Method to Classify Matching Patterns between Music and Human's Mood Using EEG Analysis Technique Considering Personality

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***Abstract*-In this paper we introduce a method to classify matching patterns between music and human mood using an electroencephalogram (EEG) analysis technique and considering personality. We analyse the EEG of the left prefrontal cortex by single-point sensing. The EEG recording device uses dry-type sensors. The feature vector is created by connecting the personality quantification results and the EEG features. Egograms—the Yatabe-Guilford personality inventory and a Kretschmer-type personality inventory are used to quantify personality. The EEG features are extracted using fast Fourier transform. Then, the matching patterns are classified using the k-nearest neighbour method. To show the effectiveness of the proposed method, we conduct experiments using real EEG data.**

***Keywords*- electroencephalogram, matching patterns, personality, egogram, Yatabe-Guilford personality inventory, Kretschmer type personality inventory, k - nearest neighbour method.**

I. INTRODUCTION

We attempt to construct a brain computer interface (BCI) using a compact device with dry-type electrodes because of using BCI in daily-life [1]. The target sensing point is the left lobe, and a single electrode is used. The prefrontal cortex is assumed to be the area of the brain that is associated with human personality [2, 3]. Electroencephalogram (EEG) activities in the prefrontal pole are variable; it has been confirmed that EEGs of frontal cortex activity show individual differences [4, 5]. Individual differences are particularly noticeable when the sensing position is the prefrontal cortex. However, the reasons for the differences are not clear. We assume the response to stimuli is associated with personality. People are affected by a variety of stimuli on a daily basis. Stimuli that are perceived as unpleasant are known as stressors, while stimuli that are perceived as pleasant have a positive effect on behaviour. We think that stimuli that have a positive effect on behaviour are those that match a person's mood. Therefore, being able to detect stimuli that match individual moods is important. This paper attempts to detect such stimuli using EEG analysis techniques.

Analysis techniques exist for a variety of EEG signals [6]. Such techniques include power spectrum, spectral centroid, event-related potential and principal component analysis [7,8] as well as factor analysis, independent component analysis, k-nearest neighbour (kNN) [6,9], linear discriminant analysis [10], neural network analysis (NN) [8] and support vector machine [11] classification. Pattern classification techniques with a learning function are susceptible to features of the input vectors. It is difficult to learn the input vectors when using EEG data with individual differences and noise elements. Therefore, we create a feature vector to resolve those issues. The feature vector consists of the personality analysis results and the EEG feature. Here the egogram [12-15], the Yatabe-Guilford personality inventory (YG) and a Kretschmer-type personality inventory (KT) are used to analyse personality. Psychological questionnaires were administered to determine egogram, YG and KT values for state, scale and type, respectively. The EEG feature is computed from time-averaged power spectra for each frequency. The classifier employs kNN because it is a popular and practical non-parametric classifier.

Finally, to show the effectiveness of the proposed method, we conduct experiments using real EEG data and classify the matching patterns between music stimuli and mood.

II. PROPOSED METHOD

The proposed method consists of four phases: (i) personality quantification, (ii) EEG recording and EEG feature extraction, (iii) feature vector creation to classify matching patterns between listening to music and mood and (iv) matching patterns classification. The feature vector is created by normalizing the quantified personality score and computing the time-averaged power spectra of each EEG frequency band. The personality is quantified using results from a psychological questionnaire for egogram, YG and KT. The classified patterns are determined based on subjective evaluation of the impression evaluation of the music.

The egogram, which depends on transactional analysis, is regarded as a psychological fingerprint: Each person has a unique profile that can be identified and measured. The egogram classifies ego states as critical parent (CP), nurturing parent (NP), adult (A), free child (FC) and adapted child (AC) [12–15]. The egogram indicates a score for 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) [15], which was developed by the Chukyo Psychosomatic Medicine Workshop. The self grow-up egogram uses a brief questionnaire composed of 50 items.The subject is asked to assign ``○” for ‘‘yes”, ‘‘×’ for ``no" or ``∆" for unsure to each item. The assigned designations are allotted 2, 0 or 1 points, respectively [15]. The 50 items on the questionnaire can be categorized into the five ego states mentioned previously. A diagram based on the calculated score from the psychological questionnaire shows the ego states that dominate an individual’s personality or nature. Figure (1) shows an example of an egogram. We normalize each ego score by dividing the score by 20 because the maximum score for each ego states is 20.

The YG can measure emotional stability, characteristics of human relations and behavioural and mentation properties. The YG comprises twelve measurable categories: Depression (D), Cyclic Tendency (C), Inferiority Feelings (I), Nervousness (N), Lack of Cooperativeness (Co), Social Extraversion (S), Ascendance (A), Lack of Agreeableness (Ag), General Activity (G), Thinking Extraversion (T), Rhathymia (R) and Lack of Objectivity (O). The related questionnaire consists of 120 items, ten items for each categories. The subject is asked to assign ``○” for ‘‘yes”, ‘‘×’ for ``no" or ``∆" for unsure to each item. Figure (2) shows an example of the YG results. We normalize each score by dividing the score by 20 because the maximum score for each item is 20.

The personality types that can be identified by the KT include Schizothymia (S), Cyclothymia (Z), Epileptic Temperament (E), Nervosity (N) and Paranoiac Temperament (P). The related questionnaire consists of 50 items. The subject is asked to assign ``○” for ‘‘yes”, ‘‘×’ for ‘‘no” or ‘‘∆" for unsure to each item, and the designations are allotted 2, 0 or 1 points, respectively. Figure (3) shows example YG results. We normalize each type score by dividing the score by 18 because the maximum score for each item is 18.

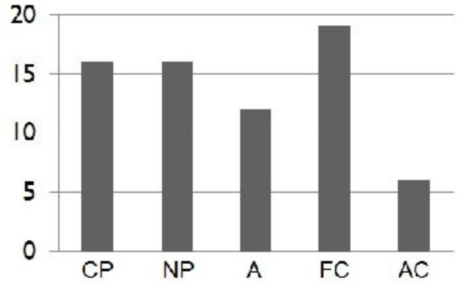

Figure (1): Example of an egogram. The vertical axis shows the ego score. CP, NP, A, FC and AC are critical parent, nurturing parent, adult, free child and adapted child, respectively.

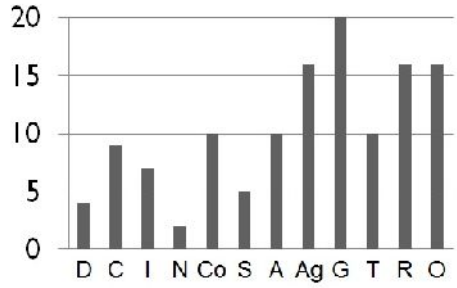

Figure (2): Example of a YG result. The vertical axis shows the score (maximum 20 points). D, C, I, N, Co, S, A, Ag, G, T, R and O are depression, cyclic tendency, inferiority feelings, nervousness, lack of cooperativeness, social extraversion, ascendance, lack of agreeableness, general activity, thinking extraversion, rhathymia and lack of objectivity, respectively.

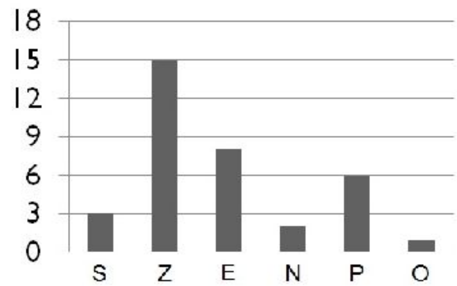

Figure (3): Example of a KT result. The vertical axis shows score for the KST personality type. S, Z, E, N, P and O are schizothymia, cyclothymia, epileptic temperament, nervosity, paranoiac temperament and other type, respectively.

In EEG recording, an EPOC device developed by EMOTIV is used to measure EEG activity. The EPOC uses dry-type sensors and covers 10ch electrodes. The two reference electrodes are attached to the bone just behind each ear lobe, and the exploring electrodes are placed according to the

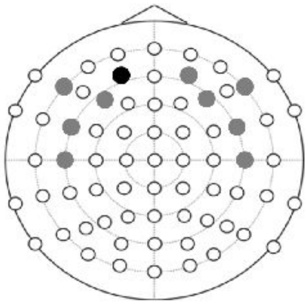

Figure (4): EEG is recorded from an association area of the left prefrontal pole (AF3) in the international 10-10 system (black point). Gray points denote covered positions in EPOC.

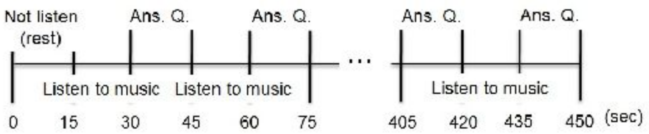

Figure (5): Time course for EEG recordings. rest, Ans. Q. and Listen to music are the rest conditions, answering the impression evaluation on listening to the music and listening to music, respectively.

international 10–10 system at AF3, AF4, F7, F8, F3, F4, T7, T8, FC5 and FC6 (Figure (4)). This device has high resolution, neuro-signal acquisition and a processing wireless neuro-headset. The EEG data are sent to a computer through a serial port. The sampling rate is 128 Hz.

In EEG feature extraction, the power spectra of EEG data per minute are calculated by fast Fourier transform (FFT). The FFT data covers frequencies from 4 to 30 Hz at 1 Hz intervals. We regard the power spectra on each EEG frequency bands (4–30 Hz at 1 Hz intervals) as the EEG feature as follows:

$$EEGFeature_i = \sum_{j=t}^{j=t+T} Pow_{ji} / T \quad (1)$$

where $EEGFeature$, i, j, T and Pow are the EEG feature data, discrete frequency number, discrete time, measurement time of the EEG data and the power spectrum of each frequency, respectively.

To classify patterns of matching human mood, the feature vector used to classify the patterns is created by connecting the normalized ego scores, the normalized scale scores for the YG, the normalized type scores for the KT and the EEG feature. The number of dimensions of the created feature vector is 50.

In matching patterns classification, the user completes an easy impression evaluation questionnaire about the music they listened to while EEG signals were being recorded (Figure (5)). Here, matching patterns are defined based on the results of the questionnaire. The criteria are whether a person matches user mood, does not match user mood or feels borderline; thus, there are three respective matching patterns, MatchMood, NmatchMood and Border.

We use k NN to classify the matching patterns because it is a popular and practical non-parametric classifier. When used in EEG analysis with high dimensional feature vectors, k NN proves to be efficient [10,13]. Assume that there are L classes $c_1, c_2 \cdots, c_L$. Let v_i be the training sample set of the i th class. The design set for the k NN classifier is $\bigcup_{i=1}^{L} v_i$. S is the total number of vectors in the design set. Vector y_i ($i = 1, 2, \cdots, S$) denotes the i th vector in the design set. For an input vector, k NN algorithm finds the k closest vectors in the design set. Let k_i ($1 \le i \le L$) be the number of closest vectors from the i th class, $k_1 + k_2 + \cdots + k_L = k$. The input vector's class label is c_I if $I = \arg\max k_i$. Then, the Euclidean metric is used for the distance measure. The feature vector sets for learning are chosen based on the repeated random sub-sampling validation algorithm for all data sets. In the repeated random sub-sampling validation, Q% in all data are chosen randomly as data sets for learning. The remainder of the data (100–Q%) are used for testing. Furthermore, the accuracy rate is computed based on the matching patterns classification.

$$Accuracy = CorrectNumber / TotalNumber \quad (2)$$

where the $CorrectNumber$ is the total number of correct answers by checking MatchMood, NmatchMood and Border. $TotalNumber$ means the total number of MatchMood, NmatchMood and Border.

III. EXPERIMENTS

The subjects in this study comprised four persons: two males (average age 25 years) and two females (average age 22 years). The experiment proceeded as follows. The subjects wore the EPOC device, sat on a chair, closed their eyes and remained quiet. The EEG was recorded more than once in the laboratory with ambient noise during the experiment. The time course of each EEG recording was 15 seconds (listening to music) and 15 seconds (answering question: impression evaluation on listening to the music) as a set, shown in Figure (5). The experiments classified MatchMood, NmatchMood and Border using the proposed method. L and S for the matching patterns classification using k NN are 1 and 3 or 2, respectively. Furthermore, the Q in the repeated random sub-sampling validation is 80. Tables (1)–(3) show the results of the egogram, YG and KT, respectively. Table (4) and Figure (6) show the results of the impression evaluation of music listened to and the matching patterns classification (1,000 trails), respectively. The three groups are the results of the three matching patterns classifications: MatchMood, Table (1): Results of the normalized score of each ego state for each subject (S1–S4). CP, NP, A, FC and AC are the same as in Figure (1).

	S1	S2	S3	S4
sex	male	female	male	female
CP	0.8	0.5	0.8	0.2
NP	0.8	0.6	0.4	0.75
A	0.6	0.5	0.4	0.3
FC	0.95	0.8	0.45	0.7
AC	0.3	0.9	0.7	0.95

Table (2): Results of the normalized scores of each scale for YG for each subject (S1–S4). D, C, I, N, Co, S, A, Ag, G, R, T and O are the same as in Figure (2).

	S1	S2	S3	S4
D	0.2	0.2	0.8	1.0
C	0.45	0.25	0.4	0.9
I	0.35	0.65	0.7	0.8
N	0.1	0.3	0.8	0.55
Co	0.5	0.6	0.5	0.7
S	0.25	0.3	0.25	0.3
A	0.5	0.05	0.15	0.1
Ag	0.8	0.4	0.15	0.4
G	1.0	0.45	0.15	0.5
R,T	0.5	0.7	0.3	0.65
O	0.8	0.4	0.1	0.25
R,T2	0.8	0.5	0.05	0.1

Table (3): Results of the normalized scores of each type for KT for each subject (S1–S4). S, Z, E, N, P and O are the same as in Figure (3).

	S1	S2	S3	S4
S	0.17	0.56	1.00	0.56
Z	0.83	0.89	0.33	0.56
E	0.44	0.89	0.39	0.11
N	0.11	0.11	0.89	1.0
P	0.33	0.33	0.28	0.33
O	0.06	0.0	0.0	0.0

NmatchMood and Border denoted by M, N and B, respectively. R indicates a response other than M, N or B.

IV. DISCUSSIONS

In Tables (1)–(3), we confirmed that each subject had different scores for each ego state, each scale in YG and each type in KT. Thus, the relationships among the results of the egogram, YG and KT were not clear. Those results suggest a variety of different scores for personality.

Table (4): Results of impression evaluation of music listened to. TotalMusic, TotalMood, TotalNmood and Total Border denote the total number of musical recordings listened to, the number of MatchMood, NmatchMood and Border, respectively.

TotalMusic	TotalMood	TotalNmood	TotalBorder
120	51	26	43

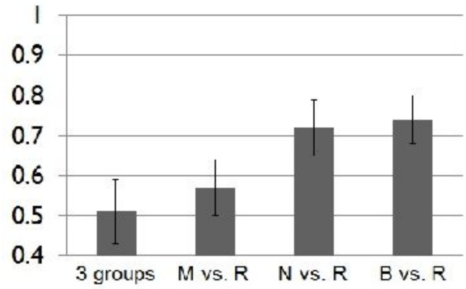

Figure (6): Mean ± S. D. of recognition accuracy of the matching patterns classification (1,000 trials). Three groups, M, N, B and R denote MatchMood, NmatchMood, Border and otherwise, respectively.

In Figure (6), we confirmed that the standard deviation (S. D.) of the accuracy rates was less than 0.08. Since the number of trials was 1,000, these results were stable. The mean of the accuracy rate of NmatchMood detection was higher than 0.7. Considering the EEG recording position, these results suggest the left prefrontal pole EEG activities for NmatchMood may be one-of-a-kind activities. However, mean and S. D. of the accuracy of the “3 groups” and “M vs. R” were low and low, respectively. These results suggest that it is difficult to detect signals related to positive effect on auditory stimuli when the EEG recording position is the left prefrontal pole.

V. CONCLUSIONS

This paper introduced a method to classify the matching patterns between the music listened to and individual mood based on EEG analysis techniques and personality. The proposed method consisted of four phases: (i) personality quantification, (ii) EEG recording and feature extraction, (iii) feature vector creation to classify matching pattern and (iv) matching patterns classification. The feature vector was created by normalizing the quantified scores of personality and computing the time averaged power spectrum of each EEG frequency band. Personality was quantified using an egogram, the YG and the KT determined by psychological questionnaires. The classified patterns were determined based on subjective evaluation through an impression evaluation of the music listened to. From the experimental results, we suggest that the left prefrontal pole EEG activities for NmatchMood may be one-of-a-kind activities. In addition, it was difficult to detect signals related to positive effect on auditory stimuli when the EEG recording position was the left prefrontal pole.

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