, the Factor Analysis (FA) is used for the EEG analysis. Because the EEG is the time series signals that more than one factor was intricately intertwined and the EEG contains much noise, the EEG has the information, which is difficult to obtain from direct observation data. The features of the FA are denoising, dimensional compression, and analyzed latent structure. Therefore, taking account of the correlation of the time transition of each frequency spectrum of the EEG, the latent structure, which explains that correlation, is analyzed by using the FA [6],[7]. Then the characteristics data of the EEG is extracted by using the FA. Finally, the neocognitron (NC) is used for the EEG analysis. The NC is capable of recognizing distorted patterns as well as tolerating positional shift [8]-[11]. The NC is used for learning and estimating the extracted characteristics data of the EEG.

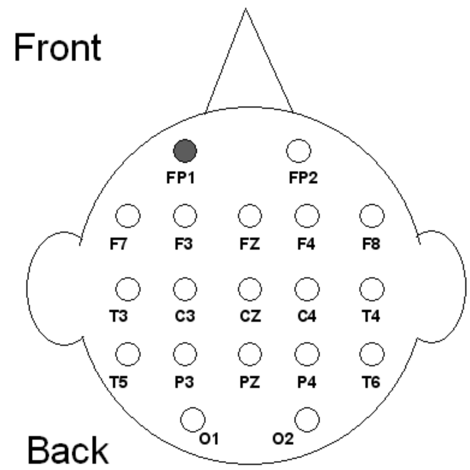

Fig. 1. Measurement points of the EEG

In other words, taking account of the EEG interface, we propose the EEG analysis method, which is using the FA and the NC. In order to show the effectiveness of the proposed method, classifying the EEG pattern does computer simulations. The EEG pattern is 4 conditions, which are listening to Rock music, Schmaltzy Japanese ballad music, Healing music, and Classical music.

2. Measurement of the EEG

In this paper, as a final target of our study team, the EEG control system by listening to any music is constructed. This system uses human's physiologic and mental effect, which the music stimulus gives to human. There is causal relation between the EEG and the music, for instance, α waves appear by listening to Classical music, and β waves appear by listening to Rock music. This system adjusts the outputs of the music automatically by that causal relation. Moreover, the EEG by listening to that music is controlled in this system. In this system, the EEG analysis, the music analysis, and the causal relation analysis are absolutely imperative. The most important part of this system is that the EEG analysis. The EEG analysis is very difficult. Therefore, the EEG analysis is done in this paper. The EEG analysis means the EEG feature extraction method.

2.1. The EEG patterns

In this paper, as basic research of constructing the EEG control system, some genre of the music is classified by the EEG. The EEG patterns are 4 conditions, which are listening to Rock music, Schmaltzy Japanese ballad music, Healing music, and Classical music. We used the following questionnaire to decide the EEG patterns. In addition, the questionnaire is done 20 people, who are boys and girls of twenty something.

2.2. Measurement conditions of the EEG

The electroencephalograph used simple electroencephalograph of the band type. This simple electroencephalograph can be measured under the practical environment. This simple electroencephalograph is made by Brain Function Research & Development Center in Japan. Measurement part place is electrode arrangement FP1 in international 10/20. As for the data, FFT is being done the EEG of one second, and frequency analysis is carried out to 24Hz at intervals of 1Hz by attached analytic software. Measuring condition are closing eyse and not moving so much. The EEG measuring is carried out in the laboratory with some noise. Then subjects wear a sensor band and headphone. Measuring time is for four minutes in each condition. In addition, the data of using frequency components are from 4Hz to 22Hz. Fig.1 shows measured points of the EEG.

3. The proposed method

In this paper, we propose the EEG analysis method, which is using the FA and the NC. The FA is used for extracting the characteristics data of the EEG. The FA is one of the statistical methods. Then the information that each variate (frequency components) with the correlation has is summarized in small number of latent factor. The features of FA are denoising, dimensional compression, latent structure analysis that structure lurks behind each variate with the correlation. In this paper, the model of the FA, which is shown Fig.2, is cross-factor model because we assume that common factor, which responds to particular stimulus, is identified when extracted common factor is noncorrelated [6],[7]. Moreover, taking account of measurement conditions of the EEG, the first common factor shows 'Change in the EEG by listening to the music', we think. The common factor is extracted by using principal factor analysis method. In this paper, the characteristics data of the EEG is the data of first factor score. Then the NC is used for estimating the extracted characteristics data of the EEG. The NC, which is 3-layer class pattern, is used for learning the characteristics data of the EEG, and the EEG pattern classification. Then backpropagation (BP) method is used for the way of learning the characteristics data of the EEG, and cross-validation (CV) method is used for test method.

3.1. The factor analysis

The FA is used for extracting the characteristics data of the EEG. The FA is one of the statistical methods. Then the information that each variate (frequency components) with the correlation has is summarized in small number of latent factor. The features of FA are denoising, dimensional compression, latent structure analysis that structure lurks behind each variate with the correlation. In this paper, the model of the FA is cross-factor model because we assume that common factor which responds to particular stimulus is able to decide when extracted common factor is noncorrelated [6],[7]. Therefore, taking account of measurement conditions of the EEG, the first common factor shows 'Change in the EEG by listening to the music', we think.

The EEG analysis method is as follows:

Step1 : The data matrix is composed. In this paper, the line of the data matrix is frequency components and the sequence of the data matrix is time.

Step2 : The correlation matrix R is calculated from the data matrix.

Step3 : The estimate which is entered into diagonal ingredient of the new correlation matrix R* is calculated. In this paper, the estimate is squared multiple correlation coefficient. Then the new correlation matrix R* is composed.

Step4 : The common factor is extracted by using the principal factor analysis. The principal factor analysis is the most popular method for common factor extraction. Then the common factor loading is calculated.

Step5 : The factor structure, which consisted of extracted common factors, is changed into the factor structure of a

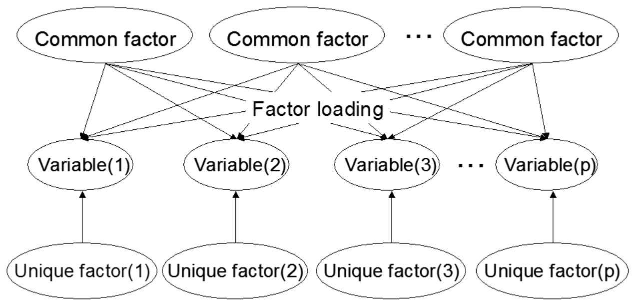

Fig. 2. Cross-factor model

standard form by using varimax rotation. The varimax rotation is the most popular factor rotation method.

Step6 : A factor score is calculated for extracting the characteristics of each category. A factor score represents the feature of each factor and can be connected with an external standard.

3.2. The neocognitron

In this paper, NC is used for estimating the extracted characteristics data of the EEG. The NC is capable of recognizing distorted patterns as well as tolerating positional shift [8]-[11]. The NC has a structure in which cells in the lowest level extract local features of the input pattern, while cells in each succeeding level respond to specific combinations of the feature detected in the preceding level. In the highest level, each cell will respond to only one input pattern, i.e., the pattern is recognized. This structure is similar to the hierarchical model of the visual system proposed by Hubel and Wiesel (1962, 1965).

The input layer is composed of a two-dimensional array of receptor cells. Each of the succeeding levels consists of a level of excitatory S-cells (S-layer) followed by a layer of excitatory C-cells (C-layer). Each C-layer also contains inhibitory V-cells (not shown in the figure). An S-layer receives excitatory connections from a certain group of C-cells in the preceding level. An S-cell also receives an inhibitory connection from a V-cell, which is turn receives fixed excitatory connections from the same group of C-cells, as does the S-cell to which it projects. After the learning stage is finished, S-cells extract features from the input patterns. Within their respective layers, S-cells and C-cells are divided into cell-planes. All the cells in such a cell-plane extract the same feature but from different positions of the input layer while different cell-planes extract different features. Each C-cell receives signals from a group of preceding S-cells, all of which extract identical features but from slightly different positions. A C-cell will be activated if at least one of these S-cells is active, and is therefore less sensitive to positional shifts of the input pattern than is an S-cell. The size of cell-planes in both S-layer and C-layer decreases with the order of the level, and in the highest level each cell-plane in the C-layer has only one C-cell, which responds, if the learning has been successful, to only one particular input pattern. Fig.3 shows the NC model.

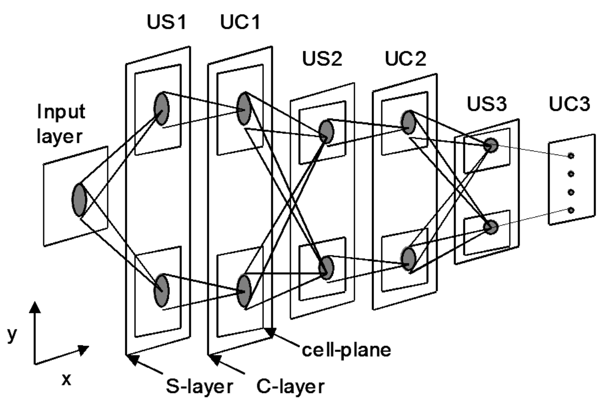

Fig. 3. The N.C. model

The output of a S-cell of the k_l-th cell-plane of S-cells in the l-th level is given by

$$u_{Sl}(k_l, \mathbf{n}) = r_l(k) \cdot \varphi \left[\frac{1 + es_l}{1 + \frac{r_l(k)}{1+r_l(k)} \cdot b_l(k) \cdot v_{Cl-1}(\mathbf{n})} - 1 \right],$$

$$es_l = \sum_{k_{l-1}=1}^{K_{l-1}} \sum_{\nu \in s_l} a_l(k_{l-1}, \nu, k_l) \cdot v_{Cl-1}(k_{l-1}, \mathbf{n} + \nu),$$

where $\varphi[x] = x$ if $x \geq 0$ and $\varphi[x] = 0$ if $x < 0$; $\mathbf{n}$ are the two-dimensional coordinates indicating the location of the cell; $a_l(k_{l-1}, \nu, k_l)$ and $b_l(k_l)$ are the strengths of the variable excitatory connection and inhibitory connection, respectively; Sl denotes the size of the connecting area; K_{l-1} is the total number of cell-planes of C-cells; r_l is a parameter controlling the intensity of the inhibitory. For the input layer, $l = 0$.

The output of an inhibitory V-cell is given by

$$v_{Cl-1}(\mathbf{n}) = \sqrt{\sum_{k_{l-1}=1}^{K_{l-1}} \sum_{\nu \in s_l} c_{l-1}(\nu) \cdot u^2_{Cl-1}(k_{l-1}, \mathbf{n} + \nu)},$$

where $c_{l-1}(\nu)$ represents the strenght of the fixed excitary connections coming from the preceding C-cells. The term $v_{Cl-1}(\mathbf{n})$ has the same connecting area, Sl, as $u_{Sl}(k_l, \mathbf{n})$.

The output of a C-cell the k-th cell-plane of C-cells in the l-th level is given by

$$u_{Cl}(k, \mathbf{n}) = \psi \left[\frac{1 + \sum_{\nu \in D_l} d_l(\nu) \cdot u_{Sl}(k, \mathbf{n} + \nu)}{1 + \frac{1}{K} \sum_{k=1}^{K} \sum_{\nu \in D_l} d_l(\nu) \cdot u_{Sl}(k, \mathbf{n} + \nu)} - 1 \right]$$
,

where $\psi[x] = x/(\alpha + x)$ if $x \geq 0$ if $x < 0$, α being a parameter determining the degree of saturation of the output; $d_l(\mathbf{n})$ is the value of the fixed excitatory connection; D_l is the connecting area for $u_{Cl}(k, \mathbf{n})$.

The variable connectios $a_l(k_{l-1,\nu,k_l})$ and $b_l(k_l)$ are updated as follows. Let cell $u_{Sl}(\hat{k_l}, \hat{\mathbf{n}})$ be selected as amaximum-output cell. The connections to this cell and to all the cells in the same cell-plane are reinforced:

$$\Delta a_l(k_{l-1}, \nu, \hat{k_l}) = q_l \cdot c_{l-1}(\nu) \cdot u_{Cl-1}(k_{l-1}, \hat{\mathbf{n}} + \nu),$$

$$\Delta b_l(\hat{k_l}) = q_l \cdot vCl - 1(\hat{\mathbf{n}}),$$

where q_l is a parameter determining the speed of reinforcement.

4. Conclusions

In this paper, taking account of the EEG interface, the simple electroencephalograph of the band type was used to measure the EEG. Additionally, we propose the EEG analysis method, which is using and the FA and the NC. The FA is used for extracting the characteristics data of the EEG. The NC is used for estimating extracted the characteristics data of the EEG. In order to show the effectiveness of the proposed method, classifying the EEG pattern is done. The

EEG pattern is 4 conditions that listening to Rock music, that listening to Schmaltzy Japanese music, that listening to Healing music, that listening to Classical music. The subjects of this paper were 3 people who are 2 boys (The average age: 22.3 years old) and a girl (age: 23 years old). Then we could confirm the effectiveness of the proposed method by the result of computer simulations. It announces for the result on that day.

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