Music Recommender System Using a Forehead-mounted Electrical Potential Monitoring Device to Classify Mental States

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***Abstract*—Music can be used in various areas such as sports training and music therapy to improve human mental and physical states. However, it is well known that music is affected greatly by human emotions as well as surrounding environment. Therefore, it is important to observe the current human emotion and the environment to increase the effectiveness of music-based sports training or music therapy. Because no suitable methods are available for detecting human emotions, we investigated the possibility of human emotion detection by using a brainwave sensor to monitor human electrical potentials. In order to find the best method for human emotion detection, we conducted two experiments to acquire brainwaves and determine human mental states. Based on the results of these experiments, we propose a suitable method for classifying mental states accurately and with low variances. Using this method, we plan to develop an accurate music recommender system, which should be effective for music-based sports training or music therapy.**

***Index Terms*—music, brainwave, music therapy, sport training, machine learning, recommender system**

I. Introduction

MUSIC is important for people because it pleasure or enjoyment but it also aids relaxation. Recently, many music search systems and internet services have been developed, e.g., a song can be identified simply by humming a tune. Songs similar to the preferred music listened to by a user can also be recommended [2].

In addition, music can facilitate recovery from disease, which is known as mental therapy. Music is also be used by sports players to make them calm and relaxed, or for stimulation [1]. However, it is difficult for users such as patients, doctors, coaches, and players to select appropriate music for a specific situation. It has been reported that less effective results can be obtained if a user always listens to the same music, which they select themselves [2]. At present, there are no suitable music recommendation systems for this purpose exist. One of the main difficulties with the development of this type of system is the determination of a user's mental state. There are clear relationships between mental states and the music that is suitable for an individual, but it is necessary to extract the mental state of the human subject before providing a selection.

Therefore, in this study, we propose a suitable method for acquiring and extracting human mental states from their brainwaves, which are obtained using a Forehead-mounted Electrical Potential (FEP) Monitoring Device. The brainwaves obtained using these devices contain high levels of noises; thus, it is important to establish the most suitable method for obtaining accurate results based on noisy brainwaves. We determined the most suitable method by testing various possible combinations of methods for obtaining brainwaves and classifying them according to human mental states.

In Section 2, we discuss related research. The process used for classifying human mental states is described in Section 3. In Section 4, we explain the experiments used to determine the most suitable method for mental state detection and the results obtained. Finally, we discuss our results and future research in Section 5.

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II. Related work

Recently, various studies have analyzed music and brainwaves in two main areas: the usage of brainwaves for music search and music analysis to determine the effects of music on brainwaves. In addition to these types of studies, general brainwave-based human interfaces have been in use for decades.

First, we consider the use of human brainwaves for music search, where we briefly describe the main research activities [3][4][5][6] in this area. Morita et al. proposed a system where a brainwave is used as an input to search for music requested by a user [3]. They also observed brainwaves while listening to music and evaluated the relationships between music-related emotions and the characteristic brainwave patterns in, several experiments. Cabredo et al. proposed an emotion-based model for music retrieval using brainwaves [4]. This model comprised 4 emotional states, i.e., stress, joy, sadness, and relaxation, which were obtained based on matrix transformations of 135 dimensional Electroencephalogram (EEG) feature vectors.

Zao et al. developed a method measuring sleep quality using EEG signals, where they aimed to develop. Finally, Schaefer et al. proposed a classification method of imagined music from EEG. Their experiments showed that music could be classified if it was actually audible, whereas imagined music could not be classified.

Various studies have analyzed the effects of music on brainwaves and we consider some of the main research [7][8][9] from this area. Based on experiments, Yamanishi et al. reported that brainwaves are affected by musical chords and chord correlations in harmony [7]. Petrantonakis et al. proposed an emotion-related information retrieval method based on brain EEG signals obtained from users when

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they observed pictures that caused emotional stimulation [8]. Nishimoto et al. proposed a method for visualizing the dynamic brain activities of users who watched movies, using data extracted from blood oxygen level-dependent(BOLD) signals measured by functional magnetic resonance imaging (fMRI) [9].

Brainwaves were not employed in this study but it is interesting that they could visualize the brain activity in movie reconstructions.

Brain-computer interface (BCI) is now a highly active research field [10]. Chuang et al. proposed a new method of for user authentication using brainwaves [11], where a user simply needs to think about "pass-thoughts" rather than inputting a password. Makeig et al. described a musical emotion BCI for communicating a user's feelings based on musical sound production from brainwaves BCI2. Many other studies of BCI have been used for machine control via brainwaves. Fr example O'Hara et al. [13] studied a simple BCI game from the viewpoint of embodiment using a BCI.

III. Mental classification from brainwaves obtained using a FEP monitoring device.

A. Single-channel brainwaves measuring devices

In the present study, brainwaves were measured using a simple single-channel EEG device to classify mental states. In general, multi-channel EEG instruments are used to monitor brainwaves, but these devices are comparatively expensive and they require long periods of time to mount the EEG sensors on a user's head, i.e., it requires over a minute to attach all of the sensors before measuring brainwaves. Thus, because we aim to apply our classification method to music therapy as well as sports training, a single-channel EEG device is more appropriate than multi-channel device. Therefore, we used a consumer-grade inexpensive single-channel EEG sensor device called a Neuro-Bridge B3-Band[1]. This device measures the electric potentials over the forehead region using a dry-contact sensor.

The B3-Band comprises three electrodes, i.e., Fp1, Fp2, and A1 in the international 10-20 EEG system, as shown in Figure 1, which can be used to measure brainwaves. In our study, we used the RAW data measured by the B3-Band, which were then processed and transformed into the frequency spectrum using Fast Fourier Transform (FFT).

The power of each frequency range described below was calculated 10 times per minute. The sampling frequency of the RAW data was 512 Hz, so the window width and sampling size were set as 1 min and 512, respectively. We implemented a frequency power calculation program using R (version 3.0.2), which is a software environment for statistical analysis.

B. FEP and the frequency ranges used

In general, brainwaves are measured using several electrodes attached to the head's surface to detect the small electrical potentials derived from the human brain. These brainwave measurements may contain noisy data derived from other unknown biological phenomena in addition to brainwaves.

[1]http://neuro-bridge.com/dev/b3band.html

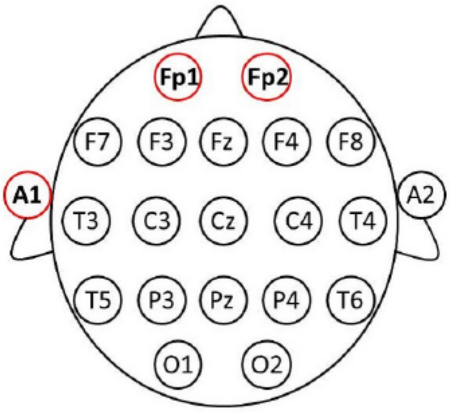

Fig. 1. International 10-20 EEG system.

It is usually difficult to remove the true brainwaves from the measured electrical potential data; thus, we refer to FEP in our study rather than brainwaves.

Eight frequency ranges were calculated from the RAW data.

δ: 0.5-2.75Hz
θ: 3.5-6.75Hz
$L\alpha$: 7.5-9.25Hz
$H\alpha$: 10.0-11.75Hz
$L\beta$: 13.0-16.75Hz
$H\beta$: 18.0-29.75Hz
$L\gamma$: 31.0-39.75Hz
$M\gamma$: 41.0-49.75Hz

C. Mental states and their classification

In this study, we aimed to classify human mental states using electrical potential measurements, where we classified three mental states: relaxed, concentration, and normal. These mental states are important because sports players may need to be relaxed or to concentrate before a game. The relaxed and concentration states are both mental states in the strain-relaxation dimensions of the three-dimensional theory of emotion proposed by Wilhelm Max Wundt[14]. We added an intermediate mental state called the normal state, which we defined as a mental state other than the relaxed and concentration states. Therefore, the data obtained from the monitoring device were classified into one of these three mental states using a machine learning method.

In order to apply a machine learning method to our classification task, it was necessary to determine two independent classification methods. As shown in Figure 2, our classification task was decomposed into two levels: the user side and the system side. On the user side, we determined how or what a user could evoke during measurements in order to obtain more accurate classification results from a user, as well as to reduce the mental burden on the user. On the system side, the data were processed and transformed into their frequency power values using the FFT for each frequency range, as described in the following. The measured and transformed data were then decomposed into two sets: a training dataset and a classification test dataset. The first training dataset was used to train a machine learning method, whereas the second classification test dataset was used to

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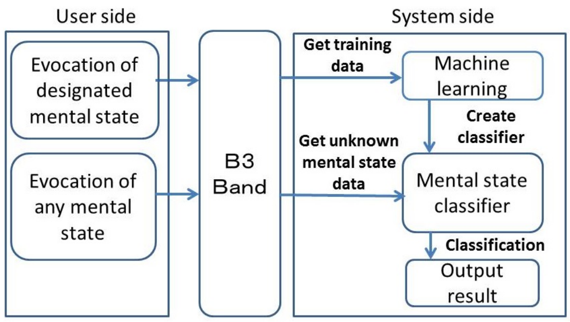

Fig. 2. Mental state classification process.

calculate the classification accuracy of the machine learning methods after training them.

First, the user's mental state evocation task for a given evocation of a mental state was executed. The data obtained were then used as a training dataset to train the learning methods. Next, the same user evoked a mental state in the same manner as the first task. In this classification task, the trained machine learning methods outputted the estimated mental states. The system then checked whether the estimated states matched the correct states.

IV. Mental state classification experiments

A. Experiments

In this section, we describe our mental state classification experiments. As mentioned in the previous section, we used machine learning methods in our study. Thus, we conducted the following two experiments to determine the optimal conditions for classifying brainwaves using the most appropriate machine learning method. Our experiments were conducted as follows.

- Experiment1: Mental state evocation method (from the user side).
- Experiment2: Mental state classification method (from the classification system side).

Experiment1 was performed to determine the optimal method for evoking mental states to facilitate their classification using machine learning methods. Experiment2 was conducted to determine the most accurate method for classifying mental states by testing various machine learning methods. Experiment1 aimed to find the classification conditions on the user side, as shown in Figure 2. Experiment2 aimed to find the classification conditions on the classification system side, as shown in Figure 2. To determine the optimal classification conditions, we calculated the classification accuracy and selected the conditions that obtained the highest accuracy in the two experiments. Both experiments were executed using R 3.0.2 packages, including e1071 and mvpart.

To conduct the two experiments, we recruited several participants and requested that they evoked each mental state, where we obtained the data using a FEP monitoring device. Each participant sat on a chair in a comfortable position and closed his/her eyes, thereby avoiding the generation of unrelated action potentials during the mental state evocation process in the experiment. Each participant evoked mental states in the order of: normal, relaxed, and concentration. The experiment comprised two steps: the training data collection step to create classifiers and the test data collection step for mental state classification. Each participant evoked each mental state once during the training data collection step and test data collection step.

A classifier was generated for each participant because their classifiers were constructed from brainwaves that differed among individuals. To consider the mental burden on the participants, we set the time required for each mental state evocation as 3 min. During this 3-min period, we used 2 min in the training data collection step to create the classifiers and 1 min in the test data collection step for mental state classification. Ten seconds were allocated as the mental state evocation transition period to reduce the mental burden on the participants during our experiments. After finishing the experiments, we excluded the first 20 seconds from the start of each mental state evocation dataset because we considered that the mental states were not stable in this interval. We generated the classifiers from the training data and applied the test data to each classifier that we generated. Finally, we compared the estimated (classified) mental states with the actual mental states evoked by the participants. We used the following equation (1) as our classification accuracy measure.

$$Accuracy = |CCS|/|ES|, \tag{1}$$

where ES is a set of the estimated mental states and CCS is a set of the correctly classified states in ES.

B. Experiment1: Mental state evocation method

Experiment1 was performed to determine the optimal method for evoking mental states suitable for machine learning methods. In this experiment, we compared two methods for mental state evocation to identify the method that obtained the highest classification accuracy. The two methods compared for mental state evocation were as follows.

1) Evocation method based on the recall of any image.
2) Evocation method using a specific action.

In the method based on the recall of any image, a mental state was evoked by imagining anything related to the corresponding mental state, i.e., any image could be selected by the participant. By contrast, in the method using a specific action, a mental state was evoked according to the following actions.

- Relaxed: Deep breathing and relaxation.
- Concentration: Mental arithmetic calculation.
- Normal: No specific actions

In this experiment, Support Vector Machine (SVM) was used as the machine learning method. We used all of the frequency power data obtained from the FEP monitoring device as input data for the SVM. We also used all of the aggregate data after calculating the average over 10s for the RAW data. In this experiment, four participants evaluated the first method by recalling any image, whereas seven participants evaluated the second method using a specific action. Table I shows the result of this classification experiment based on the evocation method where any image could be recalled. For each participant and each mental state, 31 data points were used to classify and estimate the mental states. Thus, the total number of estimated mental states was 93.

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TABLE I
EVOCATION BY ANY IMAGE

Participant	Mental state			
	Normal	Relaxed	Concentration	Total
A	51.61 %	0%	87.10 %	46.24 %
B	0%	32.26 %	48.39 %	26.88 %
C	0%	6.45 %	100 %	35.48 %
D	48.39 %	48.39 %	0%	32.26 %
Average	25.00 %	21.78 %	58.87 %	**35.22 %**

As shown in Table I, the overall average classification accuracy was 35.22% for the evocation method based on the recall of any image. It should be noted that there were large differences in the classified mental states. There were three mental states, so successful classification could be achieved by a random guess in 33.33% of cases. Therefore, the classifications of both the normal state and the relaxed state were inferior to a random guess, whereas that of the concentration state was far superior. Table I shows that the classifier could not obtain correct mental states for participants B and C. For example, the result was 0% for the normal state with participant B.

Table II shows the classification results for the evocation method using a specific action, which demonstrate that the overall average classification accuracy was 47.16%.

TABLE II
EVOCATION BY SPECIFIC ACTION

Participant	Mental state			
	Normal	Relaxed	Concentration	Total
E	35.48%	48.39%	77.42%	53.76%
F	96.77%	100 %	38.71%	78.49%
G	61.29%	41.94%	54.84%	52.69%
H	77.42%	16.13%	54.84%	49.46%
I	38.71%	38.71%	54.84%	44.09%
J	0%	38.71%	19.35%	19.35%
K	0%	0 %	96.77%	32.26%
Average	44.24%	40.55%	56.68%	**47.16 %**

Clearly, the evocation method using a specific action was superior to the evocation method based on the recall of any image in terms of the classification accuracy. Thus, we conclude that the evocation method using a specific action is more stable for mental state evocation because the accuracy of the evocation method using a specific action was higher than that of the evocation method based on the recall of any image, where the ratio with 0% of the total classification numbers was lower than that for the method based on the recall of any image.

C. Experiment2: Mental state classification method

Experiment2 was conducted to identify the optimal method for mental state classification using machine learning methods in various conditions. In particular, this experiment considered the following three factors ("views") related to machine learning.

- View A: Machine learning method
- View B: Data aggregation
- View C: Feature vector construction

For View A, we determined the optimal machine learning method that obtained the best mental state classification accuracy, where we compared seven machine learning methods.

1) SVM
2) Decision tree(CART)
3) K-Nearest Neighbor(K-NN) for K=1, 3, 5, 10, and 15

For View B, we examined the optimal data aggregation method, where we calculated the accuracy values by aggregating the RAW data obtained using various methods and window sizes. Five aggregation methods were compared.

1) Non-aggregated raw data (RAW)
2) Average for 5 seconds (Ave5)
3) Average for 10 seconds (Ave10)
4) Variance for 5 seconds (Var5)
5) Variance for 10 seconds (Var10)

For View C, we examined the combination of feature vectors that obtained the most accurate classification for machine learning. There were eight frequency regions so the number of possible combinations of regions was 255. The feature vector comprised the aggregated values for selected frequency regions.

To identify the optimal method and conditions, we calculated the classification accuracy for all 8925 combinations (7*5*255) based on the classifications results for all of the mental states. In this experiment, we employed the evocation method using a specific action and we considered the results obtained in the first experiment. This experiment was conducted with the same seven participants. Table III shows the results of our mental state classifications in Experiment2. We calculated the average classification accuracy for each combination, but only the top 20 results among the 8925 cases are shown in Table III. The amount of data used for classification differed from that used for aggregation, i.e., 40 mental states were classified based on the RAW data for each participant, 36 mental states were classified in Ave5 and Var5, and 31 mental states were classified in Ave10 and Var10.

D. Discussions

As shown in TableIII, the best combinations for mental state classification were [15NN, Ave10, $\theta+L\alpha+L\beta+H\beta$], [5NN, Ave10, $\theta+L\alpha+L\beta+H\beta$], and [Decision tree, Ave10, $\theta+L\alpha+M\gamma$], where [View A, View B, View C] represents a combination of View A, View B, and View C. The best combination was [15NN, Ave10, $\theta+L\alpha+L\beta+H\beta$] because the standard deviation of this combination was the lowest among the top three combinations.

By focusing on View A, we found that the decision tree method was listed six times in TableIII. Moreover, by focusing on View B, all of the combinations in TableIII included Ave10. Finally, by focusing on View C, the most common frequency regions included in the Top 20 feature vector constructions were [θ,$L\alpha$,$L\beta$,$H\beta$], as shown in TableIII, in the case of K-NN. For the decision tree, [δ,$M\gamma$] is the most common frequency region.

Therefore, based on our two experiments, we can conclude that the following method and conditions produced the best results.

- The evocation method using a specific action was better than the method based on the recall of any image.
- The best aggregation method was Ave10.
- The best combination of methods and conditions was [15NN, Ave10, $\theta + L\alpha + L\beta + H\beta$].

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TABLE III
TOP 20 PAIRS OF MENTAL STATE CLASSIFICATION ACCURACY

Ranking	Machine learning method	Aggregation method	Feature vector format	Average accuracy	Standard deviation
1	15NN	Ave10	$\theta + L\alpha + L\beta + H\beta$	**53.57 %**	**7.95**
1	5NN	Ave10	$\theta + L\alpha + L\beta + H\beta$	**53.57 %**	10.91
1	decision tree	Ave10	$\theta + L\alpha + M\gamma$	**53.57 %**	12.47
4	3NN	Ave10	$\theta + L\alpha + L\beta + H\beta$	53.10 %	10.82
5	10NN	Ave10	$\theta + L\alpha + L\beta + H\beta$	52.86 %	8.76
6	15NN	Ave10	$\theta + L\alpha + H\beta$	52.38 %	8.68
6	5NN	Ave10	$\theta + L\alpha + H\beta$	52.38 %	9.51
8	decision tree	Ave10	$\delta + \theta + L\alpha + H\alpha + M\gamma$	52.26 %	12.13
9	3NN	Ave10	$\theta + L\alpha + M\gamma$	51.43 %	9.19
10	15NN	Ave10	$\theta + L\alpha + L\beta$	51.07 %	6.91
10	10NN	Ave10	$\theta + L\alpha + H\beta$	51.07 %	9.22
12	10NN	Ave10	$\delta + \theta + L\alpha + H\alpha + L\beta + L\gamma$	50.83 %	7.98
12	10NN	Ave10	$\delta + \theta + L\alpha + H\alpha + L\beta$	50.83 %	9.17
12	decision tree	Ave10	$\delta + \theta + L\alpha + H\alpha + L\gamma + M\gamma$	50.83 %	9.87
12	decision tree	Ave10	$\delta + \theta + L\alpha + H\alpha + H\beta + M\gamma$	50.83 %	12.83
12	decision tree	Ave10	$\delta + \theta + L\alpha + L\beta + M\gamma$	50.83 %	13.18
17	15NN	Ave10	$\theta + L\alpha + H\alpha$	50.71 %	7.78
17	SVM	Ave10	$\theta + L\alpha + H\beta$	50.71 %	8.11
17	decision tree	Ave10	$\delta + \theta + L\alpha + M\gamma$	50.71 %	11.51
17	decision tree	Ave10	$\delta + L\alpha + L\beta + M\gamma$	50.71 %	12.15

- For K-NN, θ+$L\alpha$+$L\beta$+$H\beta$ should be included in the feature vector, while δ+$M\gamma$ should be included in the feature vector for the decision tree method.

V. CONCLUSION

In this study, we determined the best method for classifying mental states from FEP to produce a music recommender system using these brainwaves. Based on our two experiments, we can conclude that evocation using a specific action is necessary to extract a user's mental state. We can also conclude that the most accurate mental state classification method requires the use of the average over a 10-s period, a particular machine learning method such as K-NN or the decision tree, and the use of feature vectors such as θ+$L\alpha$+$L\beta$+$H\beta$ in K-NN. The development of our music recommender system still involves many issues that need to be addressed, including more detailed experiments, increased numbers of mental states, development of another evocation method to obtain better classifications, and selection of appropriate music related to the classified mental states.

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