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Common Frequency Pattern for Music Preference Identification using Frontal EEG

Yaozhang Pan*, Cuntai Guan, Juanhong Yu, Kai Keng Ang and Ti Eu Chan

***Abstract*— In this paper, we investigate the use of 2-channel frontal EEG signal to classify two music preferences: like and dislike. The hypothesis for this investigation is that the frontal EEG signal contains sufficient information on the mental state of a subject for discriminating the preference of music of the subject. An experiment is performed to collect 2-channel frontal EEG data from 12 subjects by playing various types of music pieces and asking whether they like or dislike the music in order to obtain the true labels of their music preferences. We then propose a frequency band optimization method called common frequency pattern (CFP) for feature extraction and Linear SVM for classification to identify the music preference of the subjects from the 2-channel frontal EEG. The results of using the proposed method yield an average classification accuracy of 74.77% for a trial length of 30 s over the 12 subjects. Hence the experimental results show evidence that frontal EEG signal contains sufficient information to discriminate preference of music. Furthermore, the frequency band optimization results indicate that gamma band is essential for EEG-based music preference identification.**

I. Introduction

Listening to music plays an important role among higher brain functions [1], and EEG response to music perception has been studied for some time [2]–[4]. An important aspect of music perception that gained much research interest is the music evoked emotion [5]–[7].

Among these studies, different frequency band of EEG signal were investigated and discovered to be associated with music perception. The most frequently studied frequency bands including theta (4-8 Hz), alpha (8-12 Hz), beta (12-30 Hz), while some studies also involve delta (0-4 Hz) and gamma band (30-45Hz). In [8], it was reported that the frontal brain EEG alpha power was closely related to valence and intensity of music emotion. It has also been verified in [9] that EEG alpha band power were related to emotion valence and modulated by emotional intensity. In [10], Nakamura et al. investigated EEG beta rhythm and reported that compared with the rest condition, listening to music caused a significant increase in EEG beta power spectrum (13-30 Hz). In [11], the authors found that pleasant (contrasted to unpleasant) music was associated with an increase of frontal midline (Fm) theta power. Although all these EEG bands were demonstrated to be highly associated with music perception, there was fewer studies related to gamma band on music evoked emotion or preference. As such, it would be very interesting to study the gamma band activity in EEG signal during music listening that correlate with music evoked emotion or preference. In [12], Delta and gamma rhythms in left frontal region were reported to be best features for differentiating between native and foreign languages songs. In [4], it was found while listening to music, a significant high degree of phase synchrony in the gamma frequency range globally distributed over the brain was found in subjects with musical training (musicians) compared with subjects with no such training (non-musicians).

In this paper, we present a method to classify the music preference based on the EEG response during music listening. We focus more on finding the optimal frequency band for classifying music preference as well as for understanding which frequency bands are highly correlated to the music evoked preference. As such, we propose a supervised frequency optimization method, named Common Frequency Pattern (CFP). The idea of the proposed CFP is motivated by a well-known feature extraction algorithm Common Spatial Pattern (CSP) [13]. Instead of finding the optimal spatial filter to maximize the separability of 2-class data, the proposed CFP aims to find the optimal spectral filter to maximize the separability of 2-class data.

The original CSP algorithm only focus on spatial filter optimization but cannot select optimal frequency band. Several approaches were proposed to address the issue of selecting optimal frequency band for the CSP algorithm. For example, the Common Spatio-Spectral Pattern (CSSP) which optimizes a simple filter that employed a one time-delayed sample [14]; the Common Sparse Spectral-Spatial Pattern (CSSSP) which performs simultaneous optimization of an arbitrary Finite Impulse Response (FIR) filter [15]; and the Filter Bank Common Spatial Pattern (FBCSP) [16] which selects the best frequency bands through mutual information based feature selection.

Compared to the above methods focused on spatial information of multi-channel EEG, the proposed CFP method deals with different frequency bands of each single channel EEG signal by directly reconstructing the original multi-channel EEG epoch matrix of "channels $\times$ samples" in CSP to single channel EEG epoch matrix of "filter banks $\times$ samples". Through this manipulation, we can easily find the most discriminative information from multiple filter banks of each single channel EEG through discriminative optimization. The filter banks optimization results can help us understand which frequency range of the EEG signal contains the most essential information for identify music preference. Furthermore, this modification is especially helpful to our experimental

*To whom all correspondences should be addressed. Tel. (65) 6408-2645.
Yaozhang Pan, Cuntai Guan, Juanhong Yu, Kai Keng Ang and Ti Eu Chan are with Institute for Infocomm Research, Agency for Science, Technology and Research (ASTAR), 1 Fusionopolis Way, #21-01 Connexis, Singapore 138632. Email:yzpan, ctguan, jyu, kkang, techan@i2r.a-star.edu.sg

setting that only records 2-channel EEG for potential user-friendly BCI applications.

II. METHODS

This section introduces the protocol of data collection, the algorithms used in processing the EEG data, including frequency optimization for feature extraction, feature selection and classification.

A. Data Collection Protocol

EEG signal were acquired using NeuroSky-MindBand with a sampling rate of 256 Hz, 2 EEG electrodes were attached horizontally to subjects' forehead. The left and right electrodes corresponded to FP1 and FP2 respectively.

The data were collected from 12 healthy subjects. Each subject was instructed to sit comfortably and minimize body movement during listening to music, with eyes open. Before listening to music, the subject was given some time to calm down and concentrate on the listening.

For each subject, 2 sessions were done on separate days. Each session contained 3 runs in about 1 hour. Subjects were advised to take a little break after each run. At the beginning of each session, the subject was asked to choose 4 genres from 10 available genres (Alternative Rock, Classic, Electro, Heavy Metal, Hip Hop, Jazz Blues, Oldies, Pop, Reggae, and Rock). Then 3 music lists, each contained 20 piece of music with length about 30 s, were generated by randomly selecting music from the music database of the 4 chosen genres. Each music list was played in one run, during which the subject would continuously listen to the music and label each piece of music after finishing. The subjects were then asked to tell whether they like, dislike or feel neutral with the music to obtain the true labels for the experiment. There are a total of 120 trials of EEG for each subject. Later, the "5×5-fold" cross-validation is performed on each subject's data for evaluating the performance.

B. Common Frequency Pattern for Frequency Optimization

In this work, we focus on finding the optimal frequency band which is mostly associated with the music evoked mental states. As such, we proposed a supervised frequency optimization method, named common frequency pattern (CFP) to optimize spectral filter for music preference identification.

In summary, the signal $\boldsymbol{Y}$ after optimized spectral filtering of a single trial single channel EEG $\boldsymbol{X}$ is given as

$$\boldsymbol{Y} = \boldsymbol{W}\boldsymbol{X} \tag{1}$$

where $\boldsymbol{X}$ represents a single trial and single channel EEG signal with multiple frequency bands. Each row of $\boldsymbol{X}$ is the bandpass filtered EEG signal of a filter bank, $\boldsymbol{X} \in R^{N\times T}$, N is the number of frequency bands, T represent number of temporal sample per trial. $\boldsymbol{W}$ is the projection matrix consists of optimal spectral filters as each row. Each columns of $\boldsymbol{W}^{-1}$ are the common frequency patterns.

Suppose that $\boldsymbol{X}_a$ or $\boldsymbol{X}_b$ represents single cannel signal trial EEG for "like" and "dislike" classes respectively. Similar to CSP, the method employed by the CFP algorithm is based on the simultaneous diagonalization of two covariance matrices [13].

$$\boldsymbol{\Sigma}_i = \frac{1}{Q_i}\sum_{Q_i}\frac{\boldsymbol{X}_i(\boldsymbol{X}_i)^T}{\text{trace}[\boldsymbol{X}_i(\boldsymbol{X}_i)^T]}, i \in \{a, b\} \tag{2}$$

where $\boldsymbol{\Sigma}_i$ are the covariance matrices estimate by average across all trials.

Technically, the simultaneous diagonalization can simply be achieved by solving the generalized eigenvalue problem

$$\boldsymbol{\Sigma}_a\boldsymbol{W}^T = \boldsymbol{\Lambda}\boldsymbol{\Sigma}_b\boldsymbol{W}^T \tag{3}$$

where $\boldsymbol{\Lambda}$ is a diagonal matrix and the largest and smallest diagonal elements in Λ are corresponding to the optimized spectral filters which keep most discriminative information.

The proposed CFP approach is illustrated in Fig. 1

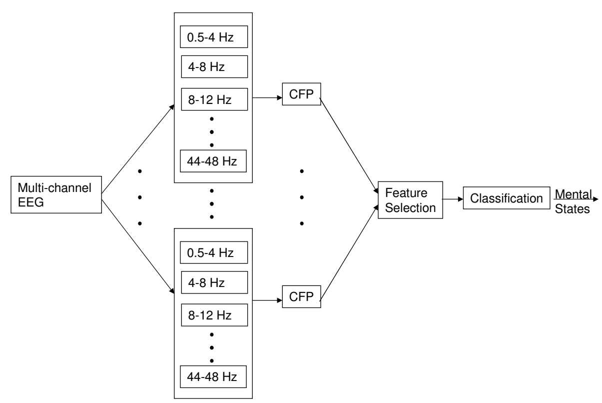


Fig. 1. Architecture of the proposed Common Frequency Pattern (CFP) machine learning approach

C. Mutual Information-based Feature Selection

In Mutual Information (MI)-based feature selection, the problem is defined as, given an initial set F with d features, find the subset $S \in F$ with k ($k < d$) features that maximizes mutual informaiton $I(S, \Omega)$ [17]. The MI between the two d-dimensional random variables is

$$I(\boldsymbol{X}, \boldsymbol{Y}) = H(\boldsymbol{Y}) - H(\boldsymbol{Y}|\boldsymbol{X}) \tag{4}$$

where

$$\begin{aligned} H(\boldsymbol{Y}) &= -\sum_{y\in\boldsymbol{Y}} p(y)\log_2 p(y) \\ H(\boldsymbol{Y}|\boldsymbol{X}) &= -\sum_{x\in\boldsymbol{X}}\sum_{y\in\boldsymbol{Y}} p(x,y)log_2 p(y|x) \end{aligned} \tag{5}$$

are the entropy of random variable $\boldsymbol{Y}$ and conditional entropy of random variables $\boldsymbol{X}$ and $\boldsymbol{Y}$, $p(\cdot)$ is probability function.

In this paper, we firstly initialize a set of d features $F = \{f_1, f_2, \ldots, f_d\}$, and then compute the MI between features and class Ω: $I(f_i, \Omega)$, $\forall i = 1, 2, \ldots, d$, $f_i \in F$. The last step is to select the best k features which maximizes $I(f_i, \Omega)$. The MIBIF feature selection algorithm requires a user-defined parameter k, we use $k = 6$ in this study.

D. Classification

In the classification stage, the feature vector is assigned to the like and dislike class by Support Vector Machine (SVM).

The SVM [18] is a linear discriminant that maximizes the spparation between two classes based on the assumption that it improves the classifier's generalization capability. This is achieved by minimizing the cost function

$$J(\boldsymbol{W}) = \frac{1}{2}||\boldsymbol{W}||^2 \tag{6}$$

subject to the constraint

$$Y_i(\boldsymbol{W}' \cdot \boldsymbol{X}_i - b) \geq 1, \forall\ i = 1, 2, \ldots, n \tag{7}$$

where $\boldsymbol{X}_i$, $i = 1, 2, \ldots, n$ are the training data, b is a bias.

III. Results

This section verify the efficiency of our algorithm, through the experimental results, and comparison to the benchmark methods.

In order to investigate the hypothesis that gamma band EEG contains important information of music perception, we calculate the test accuracy of music preference classification using different band power as features. The classification results for the 12 subjects using different band power are shown in Table I, and those of 5 selected subjects are shown in Fig. 2. It is clearly illustrated that gamma band gives best result for most of subject, but other frequency bands also have good performance in some subjects. It demonstrates that gamma band EEG is essential but the optimal bands in music preference classification is subject dependant. As such, to find the best combination of frequency bands for each subject is necessary. In this study we use CFP algorithm for the spectral filter optimization. Fig. 3 shows the largest projection weights obtained by CFP (also known as the optimized spectral filters) of two subjects, which also indicate that gamma band is essential for EEG-based music preference identification.

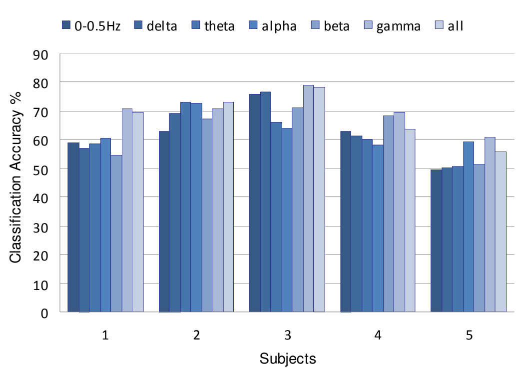
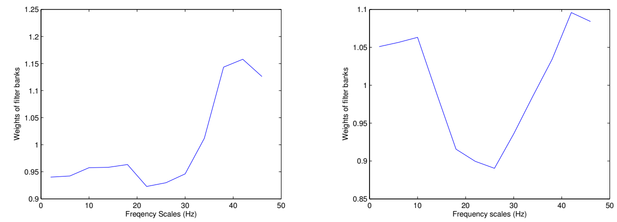


Fig. 2. Classification accuracy comparison among different frequency bands

In order to evaluate the performance of our proposed method, we compare it with some benchmark methods. Through a thorough literature review, we choose several methods in the area of music-evoked EEG processing for comparison, most of which was focus on feature extraction. The details of this methods are listed in Table II.



(a) Subject 1 (b) Subject 3

Fig. 3. Optimized spectral filters for two subjects

Classification results of several combinations of feature extraction methods and classifiers are shown in in Table III. The included feature extraction methods and classifier are good representatives of previous studies in this area. To be fair, for all methods, we used the same frequency band EEG of 0.5-48 Hz. The test accuracies are obtained by "5×5-fold" cross validation for each subject. Results shown in Table III are the average values and standard derivations across 12 subjects. Compare to all other methods, our proposed method with CFP for feature extraction and SVM for classifier obtains the highest accuracy.

TABLE III
AVERAGE ACCURACY OF DIFFERENT FEATURE EXTRACTION METHODS AND CLASSIFIERS

Classifier	BFDA	Logistic-regression	SVM
CFP	64.90 ±7.13	65.88±7.70	**74.77±5.36**
PCA	58.29 ±10.93	59.11±10.10	64.03±8.30
Spectral Filter	61.63 ±11.02	60.32±10.01	68.22±11.13
DASM	65.25 ± 10.26	61.03±7.28	65.88±10.83

IV. Discussions

The preliminary results of this paper demonstrate the feasibility of classifying music preference using frontal 2-channel EEG signal. As music is an effective emotion evoker, music preference classification has promising application potential on both cognitive and neuroscience researches, and real world applications. With the fast development of brain computer interface (BCI) and music therapy, the research on relationship among music, EEG and emotion become more valuable. The potential applications in this direction include BCI-based music recommendation system and BCI-based music therapy.

V. Conclusion

In this paper, we investigated the feasibility of identifying the music preference of subjects using 2-channel frontal EEG signal recoded during listening to music. We proposed a frequency band optimization method called common frequency pattern (CFP) for feature extraction, and used mutual information-based method for feature selection and linear SVM for classification. The frequency band optimization results of 12 subjects' EEG data showed that gamma band is essential for EEG-based music preference identification. The results of using the proposed method on the EEG of

TABLE I

TEST ACCURACY OF DIFFERENT RANGE OF SPECTRAL[1]

Frequency Bands[2]	0-0.5 Hz	δ	θ	α	β	γ	All
Subject 1	61.13	62.26	62.64	60.00	61.51	**74.34**	73.21
Subject 2	58.87	58.87	60.00	60.38	50.57	**73.96**	72.45
Subject 3	56.43	49.64	53.21	61.79	52.14	**63.93**	62.50
Subject 4	56.17	71.91	**80.43**	80.00	77.87	74.47	78.30
Subject 5	**69.62**	66.54	65.38	65.38	56.92	66.92	67.69
Subject 6	72.86	**76.07**	65.36	65.36	71.07	**76.07**	69.64
Subject 7	78.55	77.09	66.55	62.91	70.91	81.82	**86.55**
Subject 8	70.21	71.91	68.09	61.28	77.02	**80.43**	75.74
Subject 9	55.32	50.64	51.91	54.89	**59.57**	58.72	51.49
Subject 10	37.50	36.25	40.63	50.00	43.75	**60.00**	46.88
Subject 11	61.25	64.58	60.83	**68.75**	59.17	61.67	64.58
Subject 12	61.63	62.34	61.37	62.79	61.86	**70.21**	68.09

[1] Filter bank spectral analysis were used here.

[2] δ:0.5-4 Hz, θ: 4-8 Hz, α:8-14 Hz, β:14-30 Hz, γ: 30-48 Hz, All:0-48Hz.

TABLE II

PREVIOUS STUDIES ON MUSIC-EVOKED EEG CLASSIFICATION

Features	Classification	No. of subjects	No. of channel	Classes type	Result	Ref
DASM12[1] (1-50Hz),	SVM	26	32	4 emotions	82.29%	[19]
Spectral Filter (1-14 Hz)	Logistic-regression	10	64	7 musical fragments	55%	[20]
CSP (0-50 Hz)	SVM	6	64	Chinese/Japanese song	87.15%	[12]
CSP (0-0.5 Hz)	SVM	6	64	Chinese/Japanese song	86.02%	[12]
PCA (alpha,beta)	BFDA[2]	5	5	valence-arousal	90%	[21]

[1] Differential asymmetry of 12 electrode pairs.

[2] Binary fisher discriminant analysis

12 subjects yielded an average classification accuracy of 74.77%, which showed evidence that frontal EEG signal contains sufficient information for discriminating the music preference of an individual. This preliminary results showed great potential for developing novel entertainment BCI system using the proposed method.

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