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EEG Dynamics during Music Appreciation

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Abstract— **This study explores the electroencephalographic (EEG) correlates of emotions during music listening. Principal component analysis (PCA) is used to correlate EEG features with complex music appreciation. This study also applies machine-leaning algorithms to demonstrate the feasibility of classifying EEG dynamics in four subjectively-reported emotional states. The high classification accuracy (81.58±3.74%) demonstrates the feasibility of using EEG features to assess emotional states of human subjects. Further, the spatial and spectral patterns of the EEG most relevant to emotions seem reproducible across subjects.**

I. Introduction

BIO-inspired multimedia research has been a growing research topic. The ultimate goal of this field is to study the interaction between the multimedia content and psycho-physiological and neurophysiologic measures of the listeners or viewers. By combining techniques in multimedia and bio-signal processing, these studies aimed to not only create the concept of the human-centered orientation, but also build a multimedia environment in which users can fully immerse in enjoyment. This study focuses on assessing brain dynamics associated with emotions during music listening and try to analyze it from brain activity pattern.

Electroencephalography (EEG) is a noninvasive and direct measurement of brain activity with temporal resolution in milliseconds. EEG has been widely used in the field of cognitive neuroscience to investigate the regulation and processing of emotions for many years. By transforming the EEG signals into the frequency domain, several EEG spectral components have been found to reliably accompany functional states of the brain. The most widely used components are defined in different frequency ranges, such as delta (1-3 Hz), theta (4-7 Hz), alpha (8-13 Hz), beta (14-30 Hz) and gamma (31-50 Hz) [1]. In fact, several brain oscillations in various frequency bands are associated with multifold brain functions [2]. With respect to emotion research, one of the most common indicators of emotional state is the alpha power asymmetry formed by spectrum power difference between a symmetric electrode pair, when measured at the anterior portion of brain [3, 4]. Other literatures reported other brain regions such as the right parietotemporal region [5] and spectral contents such as theta [6, 7] involving in the processing of emotional information. It is, however, not too surprising that complex cognitive functions are accompanied by several brain oscillations in combination [2].

This study explores the EEG correlates of emotions during music listening using principal component analysis (PCA) to characterize spatial and spectral dynamics of EEG. The components accounting for distinct features of the EEG are used to classify different self-reported emotional states.

II. Material and Method

A. EEG Recording and Experiment Procedure

This work extended from our previous study [8] in which 26 subjects' EEG data were recorded during music listening. Data recording and experiment procedure are briefly depicted. A thirty-two (32) channel EEG system (Neuroscan, Inc) was used to record the EEG of subjects participating in the music listening experiments. Its sampling rate and filter bandwidth were set to 500 Hz and 1~100Hz respectively. Subjects were instructed to report their emotions (joy, angry, sadness and pleasure) after each of sixteen (16) 30-s segments during the music listening.

B. Feature Extraction

The recorded EEG data were first preprocessed to remove obvious and large motion artifacts using visual inspection. Then, short-time Fourier transform (STFT) with Hanning window of one second and without overlap was used to extract the power spectral density values in different frequency bands, including delta (1-3 Hz), theta (4-7 Hz), alpha (8-13 Hz), beta (14-30 Hz) and gamma (31-50 Hz). In this way each of sixteen 30-s segment of EEG recording would yield around 30 spectral points (in total of 480 points per subject). In addition, our previous study [8] showed that emotion-state classification based on spectral differences between symmetric electrode pairs, ASM12, outperformed that based on spectral values of individual scalp channels. This study adopted the method by calculating spectral differences of 12 symmetrical pairs as the input features for PCA. Fig. 1 shows 12 symmetric electrode pairs from 32-channel EEG, including Fp1-Fp2, F7-F8, F3-F4, FT7-FT8, FC3-FC4, T7-T8, P7-P8, C3-C4, TP7-TP8, CP3-CP4, P3-P4, and O1-O2.

Then, PCA is used to separate EEG spectra into uncorrelated and significant components. The goal is to reduce the dimensionality of input dataset where there are probably a large number of related variables. This is achieved

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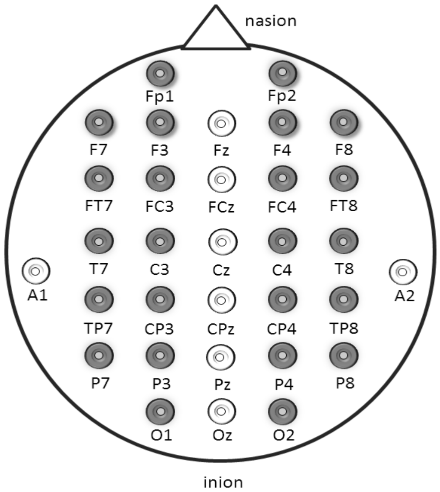

Fig. 1. The locations of 12 electrode pairs on 32-channels EEG. (Electrodes in gray represent the symmetric pairs for ASM12 feature extraction)

by combining input variables to generate a set of new variables called principal components (PCs) that are ordered by the variance counted for the input dataset. By retaining first few PCs accounting for most of the variance of the dataset, the dimensionality of the feature space could be reduced. The resultant lower-dimensional feature space was used for further analysis. Here, PCA was applied to ASM12, with spectral differences in delta, theta, alpha, beta, and gamma forming a feature dimension of 60 (12 electrode pairs x 5 frequency bands). In order to investigate how much variance should be retained to lead an acceptable performance, the results of retaining 80-100% of the total variance was compared, where the dimension of feature space would vary depending on the number of retained PCs.

The corresponding emotional class for each segment was assigned according to the subject's self report. It was noted that 30 sample points extracted from each 30-s segment have the same emotional class. Further, before feeding data to classifier, the feature vector were normalized at the range from 0 to 1.

C. Feature Classification and Selection

This study applied a support vector machine (SVM) to EEG to perform the emotion-specific classification. SVM is one of the most popular supervised learning algorithms for solving the classification problems. The basic idea is to project input data into a higher dimensional feature space via a transfer kernel function, which is easier to be separated than that in the original feature space. Depending on input data, the iterative learning process of SVM would eventually devise optimal hyperplanes with the maximal margin between each class. These hyperplanes would be the decision boundaries for distinguishing different data clusters. This study used LIBSVM software [9] to build the SVM classifier and employ radial basis function (RBF) kernel to nonlinearly map data onto a higher dimension space.

PCA is not a feature selection but a feature extraction method. Although the new attributes are obtained by a linear combination of the original attributes. Dimensionality reduction is achieved by keeping fewer components accounting for most of the variance. However, the variation of each PC is confounded with both factors coming from within- and between-classes. Therefore, in order to explore which PC is informative to differentiate different emotion states, the between-class variation need to be identified first. To this end, the study adopted a feature selection tool [10], in which an F-score statistical index was used as a feature selection criterion to iteratively generate a rank list describing the contribution of feature attributes by the SVM classifier. The F-score of the ith feature is defined as:

$$F(i) = \frac{\sum_{l=1}^{g} n_l (\bar{x}_{l,i} - \bar{x}_i)(\bar{x}_{l,i} - \bar{x}_i)'}{\sum_{l=1}^{g} \sum_{k=1}^{n_l} (x_{l,k,i} - \bar{x}_i)(x_{l,k,i} - \bar{x}_i)'}$$

where $\bar{x}_i$ and $\bar{x}_{l,i}$ are the average of the ith feature of the entire data set and class l data set (l =1~g, g=4 for four emotion labels) respectively; $x_{l,k,i}$ is the ith feature of the kth of the class l instance, and n_l is the number of instances of class l. The F-score is a simple technique for measuring the discrimination of two sets of real numbers; the larger the F-score, the greater the discrimination. It turns out that the PC with highest F-score value represents larger between-class variation and less within-class variation.

III. Result and Discussion

This section shows the results of using components obtained by PCA of ASM12 for emotion-specific EEG classification and feature selection. This study used a 10-fold cross-validation scheme with randomization to each subject's dataset to increase the reliability of the recognition rates. In a 10-fold cross-validation, the EEG feature vectors were randomly split into 10 subsets. SVM was trained with nine subsets of feature vectors, whereas the remaining subset was used for testing. This procedure was repeated 10 times with each subset having an equal chance of being the testing data. This procedure was then repeated ten times with different subset splits. The accuracy was evaluated by the ratio of correctly classified number of samples and the total number of samples.

In order to investigate how much variance should be retained to lead an acceptable performance, the results of retaining 80-100% of the total variance was compared. Fig. 2 shows an overall classification result using different percentages of retained variance from 80% to 100%. It is evident that maintaining 100% of variance with no dimension reduction would lead the highest classification accuracy of 85.72±3.22%, whereas the classification accuracy declined while less variance was retained. Retaining 95% of the variance decreases the number of remaining components significantly (from 60 to 38.58±3.43 depending on the subjects) while only marginally degraded the classification accuracy (to 81.58±3.74%). That is, PCA-based ASM12 retaining 95% of the variance could yield a satisfactory

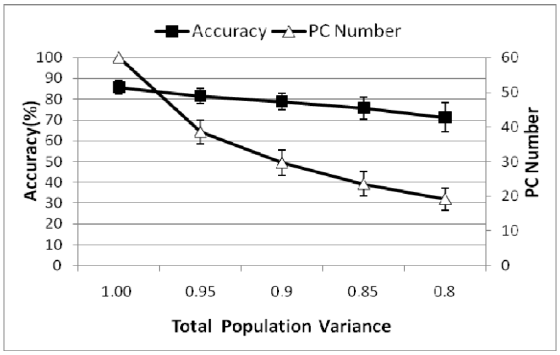

Fig. 2. Averaged subject-dependent classification results using different percentages of retained variance from 80% to 100% and the corresponding number of PCs needed.

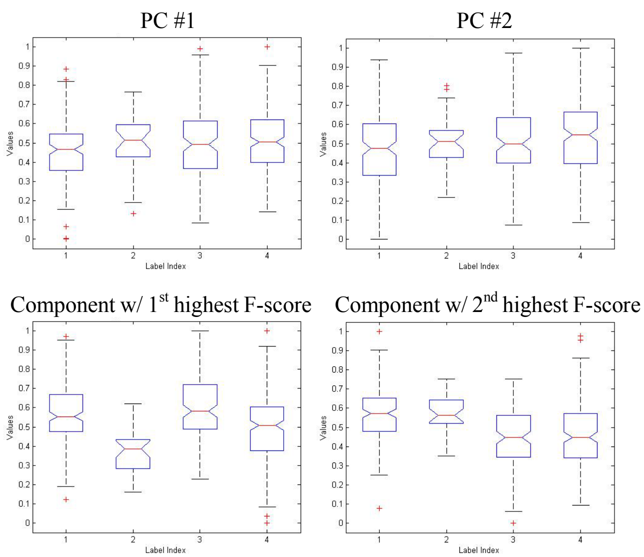

Fig. 3. An illustration of box-and-whisker plot in one subject showing the first two PCs and first two F-score selected PCs. (Label index in x-axis means the emotion classes and y-axis means the amplitude of projected PC).

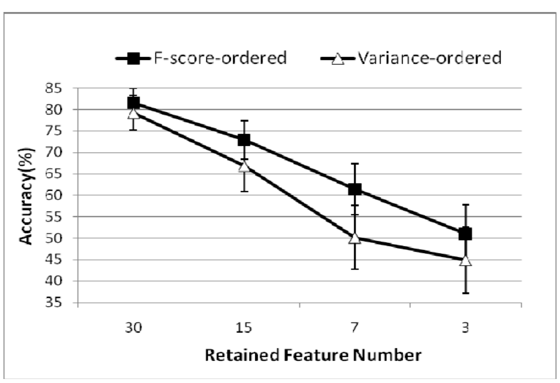

Fig. 4. The comparison of averaged subject-dependent classification results using top F-score versus top variance components.

accuracy with a dimension reduction around 36%, considerably enhancing computational efficiency.

Next, the discrimination power of PCs was assessed by the F-score index to select components with the largest ratio of between- and within-class variation. Fig. 3 shows the box-and-whisker plot of first two PCs and two PCs with highest F-scores. Even though the first two PCs summarized largest variance in the data, they mainly accounted for the within-class variation, whereas the F-score selected PCs were evidently more sensitive to between-class variation. Next, EEG-based emotion-state classification based on the same number of components with top variance (obtained by PCA directly) and top F-scores were compared. Fig. 4 shows the classification accuracy of this study. It can be seen that the classification accuracy using component with high F-scores outperformed that using components with highest variance, and the improvements were statistically significant ($p<0.05$). This study demonstrated it is beneficial to use more informative (discriminative) components than the components accounting for larger variance as inputs for EEG-based emotion classification.

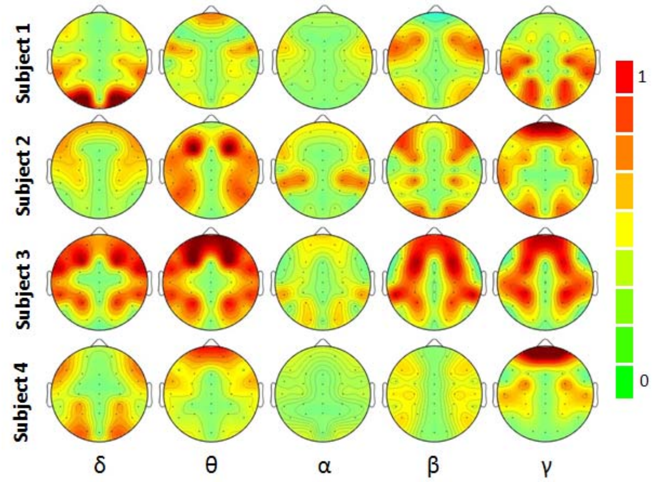

Fig. 5. An illustration of eigenvector loading on brain topology mapping at different frequency bands in four subjects. (The symmetry pattern is due to the fact that the spectral differences were between symmetrical pairs and normalized value 1 shows in red and whereas normalized value 0 shows in green)

Finally, the spatial and spectral information of components with top F-scores were assessed by examining the topographies of the components, which was implemented via EEGLAB [11]. Fig. 5 shows the weighting of ASM12 feature attributes, normalized eigenvector of the top F-score component, at different frequency bands in 4 sample subjects. As can be seen, the Fp1-Fp2 and FT7-FT8 pairs predominated the weightings in the eigenvectors at theta band. The relative weighting of the T7-T8 pair and F7-F8 pair were high in the gamma band and delta band respectively. The spatial and spectral attributes of most informative components were stable across subjects.

IV. Conclusion

This study tested the feasibility of using principal component analysis and support vector machine to characterize EEG spectra during music listening. Principal components of EEG power accounting for up to 95% of the variance in the data allowed an accurate classification of 1-s EEG segments under four self-reported emotions. Further, F-score index was effective for selecting components with most discriminative information associated with different emotional states. The factor loading topographies exhibited the reproducibility of the spatial and spectral patterns accompanying emotions during music appreciation. A natural next step is to quantitatively assess the complex subject-independent EEG correlates of emotions.

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