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EEG-based discrimination of music appraisal judgments using ZAM time-frequency distribution

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ABSTRACT

Background

Although EEG-based emotional responses to music have been studied extensively, little research has been conducted for the discrimination of music appraisal judgments. In the psychology-based literature music appraisal is mainly interpreted in terms of affective experiences, such as emotional resonance, aesthetic awe and thrill (Konečni, 2005; Schubert, 2007; Evans & Schubert, 2008).

In the field of neurophysiology, EEG-based evidence of brain activation due to emotion-evocative music is mainly reported. Altenmüller, Schurmann, Lim, and Parlitz (2002) found that pleasant music causes left frontal brain activation, while unpleasant music causes right and slightly bilateral frontal activation. Similar evidence has been produced by the study of Schmidt and Trainor (2001). Another EEG-based study showed that consonant (pleasant) music causes greater midline brain activity compared to dissonant (unpleasant) music (Slammer, Grigutsch, Fritz, & Koelsch, 2007). As far as EEG-based emotion recognition is concerned, Lin et al. (2010) achieved an accuracy of 82.29 ± 3.06% for the classification of distinct emotions due to music listening, using spectrogram-based feature extraction and support vector machines (SVM). However, the aforementioned electrophysiological evidence arises from the listening of positively/negatively valenced music that cannot be directly mapped to liked/disliked music. For instance, depending on the listeners' mood, sad-sounding musical excerpts can be occasionally preferred instead of happy-sounding ones.

In general, evidence of brain activity related to emotional responses is reported in the majority of EEG frequency bands, i.e., *theta*, *alpha*, *beta* and *gamma*. Frontal midline *theta* power modulation is suggested to reflect affective processing during consonant/dissonant music (Slammer et al., 2007). The *alpha*-power asymmetry on the prefrontal cortex has been proposed as an index for the discrimination between positively and negatively valenced emotions (Davidson, 2004). Moreover, *beta* activity has been associated with emotional arousal modulation (Aftanas, Reva, Savotina, & Makhnev, 2004), while activity in the *gamma* band is also related to arousal effects (Keil et al., 2001).

Aims

In this framework, the present study aims at classifying listeners' EEG responses that relate to music liking or disliking judgments. Specifically, the main objectives of this work are: 1) to propose energy-based time-frequency (TF) features for an efficient classification and 2) to associate the EEG-based results with evidence from the existing literature on music evoked emotions and emotional responses in general.

Method

Nine participants (two females and seven males; mean age 23.22 ± 1.72 years) were engaged in an experiment during which they listened to 60 15 s-long musical excerpts of four genres (rock-pop, jazz, electronic, and classical), while their EEG activity was recorded. Prior to the beginning of each excerpt a 3 s interval of resting preceded. After the end of each excerpt, subjects were prompted to rate their liking for the excerpt in a five-point scale (1: do not like at all; 2: do not like; 3: undecided; 4: like 5: like very much). The number of experimental trials was 9 × 60 = 540 in total. EEG signals were acquired using the Emotiv EPOC wireless recording headset from 14 channels (AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8), referenced to the common mode sense (left mastoid)/driven right leg (right mastoid) ground. The sampling frequency was 128 Hz. All acquired EEG signals were band-pass filtered offline in the range of 1-49 Hz.

Subsequent feature extraction was based on the Zhao-Atlas-Marks (ZAM) time-frequency distribution (TFD). The latter distribution belongs to the quadratic TF representations and adopts a cone-shaped kernel function in order to significantly reduce interferences between signal components (Zhao, Atlas, & Marks, 1990). The ZAM distributions were computed from the EEG epochs corresponding to the resting interval (3 s) and the interval of music listening (15 s), for all trials and recording channels. Based on the ERD/ERS theory (Pfurtscheller & Lopes da Silva, 1999), feature F was computed in each EEG frequency band [*delta* (1-4 Hz), *theta* (4-8 Hz), *alpha* (8-13 Hz), *beta* (13-30 Hz), and *gamma* (30-49 Hz)] as a fraction of the average squared amplitude of the TFD during music listening (A) over the average squared amplitude of the TFD during resting (R), i.e., $F = A - R/R$. For each trial and EEG band, the feature vector (FV) consisted of the 14 features computed for each recording channel (NoAs case). In order to take into consideration asymmetric activations that occur during emotional responses, two additional types of features – and consequently, of FVs – were computed. The first type represents a differential asymmetry index (DAs case), computed by subtracting the estimated features F for each of the seven symmetric channel pairs, i.e., AF3-AF4, F7-F8, F3-F4, FC5-FC6, T7-T8, P7-P8, and O1-O2. The second type represents a rational asymmetry index (RAs case), computed by the division of the estimated features F for each of the symmetric channel pairs. In total, 5 [EEG frequency bands] × 3 [asymmetry types (NoAs, DAs, RAs)] = 15 sets of FVs were computed.

The classification procedure was performed on two classes, namely, "Like" and "Dislike", in a user-independent way. Class "Like" comprised of 219 FVs corresponding to trials in which participants rated their liking for the musical excerpts as

5 or 4. Class "Dislike" comprised of 143 FVs corresponding to the trials in which subjects rated their liking for the musical excerpts as 2 or 1. Trials corresponding to "undecided" rating were 178 and they were omitted. Two widely used classifiers were employed, i.e., Gaussian kernel SVM and *k*-nearest neighbors (*k*-NN). For the *k*-NN classifier, the Euclidean distance was selected as the distance metric and the number of nearest neighbors was set to 4 (= *k*) after testing. The soft margin parameter and the scaling factor of the SVM kernel were selected using cross-validation checking. For each FV set, the average classification accuracy ($\overline{\mathrm{CA}}$) and the standard deviation (SD) of CA were computed over 10 runs of 10-fold cross-validation, i.e., 100 classification repetitions.

Results

CAs are reported in the format of $\overline{\mathrm{CA}} \pm$ SD%. In the NoAs case, best CAs were achieved using FVs estimated from the *beta* (74.56 ± 1.02%) and *gamma* (71.96 ± 0.87%) bands and *k*-NN, as compared to the classification performance of FVs estimated from other EEG bands (*delta*: 57.15 ± 1.03%; *theta*: 65.08 ± 0.47%; *alpha*: 70.15 ± 0.91%). The corresponding CAs, produced using SVM, were lower (*delta*: 56.52 ± 2.89%; *theta*: 61.38 ± 1.99%; *alpha*: 70.11 ± 0.89%; *beta*: 72.13 ± 0.66%; *gamma*: 67.73 ± 0.47%). Classification performance of asymmetry-based FVs (DAs and RAs) was worse compared to NoAs-based FVs. In the DAs case, highest CA was acquired through FVs estimated from the beta band (69.97 ± 0.98%) and *k*-NN, while lower CAs were produced by FVs estimated from other bands (*delta*: 56.30 ± 0.87%; *theta*: 67.57 ± 1.19%; *alpha*: 64.56 ± 1.02%; *gamma*: 68.34 ± 0.74%). In the latter case, SVM yielded similar accuracies (*delta*: 57.10 ± 2.00%; *theta*: 59.75 ± 0.97%; *alpha*: 65.33 ± 1.01%; *beta*: 66.08 ± 0.75%; *gamma*: 68.09 ± 1.20%). Down to the RAs case, best classification performance was achieved through *beta* (70.11 ± 0.92%) and *gamma* bands (70.36 ± 1.33) using *k*-NN. Lower classification performance was acquired through FVs estimated from other bands (*delta*: 56.80 ± 0.89%; *theta*: 63.70 ± 1.12%; *alpha*: 65.11 ± 1.05%). CAs, produced using SVM, were lower (*delta*: 52.49 ± 3.01%; *theta*: 57.15 ± 0.57%; *alpha*: 62.15 ± 1.35%; *beta*: 63.01 ± 2.01%; *gamma*: 64.86 ± 1.78%).

So far, best CAs were produced by the NoAs-based FVs derived from the *beta* and *gamma* bands. FVs, constructed from the fusion of the NoAs-based FVs of the latter bands, were also fed to the classifiers, in an effort to examine the combined discrimination potential of features derived from different EEG bands. For the sake of comparison, FVs, constructed by concatenating the NoAs-based FVs derived from all frequency bands, were tested in terms of classification performance. Using *k*-NN, the combined *beta*/*gamma* FVs yielded the best CA (76.52 ± 1.37%), while FVs from all bands led to worse performance (71.69 ± 0.90%). Corresponding CAs, produced by SVM, were considerably lower (*beta*/*gamma*: 71.41 ± 0.88%; all bands: 65.22 ± 2.38%).

Conclusions

FVs representing an overall brain activation (NoAs) led to a more efficient discrimination than hemispheric asymmetry-based FVs (DAs and RAs). Hemispheric lateralization has been proposed as an effective index for the discrimination of discrete emotional states (Davidson, 2004). Such emotion-related activity has been previously reported in music-based studies (Schmidt & Trainor, 2001; Altenmüller et al., 2002), but it was also found to be absent during the listening of pleasant (unpleasant) consonant (dissonant) music (Slammer et al., 2007). Lower classification performance, achieved using the asymmetry-based features in this work, might imply that the discrimination of music appraisal judgments may not depend solely on the valence of emotions induced by music, i.e., a direct mapping of positive/negative appraisal judgments to music-induced positive/negative -valenced emotions might not be sufficient. During music listening, brain responses are formed by the combined presence of processes that may relate to music perception, memory retrieval, and affection. However, music appraisal is mainly interpreted in the context of affective responses; thus, in this study, electrophysiological evidence that led to the discrimination of liking/disliking judgments is considered to be more likely related to aspects of such responses. Best classification was achieved through the activity of *beta* and *gamma* bands, which have been both suggested to reflect emotional arousal phenomena (Keil et al., 2001; Aftanas et al., 2004). Therefore, arousal could be linked to music preference, as appraisal judgments might be seen as an expression of excitation (or lack of it) over a liked (or disliked) musical piece or as a modulating factor of the intensity of the listener's emotional state, regardless of its valence.

Keywords

EEG; emotion; music appraisal; ZAM time-frequency distribution

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