PAPER

Interindividual Difference Analysis in Prefrontal Cortex EEGs Based on the Relationship with Personality

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Abstract In this study, we propose a method to analyse interindividual differences in electroencephalograms (EEGs) taken while a subject listened to music, which is based on the relationship of these EEGs to human personality. The frequencies of the EEGs that are analysed have components that contain both significant and immaterial information as well as different levels of importance. We express the different levels of importance through the weight values of frequencies using a real-coded genetic algorithm. Then, the EEG patterns, which are determined based on the evaluation of the impression on the music, are detected using the k -nearest neighbour method. We assume that differences between detection results for EEG patterns with the highest and lowest recognition accuracies show interindividual differences. Moreover, ego analysis based on psychological testing is used to analyse personality, and the ego score is determined using a questionnaire. Finally, we discuss the relationship between personality and interindividual differences observed in experimental EEGs. An interesting tendency of a person with a combined ego type is that he or she has a unique response to negative stimuli compared with that of positive stimuli.

Keywords: electroencephalogram, interindividual difference, personality, egogram

1. Introduction

We attempt to investigate human character, which contains emotion, personality, KANSEI and sensibility, because it is well known that humans respond differently to exogenous stimuli based on their character. Unpleasant stimuli are stressors, which are encountered on a daily basis, and pleasant stimuli have a positive effect. Ideally, one should routinely encounter stimuli to have good mental health.

We use music as a stimulus [1] because it is well known that music has various positive effects on humans [2]-[7]. Those effects are influenced by memories, preferences and feelings. Moreover, they are frequent causes of variations in EEG activities. The variability of the EEG activities and preferences are minimized when the subjects choose the music listened to by themselves according to their preferences. However, the mechanism causing these positive effects is not clear because of differences in how individuals feel about music. Therefore, we attempt to extract individual characteristics by analyzing prefrontal cortex electroencephalogram (EEG) activity while a subject

listens to music that matches or does not match his or her mood. The prefrontal cortex is assumed to be the area of the brain [8]-[11] associated with human character. On the other hand, there are many systems applying EEG analysis, such as a brain computer interface, a mental health system based on analyzing EEGs associated with KANSEI [12], etc. However, the relevant EEG features are difficult to read, because they contain both the EEG signal and source noise. The most important aspect of EEG extraction is that it should prominently indicate variability in personal features. We chose a simple technique for confirming the individual differences of the EEG, and we defined the EEG pattern based on tests for evaluating the impression of music.

Numerous approaches exist for analyzing EEG activity [13], such as calculating the power spectrum and spectral centroid of the EEG, special EEG feature extraction techniques, principal component analysis (PCA) [14][15], independent component analysis (ICA) [15], factor analysis (FA), EEG pattern classifiers, k -nearest neighbour (k NN) analysis [13][16], linear discriminant analysis (LDA) [17], neural network

(NN) analysis [15] and support vector machine (SVM) analysis [18]. These techniques, especially PCA, ICA, FA, NN and SVM, have many parameters to set and their extracted features are difficult to understand. Therefore, we focus on the general technique of calculating the power spectrum as an easy-to-understand technique for confirming the trend of individual characteristics, which means the inter and intraindividual differences included in the EEG signal.

In our previous researches, a model for estimating intraindividual differences was proposed [19]–[21]. Then we confirmed that it was possible to classify the EEG patterns through prefrontal cortex EEG analysis. The EEG patterns were MatchMood (the music matched the subject's mood) and NmatchMood (the music did not match the subject's mood) [19], and four music genres listened to [20][21], respectively. In the intraindividual differences estimation, the power spectrum of each frequency was weighted because the frequencies of the EEGs had components that contained both significant and immaterial information. Therefore, the power spectra have different levels of importance for a human. We expressed the different levels of importance through the weight value of the frequency, and these weight values represented intraindividual differences in the individual characteristics of the EEG. In addition, estimating weight values helped reduce noise caused by artefacts and intraindividual differences. We specified weight values using the real-coded genetic algorithm (RGA). Furthermore, we classified the EEG pattern by using the k NN method, because it is one of the most popularly adopted non-parametric classifier in practice [13], and it was efficient when used in EEG interfaces with low-dimensional feature vectors [16]. We defined the EEG patterns based on evaluations of the impression of the music. The experimental results showed that the interindividual difference estimation model was effective. Moreover, we confirmed that there was an easily classified EEG pattern for each person which meant that interindividual differences could be observed.

However, we were not sure what was being observed through interindividual differences in EEG patterns. This article proposes a method of checking EEG analysis results against subjects' personalities, because we presume that the response to stimuli belongs to personality. We analyse a subject's character by using the egogram, because the egogram is like a psychological fingerprint: each person has a unique profile that can be seen and measured [22]–[25]. The egogram is calculated based on the score for each ego state. For the EEG analysis, we express the different levels of importance through weight values on frequencies using the RGA to estimate intraindividual differences. Moreover, the EEG patterns, which are determined based on evaluations of the impressions of the music, are detected using the k NN method. Dif-

Fig. 1 Proposed method for determining the relationship between personalities and individual differences included in EEGs taken while subjects listen to music

ferences between detection results of EEG patterns with the highest and lowest recognition accuracies are expressed as interindividual differences. Finally, to analyse interindividual differences in EEGs based on ego scores, we conduct experiments using real EEG data.

2. Proposed Method

We propose a method to analyse interindividual differences in prefrontal cortex EEGs based on human personalities. The proposed method determines the relationship between personalities and individual differences included in EEGs taken while subjects listen to music, as shown in Fig. 1. In the personality analysis, ego scores of the ego states are calculated. In the EEG analysis, the RGA specifies the weight value for each frequency; then, EEG features are extracted by calculating time averages of the weighted power spectra. Moreover, EEG patterns are detected using k NN. We define the EEG patterns based on results of impressions of music listened to. There are three EEG patterns: MatchMood (the music matches the subject's mood), NmatchMood (the music does not match the subject's mood) and Other (the subject cannot decide if the music matches his or her mood). Finally, the relationship between the results of the personality analysis and the EEG analysis is discussed.

2.1 Personality analysis

We employ the egogram to analyse the personality of a human. The egogram, which depends on transaction analysis (TA), is regarded as a psychological fingerprint: each person has a unique profile that can be seen and measured. The egogram classifies ego states as critical parent (CP), nurturing parent (NP), adult

Table 1 Specifics of the brain builder unit (BBU)

Measurement accuracy of EEG	$\pm 0.6\mu\text{V}$
Amplifier performance	100db on differential input
Minimum measured voltage	$5\mu\text{V}_{\text{pp}}$
Maximum measured voltage	$80\mu\text{V}_{\text{pp}}$
Common mode rejection rate	60db over
50/60 rejection rate	60db over; SN rate: 20db over
Input impedance	$10\text{M}\Omega$
Sampling rate	128 points/sec
Analog-digital conversion	8bit
Frequency characteristic	4-23Hz: $\pm 3\text{db}$
Accuracy of frequency characteristic	4-22Hz: $\pm 5\%$, 1-4 and 22-24Hz: $\pm 20\%$
Band-path filter	4-22Hz: 96db flat, other: 6db down on 1 octave

Fig. 2 Example egogram: The horizontal axis is ego states, and critical parent (CP), nurturing parent (NP), adult (A), free child (FC) and adapted child (AC). The vertical axis is the ego score of each ego state.

(A), free child (FC) and adapted child (AC) [22]-[25]. The egogram indicates score of each ego state and total scores. Scores are calculated from the results of psychological testing. To assess personality, we adopt the self grow-up egogram (SGE) [4], which was developed by the Chukyo Psychosomatic Medicine Workshop (CPW). This is a brief questionnaire composed of 50 items. The subject is asked to assign each item as “○” for “yes”, “×” for “no” or “△” for unsure, which are allotted 2, 0 or 1 points, respectively [25]. The 50 items on the questionnaire fall into the five ego states mentioned above. A diagram based on the calculated score from the psychological questionnaire shows which ego states dominate human personality or nature. Fig. 2 shows an example of an egogram. In principle, an egogram indicates the ego state with a consistent high score as the superior ego type, and it specifies the ego state with a consistent low score as the low-order ego type (when it is not the superior ego type). If an egogram cannot be specified in this manner, it is interpreted as the combined ego type.

Fig. 3 International 10-20 system: The reference electrode is at the left ear lobe (A1) and the exploring electrode is at the left prefrontal pole (Fp1).

2.2 EEG analysis

We use the “brain builder unit (BBU)”, which was developed by the Brain Function Research Centre, to measure EEG activity. In general, EEG systems use electro caps. However, these caps with a large number of electrodes are uncomfortable and take a long time for a human to wear, and thus are unsuitable in long-time recordings for the EEG system in daily-life applications. Thus, reducing the number of electrodes in an EEG interface applying the EEG analysis results is critical [12]. The BBU uses an electro band and a few electrodes. Therefore, we think it can alleviate uncomfortable feelings and can be used under realistic conditions. The methodology we use is referential recording. In this, the reference electrode is at the left ear and the exploring electrode is placed at Fp1 in the international 10-20 system, as shown in Fig. 3. The EEG data are sent to the computer every second

through the serial port. Then, the power spectra of EEG data per minute are calculated by fast Fourier transform (FFT). The FFT data covers frequencies from 4 to 22 Hz at 1 Hz intervals based on the specifics of the BBU (see Table 1).

For EEG feature extraction, we assume that the EEG frequencies are analysed contain both significant and immaterial information and have different levels of importance. In this paper, the weight value for each frequency expresses its level of importance. However, it is difficult to specify the weight values. Therefore, the RGA is used to specify them in order to filter the frequencies.

The RGA technique for specifying weight value is as follows:

1) Individual random chromosomes form the initial group. An individual has one chromosome and the genes of that chromosome are associated with a discrete frequency component. The gene value of individual chromosomes ranges from 0.0 to 1.0. We regard the gene value as the frequency weight value.

2) The EEG feature vector (*Feature*) is extracted from an individual. The calculation of the EEG feature is as follows:

$$Feature_i = \sum_{j=t}^{j=t+T} \frac{Pow_{ji} W_i}{T} \quad (1)$$

where *Pow*, *W*, *i*, *j* and *T* are the power spectrum, weight value, discrete frequency number, discrete time and measurement time of the EEG data, respectively. The fitness value is calculated based on the distribution of the extracted EEG feature vector. Moreover, the fitness value (*Fitness*) of each individual in the present generation is calculated. The fitness function is defined to maximize the Euclidean distance between all combinations of the EEG patterns (2). There are three combinations of EEG patterns: “MatchMood and NmatchMood”, “MatchMood and Other” and “NmatchMood and Other”. The maximum fitness is given as follows:

$$\text{maximize Fitness} = \text{minimum}(Dis_a, Dis_b, Dis_c) \quad (2)$$

$$\begin{aligned} \text{subject to } Dis_a &= d_2(G_{MatchMood} - G_{NmatchMood}) \\ Dis_b &= d_2(G_{MatchMood} - G_{Other}) \\ Dis_c &= d_2(G_{NmatchMood} - G_{Other}) \end{aligned} \quad (3)$$

where d_2 indicates the Euclidean distance, and *G* indicates the calculated average vector of the EEG feature vector in each EEG pattern.

3) Finally, we set the termination criteria to be when the number of generations has reached a maximum number or when the elite solution has not changed for a certain number of generations. When the termination criteria are satisfied, we regard the

weight value related to the gene value that has the maximum fitness value as the optimal weight value. When the termination criteria are not satisfied, the next generation is calculated by genetic manipulations. The manipulation techniques are as follows: elite strategy as a selection, blend crossover (BLX- α) as a crossover operation and mutation. Then, we use the *k*NN method for detecting the EEG pattern, because this method is a popular non-parametric classifier. In addition, when used in EEG analysis with low dimensional feature vectors, *k*NN proves to be efficient [13][16]. Moreover, we employ a method based on the one versus the rest (OVR) algorithm to detect EEG patterns. The test method used is the leave-one-out cross validation (LOOCV) method.

3. Experiments

There were seven subjects in this study: five men (average age 22 years old) and two women (average age 23 years old). The experiment proceeded as follows: the EEG device was positioned on the forehead of each subject; then, the subject sat on a chair, closed his or her eyes and remained quiet. EEGs were recorded multiple times in the laboratory with environmental noise. The length of each EEG recording was 15 s (no music), 5 * *n* (*n*: the number of music selections listened to) s and 15 s (no music). Also, the subjects listened to the introduction of music. The subjects were easily able to evaluate the impression of the music by listening to the introduction of the music, because the number and kind of music selections listened to were chosen freely by each subject according to his or her preferences. After each EEG recording, each subject completed an easy questionnaire on the impression of the music listened to by either selecting the “MatchMood”, “NmatchMood” or “Other” options.

The frequency range from 8 to 13 Hz is the α rhythm, which appears easily under rest conditions. Thus, the accuracy of the frequency range from 8 to 13 Hz is guaranteed in most devices that measure EEGs. We compare the EEG analysis results from this frequency range with those for the frequency range from 4 to 22 Hz (see Table 1). To evaluate the EEG pattern detection accuracy, we calculate the false-recognition ratio *FalRec* as follows:

$$FalRec = \frac{NumFal}{TotalMusic} \quad (4)$$

where *NumFal* is the number of false-positives detected as EEG patterns, and *TotalMusic* is the total number of music selections listened to. We set *k* = 3 as the parameter for the *k*NN classifier. Tables 2 and 3 show the parameters of the RGA and the total number of music selections listened to, respectively.

Table 3 Sex of subject and the total number of music selections listened to (TotalMusic): TotalMood, TotalNmood and TotalOther represent the number of MatchMood, NmatchMood and Other responses, respectively.

	sex	TotalMusic	TotalMood	TotalNmood	TotalOther
subject 1	female	103	49	28	26
subject 2	male	78	38	12	28
subject 3	male	88	59	11	18
subject 4	male	110	33	21	56
subject 5	male	90	16	25	49
subject 6	male	95	31	46	18
subject 7	female	70	27	13	30

Table 2 Parameters of the RGA

The maximum number of generations	1,000
The number of individuals	50
The length of chromosome	19(4-22Hz) or 6(8-13Hz)
α of BLX- α	0.1
Mutation rate	0.01

4. Results and Discussions

We confirm the results of the individual difference through the ego scores and the inter-individual difference in EEG analysis. Moreover, we discuss the relationship between the ego scores and the inter-individual difference.

4.1 Individual difference through the ego scores

Table 4 shows the scores for each ego state. We confirmed that each subject had different scores for each ego state: “A” is maximum for subjects 1 and 5; “CP” and “A” are high for subject 2; “CP”, “A” and “FC” are high and “AC” is low for subject 3; “AC” is high and “NP” is low for subject 4; “A” is low and “NP” and “AC” are high for subject 6 and “CP” and “AC” are high for subject 7. Technically, subjects 1, 2, 3, 4 and 7 have the combined ego-type. Subjects 1 and 5 have the adult superior type and subject 6 has the adult low-order type. Therefore, we assume that subjects 1, 5 and 6 have particular ego-types.

4.2 Inter-individual difference in EEG analysis

Table 5 shows the mean (10 trials) of the false-recognition ratio of two-class pattern detection for “MatchMood”, “NmatchMood” and “Other”, where (a) and (b) correspond to when the frequency range for the EEG analysis 4 to 22 Hz and 8 to 13 Hz, respectively.

Table 4 Scores for each ego state for each subject: CP, NP, A, FC and AC represent the following respective ego states: critical parent, nurturing parent, adult, free child and adapted child.

	CP	NP	A	FC	AC
subject 1	17	14	18	17	14
subject 2	18	8	18	16	10
subject 3	19	16	20	20	8
subject 4	10	8	14	14	20
subject 5	10	8	18	16	10
subject 6	16	20	2	20	16
subject 7	15	3	9	6	16

We confirmed that the false-recognition ratio for the detected EEG pattern varied for each subject: subjects 2, 3, 4 and 7 had the best results in “NmatchMood”, subjects 1 and 6 had the best results in “Other” and subject 5 had the best result in “MatchMood”. It is reasonable to suppose that the differences in the false-recognition ratio represent part of interindividual differences.

Comparing the results shown in Table 5 (a) and (b), we obtained a lower false-recognition ratio for all EEG pattern classifications when the frequency range was 4 to 22 Hz. It is reasonable to suppose that necessary information in the EEG patterns was deleted when the frequency range was 8 to 13 Hz.

The false-detection ratio of “NmatchMood” had the lowest average and standard deviation of the mean. Therefore, the left prefrontal EEG activities for “NmatchMood” might be one-of-a-kind activities, and interindividual differences might be indicated by brain activities recorded with one sensing point via an easy EEG taken with the BBU.

4.3 Relationship between ego scores and inter-individual difference

We now discuss the relationship between ego scores and interindividual differences recorded with

Table 5 Mean and standard deviation of the false-recognition ratio for EEG pattern detection (10 trials): (a) and (b) correspond to when the frequency range of the EEG was 4 to 22 Hz and 8 to 13 Hz, respectively.

(a) 4 to 22 Hz

	MatchMood	NmatchMood	Other
subject 1	0.20 ± 0.10	0.07 ± 0.0	0.05 ± 0.0
subject 2	0.24 ± 0.09	0.02 ± 0.0	0.13 ± 0.0
subject 3	0.22 ± 0.0	0.02 ± 0.0	0.04 ± 0.0
subject 4	0.09 ± 0.0	0.04 ± 0.0	0.24 ± 0.07
subject 5	0.03 ± 0.0	0.08 ± 0.0	0.12 ± 0.04
subject 6	0.11 ± 0.0	0.16 ± 0.05	0.04 ± 0.0
subject 7	0.14 ± 0.02	0.03 ± 0.0	0.18 ± 0.03
Average and standard deviation of mean	0.15 ± 0.08	0.06 ± 0.05	0.11 ± 0.08
Average of standard deviation	0.03	0.01	0.02

(b) 8 to 13 Hz

	MatchMood	NmatchMood	Other
subject 1	0.44 ± 0.01	0.27 ± 0.0	0.25 ± 0.0
subject 2	0.43 ± 0.02	0.16 ± 0.0	0.35 ± 0.01
subject 3	0.33 ± 0.0	0.13 ± 0.0	0.20 ± 0.0
subject 4	0.30 ± 0.0	0.19 ± 0.0	0.46 ± 0.01
subject 5	0.18 ± 0.0	0.28 ± 0.0	0.44 ± 0.02
subject 6	0.33 ± 0.0	0.43 ± 0.0	0.19 ± 0.0
subject 7	0.36 ± 0.03	0.19 ± 0.0	0.39 ± 0.11
Average and standard deviation of mean	0.34 ± 0.08	0.24 ± 0.10	0.32 ± 0.11
Average of standard deviation	0.01	0.0	0.02

the EEG. We divide the subjects into two groups: those with an ego type of multiple superior and/or multiple low-order (subjects 2, 3, 4 and 7), and those with an ego type of one superior and/or low-order (subjects 1, 5 and 6), based on the results shown in Table 4. We can again divide the subjects into two groups: “NmatchMood” was the lowest for subjects 2, 3, 4 and 7, and “MatchMood” and “Other” were the lowest for subjects 1, 5 and 6, based on the results shown in Table 5 (a). The above results suggest that the subjects with an ego type comprised of multiple superior or multiple low-order types tend to have a lower false-detection ratio for “NmatchMood” than for “MatchMood”. “MatchMood” and “NmatchMood” indicate positive and negative stimuli, respectively. Therefore, the left prefrontal cortex activity of subjects with a combined ego type tended to show a unique response to negative stimuli compared with the response to positive stimuli.

5. Conclusions

5.1 Conclusions

We discussed the relationship between ego scores based on personality and interindividual differences by studying EEG patterns. Ego scores were used to detect personality. Then, EEG analysis was used to calculate time averages of power spectra for frequencies of EEG signals, and EEG patterns were used to evaluate whether the music matched a subject’s mood. A k -nearest neighbour classifier was used to detect the EEG patterns. The classification algorithm and test method employed OVR and LOOCV, respectively.

To discuss the relationship between ego scores and the results of EEG pattern detection, we conducted an experiment using real EEG data. The experimental results showed that subjects with a combined ego type had a specific response to negative stimuli compared with their response to positive stimuli. Therefore, a relationship may exist between personalities and in-

terindividual differences observed in prefrontal cortex EEGs.

5.2 Future works

Our future works will involve efforts to analyse human nature using psychological scales and other psychological tests, change the measurement positions and confirm the tendency. We will investigate the relationship between personality and music in detail: we will study how personality affects how we listen to music in daily life.

References

- [1] B. Philip: Music to Match Your Mood, news@nature.com, 21, July 2006.
- [2] P. Updike and D. Charles: Music Rx: physiological and emotional responses to taped music programs of preoperative patients awaiting plastic surgery, *Ann Plast Surg*, Vol.19, No.1, pp.29-33, 1987.
- [3] Ce. Guzzetta: Effects of relaxation and music therapy on patients in a coronary care unit with presumptive acute myocardial infarction, *Heart Lung*, Vol.18, No.6, pp.609-616, 1989.
- [4] K. E. Gfeller: Chapter 11 An Introduction to Music Therapy Theory and Practice, Wm. C. Brown Publishers, 1992.
- [5] J. C. Smith and C. A. Joyce: Mozart versus new age music -Relaxation states stress and ABC relaxation theory-, *Journal of Music Therapy*, Vol.41, No.3, pp.215-224, 2004.
- [6] L. A. Mitchell, R. A. R. MacDonald and E. E. Brodie: A comparison of the effects of preferred music arithmetic and humour on cold pressure pain, *European journal of Pain*, Vol.10, pp.343-351, 2005.
- [7] D. D. Walworth: The effect of preferred music genre selection versus preferred song selection on experimentally induced anxiety levels, *Journal of Music Therapy*, Vol.40, No.1, pp.2-14, 2003.
- [8] R. J. Davison: Anterior cerebral asymmetry and the nature of emotion, *Brain and Cognition*, Vol.20, pp.125-151, 1995.
- [9] R. J. Davison: Anterior electrophysiological asymmetries, emotion, and depression: Conceptual and methodological conundrums, *Psychophysiology*, Vol.35, pp.607-614, 1998.
- [10] Y. Okamoto: Perception of stressful stimulus in the prefrontal cortex -the brain mechanism of a failure in adaptation to stress, *Folia Pharmacol. Jpn.*, Vol.126, pp.194-198, 2005 (in Japanese).
- [11] M. Sato: Music processing in the brain -timber perception and amygdale-, *Higher Brain Function Research*, Vol.25, No.2, pp.139-144, 2005 (in Japanese).
- [12] Y. Wang, X. Gao, B. Hong, C. Jia and S. Gao: Brain-computer interfaces based on visual evoked potentials, *Journal of IEEE engineering in medicine and biology magazine*, Vol.27, No.5, pp 64-71, 2008.
- [13] F. Lotte, M. Congedo, F. Lecuyer and B. Arnaldi: A review of classification algorithms for EEG-based brain-computer interface, *Journal of Neural Engineering*, Vol.4, pp.R1-R13, 2007.
- [14] H. Lee and S. Choi: PCA+HMM+SVM for EEG pattern classification, *Proc. 7th Int. Symp. on Signal Processing and its Application*, 2003.
- [15] T. Hoya, G. Hori, H. Bakardjian, S. Nishimura, T. Suzuki, Y. Miyawaki, A. Funase and J. Cao: Classification of single trial EEG signals by a combined principal + independent component analysis and probabilistic neural network approach, *Proc. ICA2003*, pp.197-202, 2003.
- [16] J. F. Borisoff, S. G. Mason, A. Bashashati and G. E. Birch: Brain-computer interface design for asynchronous control applications: improvements to the LF-ASD asynchronous brain switch, *IEEE Trans. Biomed. Eng.*, Vol.51, 985-92, 2004.
- [17] B. Blankertz, G. Curio and K. R. Muller: Classifying single trial EEG - towards brain computer interfacing, *Adv. Neural Inf. Process. Syst.*, NIPS 01, Vol.14, pp.157-64, 2002.
- [18] T. Felzer and B. Freisieben: Analyzing EEG signals using the probability estimating guarded neural classifier, *IEEE Trans. Neural Syst. Rehabil. Eng.*, Vol.11, No.4, pp.361-371, 2003.
- [19] S. Ito, Y. Mitsukura, J. Cao and M. Fukumi: Method for detecting music to match the user's mood in prefrontal cortex electroencephalogram activity based on individual characteristics, *Proc. of 2007 IEEE International Conference System, Man and Cybernetics*, pp.2640-2644, 2007.
- [20] S. Ito, Y. Mitsukura, H. N. Miyamura, T. Saito and M. Fukumi: Extraction of EEG characteristics while listening to music and its evaluation based on a latency structure model with individual characteristics, *WILEY Transaction, Electrical Engineering in Japan (Translated from Denki Gakkai Ronbunshi, Vol.127-C, No.6, 2007, pp. 874-881), Vol.92, No.1, pp.9-17, 2009.*
- [21] S. Ito, Y. Mitsukura and M. Fukumi: Study on model for predicting the intra-individual difference in left prefrontal pole electroencephalogram variability and its evaluation, *WILEY Transaction, Electronics and Communications in Japan (Translated from Denki Gakkai Ronbunshi, Vol.129-C, No.1, pp. 17-24), Vol.94, No.5, pp.9-16, 2011.*
- [22] S. Shirai: How transactional analysis can be used in terminal care, *International Congress Series 1287*, pp.179-184, 2006.
- [23] E. Berne: *Transactional Analysis in Psychotherapy*, Random House, New York, pp.38-43, 1961.
- [24] J. M. Dusay: *Egogram*, Harper and Row Publishers, New York, xv, 1977.
- [25] T. Katsura, M. Ashihara and M. Murakami: *Manual of Self Grow-up Egogram*, Team Iryo Ltd., 1999 (in Japanese).

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