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Generalizations of the Subject-independent Feature Set for Music-induced Emotion Recognition

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***Abstract*— Electroencephalogram (EEG)-based emotion recognition has been an intensely growing field. Yet, how to achieve acceptable accuracy on a practical system with as fewer electrodes as possible is less concerned. This study evaluates a set of subject-independent features, based on differential power asymmetry of symmetric electrode pairs [1], with emphasis on its applicability to subject variability in music-induced emotion classification problem. Results of this study have evidently validated the feasibility of using subject-independent EEG features to classify four emotional states with acceptable accuracy in second-scale temporal resolution. These features could be generalized across subjects to detect emotion induced by music excerpts not limited to the music database that was used to derive the emotion-specific features.**

I. Introduction

OVER recent years electroencephalogram (EEG)-based emotion recognition has been an intensely growing topic in the domain of human-machine interaction (HMI). The core idea is to enable machines to recognize human emotional responses based on the modeling of non-invasively acquired spontaneous EEG patterns and to interact with human via desirable feedbacks. In contrast to audiovisual or hardware solutions for HMI applications, using emotion-specific EEG patterns as input is thought to be an alternative but more natural way for creating a human-centered interaction environment.

In this application, a crucial step is to estimate emotional responses from complex EEG signals as accurate as possible. The spectral dynamics of EEG signals defined with distinct frequency bands, such as delta (1–3 Hz), theta (4–7 Hz), alpha (8–13 Hz), beta (14–30 Hz), and gamma (31–50 Hz) [3], are commonly used either for assessing the neural activity accompanying or underlying human cognition or characterizing features for solving EEG-based classification problems. Similarly, by employing various band power amplitudes derived from different scalp electrodes as features, several studies [1, 4, 5] have proved its feasibility and effectiveness for emotion recognition. Nevertheless, most previous works mainly focused on achieving high accuracy by proposing and comparing various feature extraction ways. Only sparse works [1, 5] were concerning the practical issues on how to achieve acceptable accuracy with fewer electrodes in real-world applications. Unlike employing a specific subset of channels that was presumably sensitive for cognitive activity [5], Lin *et. al.* [1] attempted to explore the most emotion-informative electrodes throughout the entire scalp. The study reported that 30 subject-independent features, differential power asymmetry of 12 symmetric electrode pairs (DASM12), could yield an averaged emotion recognition accuracy of 74.10 ± 5.85% across 26 subjects, compared favorably to an accuracy of 71.15 ± 4.88% obtained by PSD30 (power spectrum density of 30 channels) forming a feature dimension of 150. However, prior to practical realization of the emotion-recognition system, the subject-independent feature set should be further validated in terms of gender difference which has been reported in music-induced emotional responses [6] and its generalizability for recognizing emotion induced by new self-chosen music excerpts on additional subjects.

This study aims to evaluate the Top30 subject-independent DASM12 feature set proposed in [1] with special emphasis on its feasibility for overcoming the gender difference in emotion perception and subject variability. This study also explores the possibility to reduce the number of required electrodes for practical considerations.

II. Material and Method

A. EEG Dataset

To address the gender difference issue, this study extended our previous work[1] and used the same dataset collected at [2], in which EEG data from 26 subjects (16 males, 10 females; age 24.40±2.53 yr.) were recorded in

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TABLE I
TOP30 SUBJECT- [1], MALE-, FEMALE-INDEPENDENT DASM12 FEATURES SELECTED BY F-SCORE CRITERION

Rank	Subject	Male	Female
1	TP7-TP8:Gamma	TP7-TP8:Gamma	TP7-TP8:Delta
2	FT7-FT8:Theta	FT7-FT8:Theta	T7-T8:Delta
3	T7-T8:Delta	T7-T8:Theta	O1-O2:Beta
4	TP7-TP8:Delta	F7-F8:Delta	FP1-FP2:Alpha
5	F7-F8:Beta	F7-F8:Beta	FT7-FT8:Theta
6	O1-O2:Beta	P3-P4:Theta	P7-P8:Theta
7	F7-F8:Delta	T7-T8:Delta	CP3-CP4:Theta
8	T7-T8:Theta	FT7-FT8:Beta	C3-C4:Delta
9	FT7-FT8:Delta	F7-F8:Theta	FT7-FT8:Delta
10	P7-P8:Theta	FT7-FT8:Delta	TP7-TP8:Alpha
11	P3-P4:Theta	FP1-FP2:Gamma	P3-P4:Theta
12	C3-C4:Delta	O1-O2:Theta	F7-F8:Beta
13	FP1-FP2:Alpha	C3-C4:Delta	F7-F8:Theta
14	CP3-CP4:Theta	FP1-FP2:Delta	P3-P4:Gamma
15	F7-F8:Theta	F3-F4:Gamma	P3-P4:Delta
16	FT7-FT8:Beta	O1-O2:Gamma	F3-F4:Delta
17	F3-F4:Gamma	FC3-FC4:Beta	FC3-FC4:Delta
18	TP7-TP8:Alpha	CP3-CP4:Gamma	F3-F4:Gamma
19	FP1-FP2:Delta	F3-F4:Delta	CP3-CP4:Beta
20	F3-F4:Delta	CP3-CP4:Alpha	P3-P4:Beta
21	FP1-FP2:Gamma	P7-P8:Gamma	FP1-FP2:Theta
22	P3-P4:Delta	CP3-CP4:Theta	P7-P8:Beta
23	O1-O2:Theta	O1-O2:Alpha	FP1-FP2:Delta
24	CP3-CP4:Beta	CP3-CP4:Beta	F3-F4:Theta
25	P3-P4:Gamma	P3-P4:Delta	F7-F8:Delta
26	FC3-FC4:Delta	FP1-FP2:Beta	CP3-CP4:Delta
27	O1-O2:Gamma	T7-T8:Beta	F3-F4:Alpha
28	CP3-CP4:Gamma	CP3-CP4:Delta	P7-P8:Alpha
29	CP3-CP4:Delta	P7-P8:Delta	FT7-FT8:Beta
30	CP3-CP4:Alpha	TP7-TP8:Alpha	FC3-FC4:Theta

Attributes in black represent the common features selected separately by different subject groups. Attributes in cyan represent the common features between subject- and male-independent set, where attributes in red indicate the commonality between subject- and female-independent set. Gender-specific attributes are marked in cyan / green for male and in red / orange for female.

music-listening experiments. The data acquisition and experiment procedures are briefly described here. A thirty-two (32) channel EEG module (Neuroscan, Inc) arranged according to international 10-20 system was used for sampling the EEG signal at 500 Hz with a 1-100 Hz bandpass filter. Subjects had minimal formal musical education and could thus be considered as non-musicians. Subjects were instructed to keep their eyes closed and remain seated in the music-listening experiment. This study examined four basic emotional states following a 2D valence-arousal emotion model [7], including joy (positive valence and high arousal), angry (negative valence and high arousal), sadness (negative valence and low arousal), and pleasure (positive valence and low arousal). Sixteen excerpts from Oscar's film soundtracks were selected as stimuli according to the consensus tagging reported from hundreds of subjects [8]. Each was edited into a 30-sec music excerpt. The subjects were instructed to report emotional states (joy, anger, sadness, or pleasure) to each 30-second music excerpt based on what they felt via a tool FEELTRACE [9] for labeling on a 2D emotion model. Each experiment thus consisted of sixteen (16) 30-s emotion-specific EEG segments for further analysis, whereas the given self-reported emotional states were used to verify EEG-based emotion classification. A 512-point short-time Fourier transform (STFT) with a non-overlapped Hanning window of one second was applied to the EEG data to compute the spectrogram for each channel. The spectral time series for each subject thus consisted of around 480 samples (1-s spectra, 16 30-s EEG segments x around 30 points per segment). This dataset containing EEG data from 26 subjects was labeled as Ss26 in the following sections to evaluate the gender difference issue.

To test the generalizability of the EEG features, new EEG data were acquired from additional four male subjects (age 23.00±0.00 yr.) when they listened to self-chosen emotional music excerpts according to their self-preference in daily life. This additional music experiment adopted the same procedures mentioned above, except the music excerpts were selected by the subjects. Note that these individually handpicked music excerpts varied largely from subject to subject, which were dramatically different from music excerpts conducted in [2]. The purposes of using self-chosen music excerpts were twofold: (1) it is more natural to let subjects to listen to their preferred music excerpts that would induce their emotion; (2) it is more stringent to test the proposed algorithm to recognize different emotions induced by the excerpts outside our music database. The new dataset, labeled as Ss4 below, also consisted of 16 30-s emotion-specific EEG segments and the corresponding self-reported emotional labels for each subject.

B. *Feature Extraction, Selection and Classification*

The objective of previous study [1] focused on systematically exploring the association between EEG spectral dynamics and music-induced emotion and assessing an optimal set of emotion-specific features for solving four-class emotion classification problem. The results of the study demonstrated that DASM12, differential asymmetry of hemispheric EEG power spectra derived from 12 symmetrical electrode pairs (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) throughout 30 channels, were very informative for recognizing induced emotions. After the STFT estimation, DAM12 was used to extract spectra at 5 bands, including delta (1–3 Hz), theta (4–7 Hz), alpha

(8–13 Hz), beta (14–30 Hz), and gamma (31–50 Hz) across 12 electrode-pairs, forming a 60-dimensional feature vector. In addition, a subset of 30 DASM12 features was further identified to be most relevant for emotion classification by F-score feature selection, which was an efficient method to measure the ratio of between- and within-class variance (see Table Ⅰ). As mentioned above, the number of sample points from each subject was around 480 disjoint 1-second spectra. A 10 times of 10-fold cross-validation scheme with randomization was applied to dataset from each subject in order to increase the reliability of the recognition results. Support vector machine (SVM) was trained with the EEG features to recognize subject emotions based on 1-sec of EEG features. Results showed that the Top30 F-score-ranked features were insensitive to subject variability across 26 subjects. The averaged classification accuracy of 74.10% ± 5.85% was obtained on the dataset Ss26, comparable to an averaged accuracy of 75.75% ± 5.24% obtained by using the Top30 subject-*dependent* features.

This study tests the generalization of the Top30 subject-independent DASM12 features. To this end, this study adopts the procedures of feature extraction of Top30 subject-independent DASM12, F-score feature selection, and the SVM classification [10] proposed in [1]. Prior to classification procedure, each feature value was normalized to the range from 0 to 1. Note that a ten times of 10-fold cross validation was applied to each subject to get more reliable accuracy.

III. Result and Discussion

A. Gender Difference

Flores-Gutierrez *and colleagues* recently reported gender-specific coherent patterns in emotional and perceptual processing of music [6]. For example, unpleasant emotions were accompanied by an increased coherent activity between midline and posterior regions in the right hemisphere in men and by bilateral networks engaging anterior regions in women. The study suggested that the men and women should not be analyzed together in neurobiological studies of musical emotion. To address this issue, this study further assess the gender-specific feature sets by conducting F-score feature selection on EEG spectra of male and female subjects separately from the dataset Ss26 (see Table Ⅰ). As can be seen, though the features were selected from distinct subject groups, male and female subjects have 17 identical (common) attributes (in black) that contributed over a half of Top30 subject-independent feature set. The remaining part of subject-independent features was respectively consisted of 7 attributes from male subjects (in cyan) and 6 attributes from female subjects (in red). Next, as inspecting the gender-specific feature sets, in total of 13 distinct attributes were found either specific for male subjects (in cyan and green) or for female subjects (in red and orange), in which 6 green attributes and 7 orange

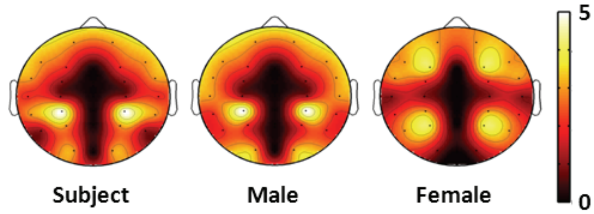

Fig. 1. The color-coded degree of use of each electrode pair in the Top30 subject- [1], male-, and female-independent DASM12 features (The symmetry pattern is due to the fact that the spectral differences were derived from symmetrical electrode pairs).

TABLE Ⅱ
THE COMPARISON OF AVERAGE RESULTS (STANDARD DEVIATION) USING TOP30 SUBJECT-, MALE-, AND FEMALE-INDEPENDENT FEATURE SETS ON MALE AND FEMALE SUBJECTS

Subject	Independent feature set		
	Subject	Male	Female
Male	72.90 (4.78)	72.91 (4.62)	73.36 (4.69)
Female	75.97 (6.97)	74.48 (7.34)	75.93 (7.54)

attributes did not contribute to the subject-independent feature set. Fig. 1 plots the density of selected features across scalp locations in the Top30 subject-, male-, and female-independent DASM12 feature sets. This feature-space topography suggested that the subject-independent feature set tends to be dominated by the male subjects, which might be due to the fact that over 60% of subjects were male. It is worth mentioning that the informative features from male and female subjects were very close or adjacent, except features from the pairs F3-F4 and P3-P4 in female subjects and the pairs Fp1-Fp2 and CP1-CP2 in male subjects.

A natural next step is to test to what extent the emotion-recognition performance of using Top30 subject-independent DASM12 feature set in emotion classification would degrade due to gender difference. Table Ⅱ summarizes the averaged recognition rates by applying male-, female- and subject-independent feature set on male and female subjects. Results showed no significant differences between applying gender-specific and subject-independent feature set (p>0.05) on either male or female subjects. Although the gender-specific features were evident in Table I and Fig. 1, the proximity of informative channel pairs between different gender groups gave the selected EEG features sufficient information to recognize music-induced emotion of different subject groups. The feasibility of using the Top30 subject-independent DASM12 feature set for different gender groups was thus suggested by relative high accuracy of emotion recognition.

B. Generalization of emotion recognition

This study further tests the practicability of emotion recognition to detect emotion of additional subjects listening to their self-chosen music excerpts. Table III (middle column) shows the emotion-recognition results based on the

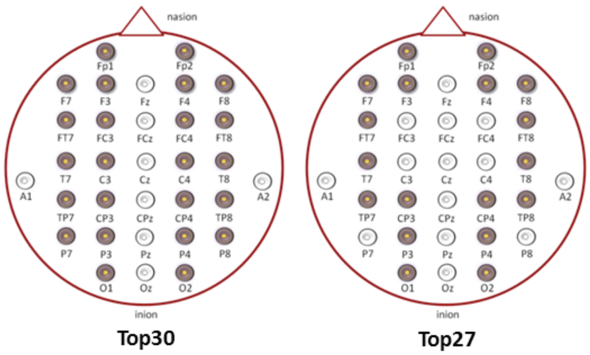

Fig. 2. Different electrode placements according to feature extraction of Top30 and Top27 subject-independent DASM12 feature set.

TABLE Ⅲ
THE COMPARISON OF AVERAGE RESULTS (STANDARD DEVIATION) BY CONDUCTING TOP30 AND TOP27 SUBJECT-INDEPENDENT FEATURE SETS [1] ON SS26 AND SS4 DATASETS

Dataset	Subject-independent feature set (Ss26)	
	Top30	Top27
Ss26	74.10 (5.85)	72.75 (5.69)
Ss4	75.42 (3.65)	73.95 (3.44)

Ss26: EEG data were collected from 26 subjects [2].
Ss4: EEG data were acquired from additional 4 subjects in a new music experiment.

Top30 subject-independent features. The result of emotion recognition of the new subjects listening to self-chosen music excerpts (75.42±3.65%) was comparable to that of the original dataset (Ss26, 74.10±5.85%).

In addition, this study also evaluates the feasibility of employing fewer channel pairs, the montage of the Top27 subject-independent DASM12 feature set proposed in [1], for emotion recognition. Table I shows three feature attributes within the Top30 subject-independent feature set were very sparsely extracted from three electrode-pairs: FC3-FC4(Delta), P7-P8(Theta) and C3-C4(Delta). Excluding these features would reduce the number of required electrodes from 24 to 18 (see Fig. 2) while only marginally degraded the classification accuracy from 74.10±5.85% to 72.75±5.69% and 75.42±3.65% to 73.95±3.44% for Ss26 and Ss4, respectively (see TableⅢ). The montage of the resultant Top27 subject-independent DASM12 feature set required fewer electrodes and could be roughly fitted into a circular head band. These results have evidently validated that both Top30 and Top27 subject-independent DASM12 feature sets could effectively characterize EEG spectral changes associated with emotions induced by music excerpts outside the confines of music database, but also generalize to recognize the emotion of subjects whose datasets have not been previously trained or analyzed. Yet, a larger dataset is required to significantly test the robustness of the subject-independent DASM12 feature sets in the future.

IV. CONCLUSION

This study evaluated the Top30 subject-independent EEG features for recognizing music-induced emotions in second-scale temporal resolution with special emphasis on its feasibility to overcome the gender difference and subject variability. The feasibility of EEG-based emotion recognition was demonstrated by the acceptable recognition accuracy of emotion induced by music excerpts outside the confines of selected music database that was used to induce the emotion-related EEG features. The practical potential of such system was further promoted by the reduction of the number of required electrodes.

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