Feature Vectors in Mental-State Classification Using Forehead-mounted Electrical Potential Monitoring Device

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***Abstract*—Music can improve human mental and physical states. Thus, music is used in various areas such as sport training and music therapy. 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. This paper examined the practical method to identify human emotion using brainwaves. In order to find the best method for human emotion detection, this paper conducted experiments to acquire brainwaves and determine human mental states. Based on the results of these experiments, the author proposes the optimal condition for classifying mental states using machine learning. The results show that Lγ and Mγ are elements of the important feature vector to improve classification accuracy. Using this method, the author plan to develop an accurate music recommender system, which should be effective for music-based sports training or music therapy can be developed.**

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

I. Introduction

Music is important for people because it makes people pleasure or enjoyment and it aids relaxation. Recently, It has been performed various services related to music. For example, 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 [1].

Moreover, music can improve human mental and physical states. For example, music can facilitate recovery from disease, which is known as mental therapy. Music is also used by sports players to make them calm and relaxed, or for stimulation [2]. 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 [1]. 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.

In our previous study [3], we proposed 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. Furthermore, 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 this paper, we determine the optimal condition by focusing feature vectors. Moreover, we calculate the influence on accuracy for each feature vector by considering all combinations.

In Section 2, we describe Forehead-mounted Electrical Potential and mental state classification method. In Section 3, we describe our previous study. Accuracy influence factor is described in Section 4. In Section 5, we describe evaluation experiments. Finally, we discuss our results and future research in Section 5.

II. Mental States Classification Method Using FEP

A. Single-channel Brainwaves Measuring Devices and FEP.

In general, multi-channel EEG instruments are used to monitor brainwaves. However, since we aim to apply our classification method to music therapy as well as sports training, brain waves were measured using a simple single-channel EEG device to classify mental states in our research. Brainwaves measurement may contain noisy data derived from other unknown biological phenomena in addition to brainwaves. It is difficult to remove the true brainwaves from the measured electrical potential data; thus, we refer to FEP in our study rather than brainwaves. The following eight frequency bands are used to calculate FEP.

δ: 0.5–2.75Hz
θ: 3.5–6.75Hz
Lα: 7.5–9.25Hz
Hα: 10.0–11.75Hz

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Lβ: 13.0–16.75Hz
Hβ: 18.0–29.75Hz
Lγ: 31.0–39.75Hz
Mγ: 41.0–49.75Hz

We used a consumer-grade inexpensive single-channel EEG sensor device called a Neuro-Bridge B3-Band. 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. 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 1 times per second. The sampling frequency of the RAW data was 512 Hz, so the window width and sampling size were set as 1 sec 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. *Mental States Classification Method and Experiments*

In our 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 to sports players before a game. Therefore, the data obtained from the monitoring device were classified into one of these three mental states using a machine learning method. The mental states classification is done as shown in Fig. 1.

First, the participant evokes designated mental states. The data obtained were used as a training dataset to generate classifier. A classifier was generated for each participant because their classifiers were constructed from brainwaves that differed among individuals. Next, the participant evokes a mental state in the same manner as the first. The data obtained were used as a test dataset. Then we 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 (1) as our classification accuracy measure.

$$Accuracy = \frac{|CCS|}{|ES|} \tag{1}$$

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

During measurement, 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. Furthermore to consider the mental burden on the participants, we set the time required for each mental state evocation as 2 minutes in the training data collection step, and 1 minute in the test data collection step. Ten seconds were allocated as the mental state evocation transition period to reduce the mental burden on the participants during our experiments. And, 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.

III. Previous Experiments [3]

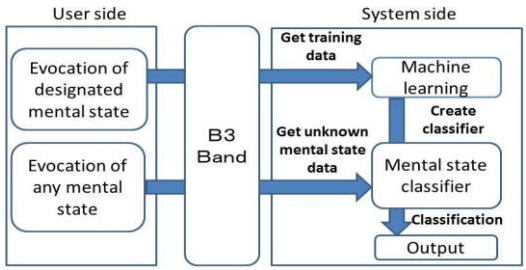

Figure 1. Mental state classification flow

In our previous study, we determined a suitable method for machine learning in the flow as described in Fig. 1. We conducted the following two experiments.

Experiment 1: Mental state evocation method.
Experiment 2: Mental state classification method.

Experiment 1 was performed to determine the optimal method for evoking mental states to facilitate their classification using machine learning methods. Experiment 2 was conducted to determine the most accurate method for classifying mental states by testing various machine learning methods.

A. *Experiment 1: Mental State Evocation Method*

In this experiment, we compared two methods as follows for mental state evocation to identify the method that obtained the highest classification accuracy.

- Evocation by any image
- Evocation by specific action

In the first method, mental states were evoked by imagining anything related to the corresponding mental state, i.e., any image could be selected by the participant. By contrast, in the second method, mental states were 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 as input data for the SVM. We also used all of the aggregate data after calculating the average over 10 seconds for the RAW data. In this experiment, four participants evaluated the first method, whereas seven participants evaluated the second method. Table I shows the average classification accuracy of each evocation method.

As shown in Table I, classification accuracy of the evocation method by specific action is superior to classification accuracy of the evocation method by any image by 11.94%.

TABLE I. Accuracy of Evocation Method

Method	Normal	Relaxed	Concentration	Total
Image	25.0	21.8	58.9	35.2
Action	44.2	40.6	56.7	47.2

B. Experiment 2: Mental State Evocation Method

Experiment 2 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 related to machine learning. The first factor is Machine learning method. We compared seven machine learning methods to identify the optimal method. There were SVM, Decision tree (DT) and K-NN (K=1, 3, 5, 10, 15). The second factor is data aggregation method. We calculated the accuracy values by aggregating the RAW data obtained using various methods and window sizes. We compared five aggregation methods as follow.

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

The third factor is feature vector construction. We examined the combination of feature vectors that obtained the most accurate classification. There were eight frequency regions so the number of possible combinations of regions was 255. 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 II shows the top 20 results of Experiment 2.

As shown in Table II, by focusing on the first factor, we found that the decision tree method was listed six times in top 20. Moreover, by focusing on the second factor, all of the combinations in top 20 included Ave10. Finally, by focusing on the third factor, the most common frequency regions in decision tree were [δ, Mγ].

We considered only top 20 results in this experiment. Therefore, it is difficult to identify the optimal condition of feature vectors from the result of only top 20. It is because all combinations are 255 ways more than 20. Therefore, we determined to focus on feature vectors, and we perform experiments to determine the optimal condition by considering all combinations.

IV. Accuracy Influence Factor

As described before, we determined the optimal conditions for each three factors from the result of top 20. In the first and the second factors, it is possible to determine the optimal conditions, because the choices can be made from only several types. However, it is difficult to determine optimal condition in the third factor, because the choices are combinations of many vectors.

Furthermore, even if a vector v often shows in high classification accuracy, v is not necessarily an important vector for classification accuracy. Because there is a possibility that the classification accuracy of combinations besides v is high. For example, both classification accuracy of the 12th and the 13th in Table II are not much different by presence or absence of Lγ. Namely, the important vector is a vector except Lγ. Lγ is not important to classification accuracy, because it doesn't influence classification accuracy. Moreover, if the classification accuracy of combinations besides v is higher than classification accuracy of combinations including v, v is an unnecessary vector because v exerts a bad influence for classification accuracy. For example, both classification accuracy of the 3rd and the 19th in Table II are lowered by δ.

TABLE II. Top 20 Pairs

Ranking	Machine learning	Aggregation	Feature vector	Accuracy
1	15NN	Ave10	θ,Lα,Lβ,Hβ	53.57
2	5NN	Ave10	θ,Lα,Lβ,Hβ	53.57
3	DT	Ave10	θ,Lα,Mγ	53.57
4	3NN	Ave10	θ,Lα,Lβ,Hβ	53.10
5	10NN	Ave10	θ,Lα,Lβ,Hβ	52.86
6	15NN	Ave10	θ,Lα,Hβ	52.38
7	5NN	Ave10	θ,Lα,Hβ	52.38
8	DT	Ave10	δ,θ,Lα,Hα,Mγ	52.26
9	3NN	Ave10	θ,Lα,Mγ	51.43
10	15NN	Ave10	θ,Lα,Lβ	51.07
11	10NN	Ave10	θ,Lα,Hβ	51.07
12	10NN	Ave10	δ,θ,Lα,Hα,Lβ,Lγ	50.83
13	10NN	Ave10	δ,θ,Lα,Hα,Lβ	50.83
14	DT	Ave10	δ,θ,Lα,Hα,Hβ,Mγ	50.83
15	DT	Ave10	δ,θ,Lα,Hα,Lγ,Mγ	50.83
16	DT	Ave10	δ,θ,Lα,Lβ,Mγ	50.83
17	15NN	Ave10	θ,Lα,Hα	50.71
18	SVM	Ave10	θ,Lα,Hβ	50.71
19	DT	Ave10	δ,θ,Lα,Mγ	50.71
20	DT	Ave10	θ,Lα,Lβ,Mγ	50.71

From this discussion, we focus on feature vectors and conduct experiments to determine the optimal condition only using feature vectors. Specifically, we determine the optimal condition by not the vectors that frequent in the combination of higher rank classification accuracy but influence on classification accuracy of each vector. Namely, we compare classification accuracy of combination including the specific vector with classification accuracy of combination except the specific vector, and we focus on the difference of classification accuracy. Moreover, we calculate influence on classification accuracy of each vector, and determine the optimal condition. In this study, we define Accuracy Influence Factor (AIF) as the influence on classification accuracy of each vector.

AIF is obtained by following process. Assume that there is a vector v_i, where $\{v_i\}_{i=1\sim8}$ are δ, θ, Lα, Hα, Lβ, Hβ, Lγ and Mγ, respectively. Furthermore, v_i is 1 when v_i is used in combination, otherwise v_i is 0. The classification accuracy using $\{v_i\}_{i=1\sim8}$ is $S(v_i)$. Moreover, the classification accuracy is 1, because it is necessary to

use one or more than one. Hence, $S(v_i)$ is denoted following (2).

$$S(v_i) = \begin{cases} 1 & if \quad \left(\{v_i\}_{i=1\sim8} = \{0\}\right) \\ P\left(Correct \middle| \{v_i\}_{i=1\sim8}\right) & otherwise. \end{cases} \tag{2}$$

Next, we defined the AIF for each vector = $\{AIF_n\}_{n=1\sim8}$, respectively. AIF_n is obtained by (3), because AIF_n is obtained by calculating the average of all combinations of $S(v_i|v_n=1)/S(v_i|v_n=0)$.

$$AIF_n = \frac{1}{2^7}\sum_{\{v_i\}_{i\neq n}} \log\frac{S(v_i|v_n=1)}{S(v_i|v_n=0)} \tag{3}$$

If AIF_n is positive value, we speculate the classification accuracy can be improved with the vector n. In contrast, if AIF_n is negative value, we speculate the classification accuracy may be reduced with the n. Thus, we speculate that the optimal condition for machine learning can be obtained by choosing the vector of such positive value.

V. Evaluation Experiments

In this section, we describe evaluation experiments using AIF. We calculate the classification accuracy of all feature vector combinations using the FEP data that were obtained by process of Section 2. Furthermore, we calculate the AIF for each feature vector. Moreover, we compare the classification accuracy corresponding to AIF with the other combinations. In this experiment, since we focus on the optimal condition of feature vectors, we employ decision tree and Ave10. The experiments are conducted with four participants, and we conducted two times for each participant. For each measurement 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. Table III shows the result of average AIF for each feature vector.

TABLE III. Average AIF for Each Feature Vector

Vector	Average AIF	Standard deviation
δ	0.04	0.25
θ	0.08	0.27
Lα	0.15	0.38
Hα	0.06	0.18
Lβ	-0.03	0.19
Hβ	0.10	0.49
Lγ	0.25	0.32
Hγ	0.26	0.37

Table IV shows the classification accuracy using feature vectors of positive value in Average AIF. Moreover, Table IV shows ranking of the classification accuracy in the all combinations.

Table IV shows the classification accuracy is higher than average accuracy and the ranking is upper in A1, C1, A2, C2 and D2. However, the classification accuracy is a little lower than average accuracy and the ranking is middle of those of B1 and B2. Moreover, the classification accuracy is lower than average accuracy and the ranking is lower in D1.

TABLE IV. Accuracy and Ranking

	Measurement	A	B	C	D
1st	Accuracy of using AIF	59.1	30.1	52.7	30.1
	Average of all Combinations	54.5	32.7	47.8	34.9
	Ranking	6	140	78	185
2nd	Accuracy of using AIF	66.7	50.5	33.3	50.5
	Average of all combinations	55.5	52.4	31.9	35.3
	Ranking	1	146	16	18

The result in Table IV, shows classification accuracy using all feature vectors with a positive value in Average AIF. However, as shown in Table IV, there are many cases attained that high classification accuracy using comparatively less feature vectors. Thus, we estimate that using all feature vectors with a positive value is not always good result. Therefore, first, we calculate the classification accuracy using only the highest vector in average AIF. Next, we calculate the classification accuracy, every time we increase number of feature vector used in machine learning in the order of AIF. The result is shown in Table V.

As shown in Table V, when we used the feature vectors of top 5 the value of AIF, the average accuracy is the highest.

A. Discussions

First, we should note AIF for each feature vector. As shown in Table III, the Average AIF of δ, θ, Lα, Hα, Hβ, Lγ and Mγ is positive value. Thus, we estimate that the classification accuracy can improved by using the such feature vector. In particular, the AIF of Lγ and Mγ is especially high. Moreover, the AIF of δ and Hα is high. Therefore, δ, Hα, Lγ and Mγ is important feature vector to improve classification accuracy. In contrast, the AIF of Lβ is negative value.

Thus, Lβ is an unnecessary feature vector, because Lβ exert a bad influence for classification accuracy.

TABLE V. Accuracy and Ranking using AIF

Number of used Feature Vectors	Average Accuracy	Ranking
1	36.4	179
2	46.9	93
3	46.8	73
4	48.7	**44**
5	**49.5**	55
6	48.0	62
7	46.6	74
8	45.8	81

The next important thing to be noted is the relationship between the classification accuracy and the number of feature vector. As shown in Table V, the classification accuracy is much improves in all participants, when the number of feature vector is increased from 1 to 2. Moreover, the overall classification accuracy is gradually improving every time the number of feature vector is increase. When the number of feature vector is five, the average classification accuracy is maximum value. However, the classification accuracy is down in the later. Thus, the classification accuracy is higher in the most stable, when we use θ, Lα, Hβ, Lγ and Mγ.

VI. Related Work

Various studies have analyzed music and brainwaves in two main areas: the usage of brainwaves for music search and music analysis. Furthermore, general brainwaves-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 [4] [5] [6] [7] in this area. Morita et al. proposed a system where brainwaves are used as an input to search for music requested by a user [4]. Cabredo *et al*. proposed an emotion-based model for music retrieval using brainwaves [5]. This model comprised 4 emotional states, 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. We consider some of the main research [8] [9] [10] from this area. Based on experiments, Yamanishi et al. reported that brainwaves are affected by musical chords and chord correlations in harmony [8]. Petrantonakis *et al*. proposed an emotion-related information retrieval method based on brain EEG signals obtained from users when they observed pictures that caused emotional stimulation [9]. Nishimoto *et al*. proposed a method for visualizing the dynamic brain activities of users who watched movies, using fMRI [10].

Brain-Computer Interface (BCI) is now a highly active research field [11]. Chuang *et al*. proposed a new method of for user authentication using brainwaves [12], 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 [13]. Furthermore, O'Hara *et al*. [14] studied a simple BCI game from the viewpoint.

VII. Conclusion

In this study, we determined the optimal condition of feature vector by calculating AIF. Based on evaluation experiment, we can conclude Lγ and Mγ is important feature vector to improve classification accuracy. Moreover, Lβ is an unnecessary feature vector, because Lβ exert a bad influence for classification accuracy. Furthermore, the optimal condition of feature vector is θ, Lα, Hβ, Lγ and Mγ. Our mental states classification systems still need to improve classification accuracy. The classification accuracy is low, because the participants of experiment less. Therefore, we would like to conduct experiments to increase the participants in the future work.

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