www.ij-psychol.org International Journal of Advances in Psychology (IJAP) Volume 3 Issue 3, August 2014
doi: 10.14355/ijap.2014.0303.03

Preference Analysis Method Applying Relationship between Electroencephalogram Activities and Egogram in Prefrontal Cortex Activities

How to collaborate between engineering techniques and psychology

Shin-ichi Ito[1], Momoyo Ito[1], Katsuya Sato[1] , Shoichiro Fujisawa[1], Minoru Fukumi[1]

[1] Institute of Technology and Science, The University of Tokushima, Tokushima, Japan

[1]{s.ito, katsuyas, s-fuji} @eco.tokushima-u.ac.jp, {momoito, fukumi} @is.tokushima-u.ac.jp

Received Oct 16, 2013; Revised Dec 20, 2013; Accepted Mar 1, 2014; Published Jun 18, 2014

Abstract

This paper introduces a method of preference analysis based on electroencephalogram (EEG) analysis of prefrontal cortex activity. The proposed method applies the relationship between EEG activity and the Egogram. The EEG senses a single point and records readings by means of a dry-type sensor and a small number of electrodes. The EEG analysis adapts the feature mining and the clustering on EEG patterns using a self-organizing map (SOM). EEG activity of the prefrontal cortex displays individual difference. To take the individual difference into account, we construct a feature vector for input modality of the SOM. The input vector for the SOM consists of the extracted EEG feature vector and a human character vector, which is the human character quantified through the ego analysis using psychological testing. In preprocessing, we extract the EEG feature vector by calculating the time average on each frequency band: θ, low-β, and high-β. To prove the effectiveness of the proposed method, we perform experiments using real EEG data. These results show that the accuracy rate of the EEG pattern classification is higher than it was before the improvement of the input vector.

Keywords

Preference; Egogram; Electroencephalogram; Individual Difference; Self-organizing Map; Pattern Classification

Introduction

Human beings are known to respond in different ways, depending on their characters, to exogenous stimuli. To this end, we attempt to investigate human character, including a person's feelings, personality, sensibility and so on. Exogenous stimuli that a person finds unpleasant are known as stressors, which are encountered on a daily basis and have a negative effect on that person's behavior; on the other hand, pleasant stimuli are known to have a positive effect on the person's behavior. Ideally, one should encounter stimuli that helps improve one's mental health on a regular basis. We can then assume that the response to the stimuli depends on the person's personality and hence analyses their character using an egogram. This is because the egogram is considered as a psychological fingerprint; each person has a unique profile that can be seen and measured (Shirai, 2006; Berne, 1961; Dusay, 1977; Katsura, Ashihara, & Murakami, 1999). The egogram is obtained by calculating the score of each ego state.

An electrocap with several electrodes is uncomfortable for human beings to wear, and is thus unsuitable for long-term recordings with the use of a brain–computer interface (BCI) in day-to-day applications (Wang et al., 2008). Therefore, we attempted to construct a BCI using a compact device with dry-type electrodes, using a single electrode and the target-sensing point at the left lobe. For humans, the prefrontal cortex is assumed to be the brain area (Davison, 1995, 1998); hence, the electroencephalogram (EEG) activities in the prefrontal pole are variable. Further, it has been confirmed that an EEG of frontal cortex activity is differs from person to person (Allen, 2004; Coan, Allen, & Mcknight, 2006). This difference (hereinafter, the "individual difference") is one of the factors affecting the variability and is particularly noticeable when the sensing position is the prefrontal cortex. However, the reasons for this difference are not clear. Therefore, in this paper, we propose a method for mitigating the adverse effects of this individual difference in EEG with single-point sensing by analyzing the EEG.

There are numerous approaches in engineering for analyzing the EEG activity (Lotte et al., 2007), such as the EEG features of power spectrum and spectral centroid, special EEG feature extraction techniques, principal component analysis (Lee & Seungjin, 2003; Hoya et al., 2003), independent component analysis (Hoya et al., 2003), factor analysis, EEG pattern classifiers, nearest neighbor algorithm (Hoya et al., 2003; Borisoff et al., 2004), linear discriminant analysis (Blankertz, Curio, & Muller, 2002), neural networks (Hoya et al., 2003), support vector machine (Felzer & Freisieben, 2003), and self-organizing map (SOM) (Khorsrowabadi et al., 2010). The EEG pattern classification techniques that have a learning function are susceptible to the features of the input vectors. It is difficult to learn the input vectors when including the inter-individual difference and noise elements. We propose an input modality that can mitigate the individual difference for the SOM. The proposed SOM is capable of classifying EEG patterns because it is applied to confirm various multivariate data sets and has advantages over statistical and other non-traditional methods of cluster analysis (Khorsrowabadi et al., 2010).

Considering the individual difference in EEGs of the prefrontal cortex, we find that the input modality consists of the EEG feature vector and the human character vector (the egogram) based on transactional analysis (TA). Furthermore, we have confirmed in a previous study that EEG activity in the left prefrontal cortex exhibited the individual difference when the subject was listening to a sound (Ito et al., 2010). We confirmed that an interesting tendency of a person with a combined ego type is that a person has a unique response to negative stimuli compared to their response to positive stimuli (Ito et al., 2012). In addition, we confirmed that individual difference, including the one found in prefrontal cortex EEG activities, express visually using the SOM (Ito et al., 2011). However, a technique for classifying preference patterns by applying the relationship between the EEG activities and the egogram was not possible. Instead, we classified the preference patterns obtained for a subject that was listening to a sound by analyzing the prefrontal cortex EEG activity on the basis of the personality analysis.

Finally, to show the effectiveness of the proposed method, we conducted experiments using real EEG data.

Applied Algorithm to use the Relationship Between Egogram and EEG Activities

The proposed method consists of four phases: psychological testing and human character quantification, EEG recordings and EEG feature extraction, feature construction using human character vector and EEG feature vector, and evaluation for constructed feature vector based on the EEG pattern classification, respectively. Fig. 1 shows the procedure of the proposed method.

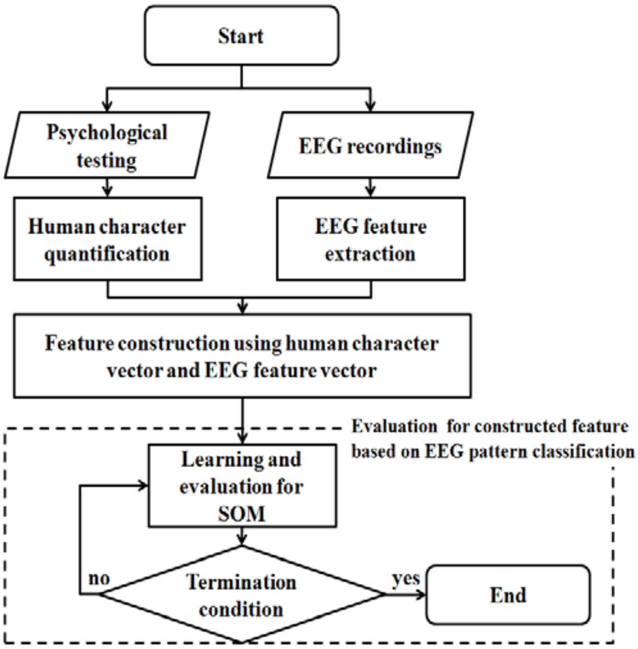

FIG 1 PROCEDURE OF THE PROPOSED METHOD

Psychological Testing

To quantify the human character, we adopted the egogram processing. The egogram, which is based on transaction analysis (TA), is like a psychological fingerprint—each individual has a unique profile, which can be seen and measured. An individual profile is shown on the egogram, where ego states are classified as critical parent (CP), nurturing parent (NP), adult (A), free child (FC), and adapted child (AC) (Shirai, 2006; Berne, 1961; Dusay, 1977; Katsura et al., 1999). The egogram is the detected score on ego states and the balance between them. Score is calculated on the basis of psychological testing. To assess personality, we adopted the self grow-up egogram (SGE; Katsura, Ashihara, & Murakami, 1999), which was developed by the Chukyo Psychosomatic

TABLE 1 QUESTIONNAIRE FOR SGE

Question
You are very opinionated.
You are always on time.
You follow rules and regulations strictly.
You are judgmental about other people and yourself.
You always consider what should and what must be done.
Once you have decided something, no one can change your mind.
You become very worried about money matters especially when you have to set a repayment date.
You never break a promise.
You do not compromise with injustice.
You cannot accept someone who will take no responsibility for themselves.
You are very concerned about other's welfare (warm hearted).
You are very good at praising others.
You are a good listener.
You are always thinking about how the other person is feeling.
You like to repay people for a present or favor even when they say it is not necessary.
You are quick to forgive.
You like to do favor and help others.
You always greet others warmly.
When you see others in trouble you automatically begin to think of ways to help them.
You think of children and others who are typically looked down on by others as on the same level as yourself.
You think about a main problem many times before figuring out how to fix it.
You analyse a situation and find how it relates to the truth.
You always ask yourself “Why”.
You are more logical than emotional.
You are especially interested in the current affairs part of the newspaper.
You consider the end result and then proceed with preparations.
You calmly judge things without getting emotional about it.
You think a study about things until they become clear to you.
You are a memo fanatic.
You always put yourself in the other persons shoes.
There are many things you want to do and see.
You are good at relaxing.
You smile often.
You are very curious.
You always see the silver lining of the cloud.
When in trouble you get out of it by being humorous.
You like new things.
You look forward to a bright future.
You have many hobbies.
You often use words like “Great!”,“ Wow!” or “Unbelievable!”.
You are considerate of other person's mind.
You tend to be shy.
You often regret your decisions.
You are overly sensitive.
You tend to bottle up your anger.
You want others to think you are a good person.
You follow the crowd and never do your own thing.
You have a tendency to hesitate.
You never have your own opinion, you always borrow others opinions.
You always blame yourself even when you are not to blame.

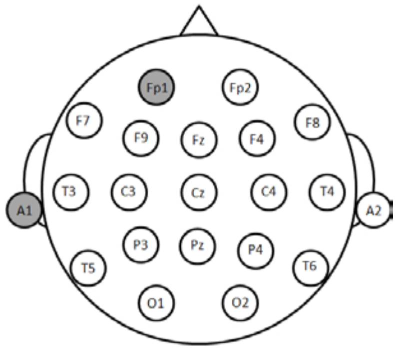

FIG 2 INTERNATIONAL 10-20 SYSTEM. REFERENCE ELECTRODE IS AT THE LEFT LOBE (A1) AND EXPLORING ELECTRODE IS THE LEFT PREFRONTAL POLE (FP1)

Medicine Workshop (CPW) for personality assessment. It is a brief questionnaire composed of 50 items, as shown in Table 1. The subject is asked to assign each item “○” for “yes,” “×” for “no,” or “∆” for “unsure.” These states are allotted 2, 0, or 1 point, respectively (Katsura, Ashihara, & Murakami, 1999). The 50 items on the questionnaire fall into five ego states: CP, the evaluating self; NP, the considerate self; A, the rational self; FC, the unadjusted self; and AC, the adjusted self. The diagram based on the calculated score of the psychological questionnaire is useful in showing which ego states dominate human personality and/or nature. Ego scores are normalized by dividing the limit score (20 points).

EEG Recordings

In EEG recording, we use the “MindTune (MT)” device—developed by TOSHIBA (in Japan)—to measure EEG activity. Generally, EEG systems use an electrocap. However, an important issue is that an electrocap with a large number of electrodes is uncomfortable for humans to wear and is thus unsuitable for long-term recordings with BCI in daily-life application. Furthermore, the preparation of the EEG recording prior to BCI operation means that subjects must spend a long time wearing the electrocap. Reducing the number of electrodes in the BCI system is a critical issue. The MT uses a dry-type sensor and a small number of electrodes in the headphone; it does not require gel and/or water. Therefore, we believe it can alleviate uncomfortable feelings and can be used in realistic conditions. This methodology employs a referential recording technique. The reference electrode is at the left ear and the exploring electrode is at Fp1 in the international 10-20 system shown in Fig. 2. The obtained EEG data are sent to the computer every second through the serial port. The power spectra of EEG data per second are calculated by fast Fourier transform (FFT); this FFT data covers the following frequency bands: δ (4–7 Hz), θ, low-α (8–9 Hz), high-α (10–12 Hz), low-β (13–22 Hz), high-β (23–30 Hz), low-γ (31–40 Hz), and high-γ (41~Hz).

After the EEG recording, the users complete an easy-questionnaire to evaluate preference of the sound listened to. The criterion of the questionnaire is whether one likes the sound ("LikeSound"), dislikes it ("DislikeSound") or feels other ("Other").

Feature Vector Construction Using Egogram and EEG Features

The feature vector consists of the human character factor combined with EEG feature vector. In general, the input vector for the SOM is the extracted EEG feature vector insofar as the EEG pattern classification is concerned; the factors considered are not only one's character but also one's gender and sex. One is affected by his/her hereditary component, past experience and growth environment when making decisions, judgments, and distinctions of preference. EEG activity, especially on prefrontal cortex, may also be affected by these factors. We adopt the egogram as one of the ways to consider these affect factors. Because it is not easy to adapt complex intelligence techniques for extracting EEG features with single point sensing, this paper incorporates an effect factor.

In feature creation, to classify preference patterns, we correlate the time-averaged power spectra of each set of EEG frequency bands and the normalized ego scores as follows:

$$Feature = \left[s_{cp}, s_{np}, s_a, s_{fc}, s_{ac}, p_\theta, p_{low-\beta}, p_{high-\beta} \right]$$

where $Feature$, p, and s denote the feature vector, the time-averaged power spectra of each EEG frequency bands, and normalized score of each ego state, respectively.

Evaluation Algorithm Based on EEG Pattern Classification

The algorithm for evaluating the proposed method shown in Fig. 3 is as follows:

Step 1. The EEG feature vector and the ego scores are computed. First, the time series power spectra of five frequency bands that are θ, low-β, high-β are picked up in an EEG data pattern. Because the frequency bands of δ, low-γ and high-γ all have special EEG meaning activity, they are not included in the EEG feature vector. In addition, α bands are not

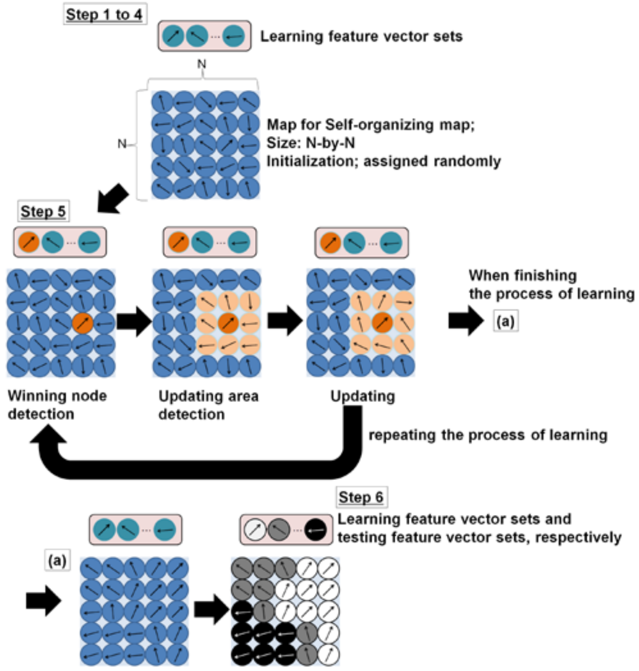

FIG 3 PROCEDURE OF EVALUATION ALGORITHM BASED ON EEG PATTERN CLASSIFICATION USING SOM

included. Second, the sporadic rate of each frequency band on each second during listening to the sound is calculated. Moreover, the discrete time average of the sporadic rate is computed. Third, the ego scores are calculated on the basis of the psychological testing. Furthermore, the egos scores are normalized by dividing the limit score (20 points). We construct the feature vector for the SOM as the improved input vector. These operations are applied to all EEG data patterns in all subjects.

Step 2. The N-by-N mapping for the SOM sets including the nodes that consist of 8-dimensional vectors as the weight vector.

Step 3. The weight vectors are assigned randomly or 1.0 as an initialization.

Step 4. The feature vector sets for learning are chosen based on the repeated random sub-sampling validation algorithm. In the repeated random sub-sampling validation, Q % in all data is chosen randomly.

Step 5. The weight vectors are updated recursively after the presentation of each input vector. As each input vector is presented, the Euclidian distance between the input vector and each weight vector is calculated using:

$$D_{ij}(w_{ij}(k), x(k)) = \left\| x(k) - w_{ij}(k) \right\|$$

The winning node (denoted by subscript c) is specified by:

$$d_c(k) \equiv \min \quad D_{ij}(k)$$

The weight vectors are updated by:

$$w'_{ij}(k) = w_{ij}(k) + \alpha[x(k) - w_{ij}(k)] : i, j \in h_{ck}$$

where α indicates the learning-rate factor, and h_{ck} is the neighborhood function, which is typically a decreasing function of the distance between nodes c and k in the two-dimension lattice. The standard neighborhood function is used:

$$h_{ck} = h_{ck}(0)(1 - LearnNum / TotalLearnNum)$$

where $LearnNum$ and $TotalLearnNum$ indicate the number of learning and its total, respectively. The initial value ($h_{ck}(0)$) of the width for learning is half the size of the map. This operation is repeated until the number of learning is met for more than a set number.

Step 6. To evaluate, the accuracy rates are computed using the learning feature vector sets (Q%) and the remaining feature vector sets (100-Q %) as testing feature vector sets. Then, the accuracy rate is computed based on the classification of the EEG patterns:

$$Accuracy = CorrectNumber / TotalNumber$$

where the $CorrectNumber$ is the total number of correct answers selected by checking LikeSound, DislikeSound and Other. $TotalNumber$ refers to the total number of sounds listened to. This paper defines the EEG patterns based on the results of the preference evaluation. There are three EEG patterns: LikeSound, DislikeSound and Other.

Step 7. Operations 3 to 6 are repeated until the number of trials is met for more than a set number.

Experiments

Participants

The subjects in this study were health volunteers. The sample size consisted of 5 students: four males (mean age = 22.5 years), and 1 female (aged 22 years), from the University of Tokushima, Japan. The subjects had no history of a serious disease. Written informed consent based on the Helsinki Declaration was obtained from the subjects after a detailed description of the experiment's purpose and procedures.

Experimental Design

The experiment proceeded as follows. First, the subjects completed the psychological testing for SGE. After the psychological testing, the EEG device was positioned on the forehead of a subject. Then, the subjects sat on a chair, closed their eyes, and remained silent. The EEG was recorded more than once in the laboratory with ongoing background noise. The time for each EEG recoding was 15 seconds (no sound) and 15 seconds (listening to a sound) as a set. After the EEG recording, the subjects completed the easy-questionnaire for preference evaluation of the sounds listened to by checking LikeSound, DislikeSound, and Other, respectively. Note that the sounds did not include human voices or music. The total number of sounds listened to was 375 for all subjects. Tables 2 and 3 show the kinds of sounds listened to and the preference evaluation results on the sounds listened to, respectively. In the parameters for the SOM, the map size and learning rate α are 20-by-20 and 0.02, respectively. The number of learning and trials are 10,000 and 100, respectively. The division rate Q for the repeated random sub-sampling validation is 80%. Fig. 4 shows the results of the normalized ego scores on each ego state. Table 4 shows the results of the improved input modality versus the input vector not including the human character vector (also illustrated in Fig. 5); the 3-freq in Fig. 5 and Table 4 indicates that the adapted number of frequency bands that are θ, low-β, and high-β is three. In 5-freq, the adapted frequency bands to the improved input modality are θ, low-α, high-α, low-β, and high-β. Learning and Testing denote the accuracy rate for learning the constructed feature vector sets (80% in all data sets) and testing the constructed feature vector (20% in all data sets), respectively.

TABLE 2 KINDS OF SOUNDS LISTENED TO

fire engine siren	wind bells sound	helicopter noise
cicada buzz	grade crossing	scotch tape
roar of waves	bush warbler buzz	Mosquito
fireworks	soda water	unwrapping the paper
drill noise	train noise	frictional noise of styrene foams

TABLE 3 RESULTS OF PREFERENCE EVALUATION ON SOUNDS. TOTAL INDICATE THE TOTAL NUMBER OF SOUNDS ON ALL AND/OR EACH SUBJECTS. ALL AND S1 TO S5 CORRESPOND WITH ALL SUBJECTS AND SUBJECT1 TO 5, RESPECTIVELY

	All	S1	S2	S3	S4	S5
Sex	-	male	male	male	male	female
Like	44	9	13	8	0	14
Dislike	178	35	48	39	24	32
Other	153	31	14	28	51	29
Total	375	75	75	75	75	75

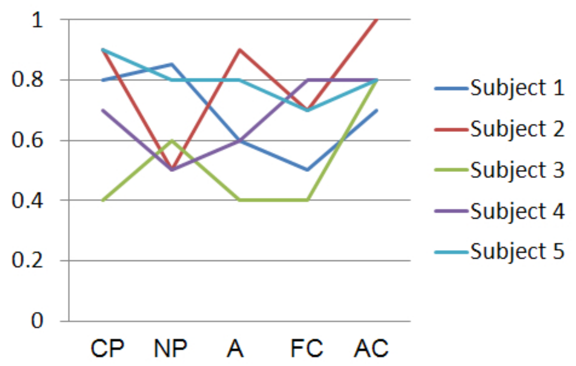

FIG 4 RESULTS OF THE NORMALIZED EGO SCORES ON EACH EGO STATES

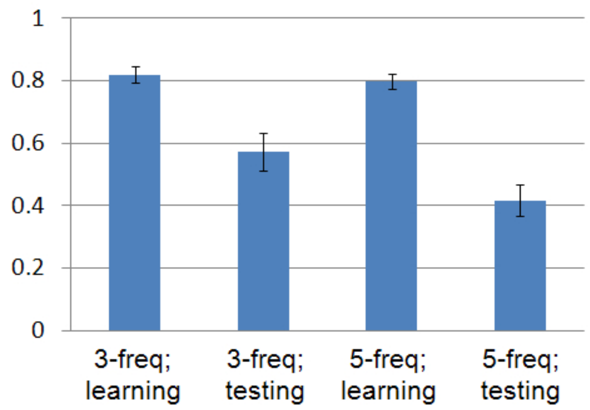

FIG 5 MEAN AND S. D. OF ACCURACY RATE FOR THE EEG PATTERN CLASSIFICATION (100 TRAILS)

TABLE 4 MEAN AND S. D. OF ACCURACY RATE FOR EEG PATTERN CLASSIFICATION (100 TRAILS). IMPROVE AND NORMAL DENOTE THE CONSTRUCTED FEATURE VECTOR AND EEG FEATURE VECTOR, RESPECTIVELY

	3-freq	5-freq
Improve	0.57 ± 0.06	0.41 ± 0.05
Normal	0.41 ± 0.06	0.42 ± 0.06

Discussions

In Fig. 4, although we did not interpret the personality of each subject, we confirmed the variation of the egogram. It is difficult to interpret the personality because it is not satisfied only by the egogram.

In Fig. 5, we acquired good results for EEG pattern classification as the preference pattern classification on learning feature vector sets of 3-freq and 5-freq. These results suggest that the direction of the proposed applied algorithm method is indeed correct. If it were incorrect, using the SOM for learning feature vector sets could not be successful and we would not be able to acquire the appropriate accuracy rate. However, we cannot obtain good results for testing feature vector sets. The preference pattern based on subjective criteria while listening to sounds includes the fuzzy pattern ("Other"). In addition, the subjects received stimuli that share similar characteristics as listening to sounds. This indicates that the experimental conditions may be problematic. Therefore, the accuracy rate of the EEG pattern classification was low.

In Table 4, the accuracy rate when adapting three frequency bands to the input vector (3-freq) was better than when adapting five frequency bands (5-freq). These results suggest that the frequency range of α bands does not include the significant information for the EEG pattern classification as in the case of these experimental conditions. There is a tendency for the spectra of α bands to predominate when the experimental conditions include sitting on a chair, closing one's eyes and remaining quiet. Although the α bands may be focused on for analyzing the EEG and classifying the EEG pattern in general, we think that the information on the bands is not needed for comparison with the rest condition, which indicates a steady-state situation. In 3-freq, the accuracy rate of the improved input vector was better than that of the unimproved one. These results suggest that the variability caused by the individual difference is reduced by including the human character vector in the input vector.

In this respect, a crucial point of discussion concerning the experiment is to evaluate the effectiveness of the improved input modality. It is reasonable to suppose that the variability caused by the individual difference is reduced based on the results shown in Table 4.

Conclusions

We proposed a method to analyze preference using an electroencephalogram (EEG) analysis in prefrontal cortex activities. The proposed method applied the relationship between the EEG activities and the egogram. The EEG sensed a single point (Fp1; left prefrontal pole in the international 10-20 system). The device for recording the EEG used the dry-type sensor and a small number of electrodes. The EEG analysis adapted the feature mining and the clustering on EEG patterns using the SOM. The EEG activities of prefrontal cortex displayed individual difference. To consider the individual difference, we constructed the feature vector for input modality of the SOM. The input vector for the SOM consisted of the extracted EEG feature vector and the human character vector, which is the human character quantified through ego analysis using psychological testing. The Self Grow-up Egogram was adopted to quantify the human character.

To show the effectiveness of the proposed input modality, we did experiments using real EEG data. The EEG pattern classification results suggest that the variability caused by the individual difference is reduced by including the human character vector in the input vector. We conclude that it is possible to reduce the variability caused by individual difference through applying a relationship between the EEG activities in the prefrontal cortex and the egogram.

ACKNOWLEDGMENT

This work was supported by MEXT KAKENHI Grant Number 24700210.

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Shin-ichi Ito has received the B. E. and M. E. degrees from the University of Tokushima in 2002 and 2004, respectively, and the D. E. degree from Tokyo University of Agriculture and Technology in 2007. He has worked at Japan Gain the Summit Co., Ltd. and Tokyo University of Agriculture and Technology as a System Engineer and an Assistant Researcher, in 2004 and 2007, respectively. Since 2009, he has been an Assistant Professor at the University of Tokushima. His current research interests are EEG analysis, bio-signal processing, and individual difference analysis. He is a member of The Japanese Society for Cognitive Psychology, Japanese Society of Transactional Analysis, IEEE, IEICE, JSMBE, HIS, and IEEJ.

Momoyo Ito has received the B.E., M.E., and D. E. degrees in Faculty of Engineering and Resource Science, Akita University, Akita, Japan, in 2005, 2007, and 2010. She has been an Assistant Professor at The University of Tokushima since 2010. Her research interests include intelligent image processing and human behavior analysis using image information. She is a member of IEEE, IEICE, IPSJ, and RISP.

Katsuya Sato has received the B.E., M.E. and D.E degree from Kobe University in 2000, 2002 and 2005 respectively. He was an assistant professor at Yamaguchi University from 2005. Since 2009, he is an Associate Professor at The University of Tokushima. His current research interests are Cell Biomechanics and MEMS. He is a member of JSME, JSMBE, BPSJ.

Shoichiro Fujisawa has received the B.S. degree in Mechanical Engineering from Osaka Institute of technology, Osaka, Japan, 1976, and the Ph.D. degree in Engineering from Shinshu University, Nagano, Japan, in 1999. In 2008, he became a Professor with the Department of Ecosystem Engineering, the University of Tokushima. During 2004-2007, he has been an Associate Professor in the same department. During 1999-2004, he was with the Department of Electro-Mechanical Systems Engineering, Takamatsu National College of Technology, where he was an Associate Professor from 2000 to 2004. From 1971 until 1999, he worked for Osaka Prefectural College of Technology as a Mechanical Engineer. His research interests are Assistive Technology for Persons with Disabilities, and Learning Control.

Minoru Fukumi has received the B.E. and M.E. degrees from the University of Tokushima, in 1984 and 1987, respectively, and the doctor degree from Kyoto University in 1996. Since 1987, he has been with the Department of Information Science and Intelligent Systems, University of Tokushima. In 2005, he became a Professor in the same department. He received the best paper awards from the SICE in 1995 and Research Institute of Signal Processing in 2011 in Japan, and best paper awards from some international conferences. His research interests include neural networks, evolutionary algorithms, image processing and human sensing. He is a member of the IEEE, SICE, IEEJ, IPSJ, RISP and IEICE.