Brain and Music:
Music Genre Classification using Brain Signals

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Abstract—Genre classification can be considered as an essential part of music and movie recommender systems. So far, various automatic music genre classification methods have been proposed based on various audio features. However, such content-centric features are not capable of capturing the personal preferences of the listener. In this study, we provide preliminary experimental evidence for the possibility of the music genre classification based on the brain recorded signals of individuals. The brain decoding paradigm is employed to classify recorded brain signals into two broad genre classes: Pop and Rock. We compare the performance of our proposed paradigm on two neuroimaging datasets that contains the electroencephalographic (EEG) and the magnetoencephalographic (MEG) data of subjects who watched 40 music video clips. Our results indicate that the genre of the music clips can be retrieved significantly over the chance-level using the brain signals. Our study provides a primary step towards user-centric music content retrieval by exploiting brain signals.

Index Terms—Brain decoding, music genre classification, multimedia content retrieval, brain signal processing, EEG, MEG.

I. INTRODUCTION

Nowadays, with the rapid growth of the Internet, a large amount of data has become available on-line. Among all the different sources of information, music certainly is one of the most important ones for entertaining people. This has arisen the need for organizing and managing these large digital music databases. Among many music descriptors such as song title, artist, album, etc, probably, the most widely used meta-data for indexing and retrieving music is the genre of the music [1], [2], [3]. As a result of this, music genre classification is one of the major research directions in music information retrieval systems since music genre is one of the main elements in automatic music recommendation systems.

Among all different approaches for searching for a music song, probably, the most common one is the content-based approach. So far, various content-based genre classification methods have been proposed based on a variety of features. These features include MFCC, spectral centroid, spectral flux, zero crossings, energy, pitch, rhythm patterns, harmonic contents and etc [4], [5], [6], [7], [8]. However, in spite of all efforts done during the last years, content-based approaches are always dependent on the availability of multimedia contents. When such contents are not accessible, these approaches are not applicable anymore. Besides, the main drawback of such approaches is that they are not able to capture the personal preferences of the human listeners. Such preferences matter

since there might be disagreement between human beings on the definition of the musical genre due to the fuzzy boundaries between the different genres. In light of this, in this paper we use an alternative method for music genre classification which is a user-centric approach that aims at capturing the perception of people. The rationale behind this is that the recommendation system that accesses the people's perception of the music (e.g. via neurophysiological data), might be able to distinguish the music genre better.

Recent works on affective computing, suggests the possibility of decoding affects from neurophysiological data. In [9], authors captured physiological responses of participants while they were watching movie scenes. They showed that the predicted affects from physiological responses of participants are significantly correlated with their self-assessed emotional responses. Koelstra et al. [10] and Abadi et al. [11] studied emotional responses of subjects induced by excerpts of music and video clips. They show that emotional information is encoded in brain signals. Inspired by these works, in this paper, we address the specific problem of genre classification of music video clips using brain data. We show that music genre can be decoded from brain signals using a brain decoding paradigm. We tested our hypotheses on two neuroimaging datasets: (1) DECAF dataset [11] that contains magnetoencephalographic data of 30 subjects who watched 40 music video clips and (2) DEAP dataset [10] which contains electroencephalographic data of 32 subjects who watched the same 40 music clips. Figure 1 illustrates the overall framework used in our study.

To summarize, our main contributions are: (1) we study the possibility of user-centric genre classification by employing brain signals; (2) we apply our classification paradigm on two different brain datasets that contain different neuroimaging modalities (magnetoencephalographic data [11] and electroencephalographic data [10]); (3) we augment the aforementioned EEG and MEG datasets by providing music genre labels for each music clip which can be used and investigated in other studies. This study will contribute to various disciplines and research areas ranging from multimedia retrieval (music information retrieval) to neuroscience.

The rest of this paper is organized as follows. In section II we briefly review the literatures on genre classification. Afterwards, in section III we explain the employed datasets, data preprocessing, feature extraction and classification procedure. Furthermore, the method used regarding music
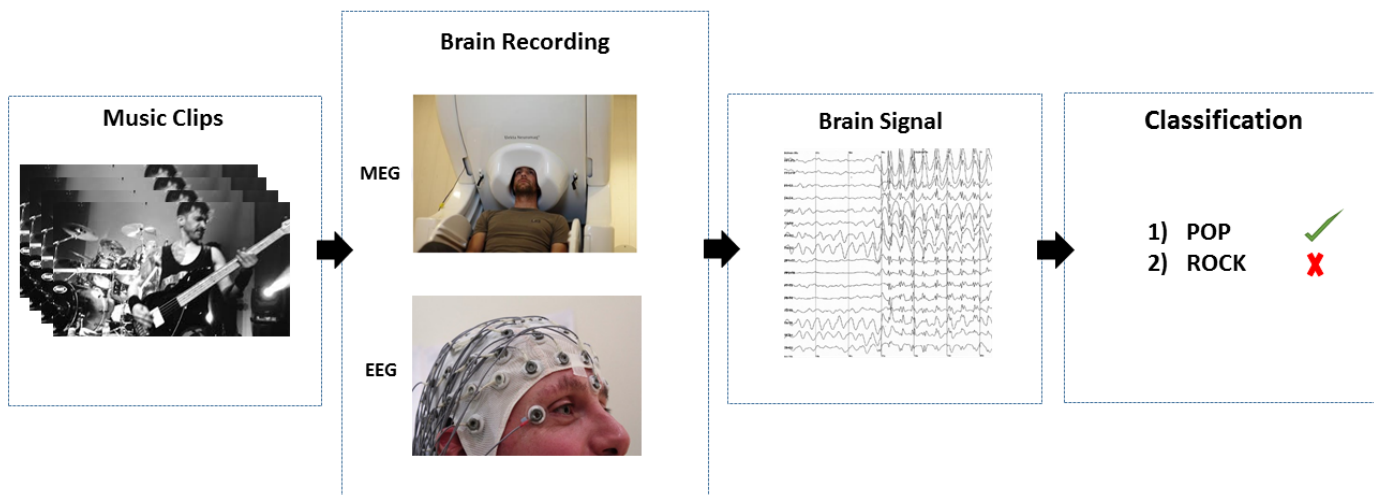
Fig. 1. The framework used in this study for music genre classification by exploiting brain signals.

genre annotation is discussed. Section IV elaborates our experimental results with a brief discussion. Finally, section V concludes the paper by stating the future directions.

II. RELATED WORKS

A. Content-Centric Music Genre Classification

There is a large body of works on content-based genre classification approaches. One of the earlier works is introduced by Tzanetakis and Cook [4] where the authors represent a music piece using timbral texture, rhythmic features, and pitch-related features. Their proposed features set has been widely used for music genre classification [5], [6], [7], [8]. Other characteristics such as contextual informational [12], temporal information [13], and semantic information [14] have been investigated in the literatures to improve the accuracy of genre classification. Recently, "sparse feature learning" methods have also been investigated for constructing a codebook for music songs [15], [16], [17], [18]. Elsewhere, Costa, et al. [3] proposed a robust music genre classification approach by converting the audio signal into a spectrogram and extracting features from this visual representation by treating the time-frequency representation as a texture image.

B. Affective Content and Brain Decoding

Brain decoding has recently received considerable attention across many domains particularly in brain computer interfacing and rehabilitation communities due to its potential for helping people who suffer from brain injuries [19], [20]. Nevertheless, in most cases, the performance of such brain decoding algorithm is not very high because of low signal-to-noise ratio and non-stationarity of brain signals.

However, in spite of these limitations, recent works on affective computing, shows the possibility of decoding affects from brain data. In [10], authors studied emotional responses of experimental subjects induced by music video excerpts. They employed electroencephalography (EEG) to record brain activity of participants while they were watching music video clips. A similar study was done in [11] with magnetoencephalography. These two studies indicate that emotional information is encoded in brain signals (MEG and EEG). In a recent work by Ghaemmaghami et al. [21], authors investigated the possibility of movie genre classification by employing MEG brain signals. They adopted a brain decoding paradigm to classify (MEG) data of experimental participants, who watched excerpts of movie clips, into four broad genre classes (Comedy, Romantic, Drama, and Horror). Moreover, they showed that there is a significant correlation between audio-visual features of the movie excerpts and MEG features extracted from visual and temporal areas of the brain.

Our brief review of literatures reveals that music genre classification has been achieved so far with content-based approaches. On the other hand, brain decoding algorithms were successfully employed on many tasks using various neuroimaging techniques. However, the efficacy of the brain decoding approaches on music genre classification has not been explored. Therefore, this study aims at investigating the possibility of classifying musical genres using brain data. As far as we know, we are the first showing that the extracted features from brain signals can be used for the music genre classification task.

III. EXPERIMENTAL SETUP

In this section, we describe the employed datasets, annotation process, feature extraction and classification procedure.

A. Datasets

In our experiments, we used two publicly available datasets. These datasets contain the electroencephalographic (EEG) and the magnetoencephalographic (MEG) data of volunteers who watched 40 music video clips. The advantage of using these two datasets is that they contain the same music clips (the duration of each clip is 60 seconds) so that the results can be compared. The details of these datasets are described below.

MEG dataset: The MEG dataset, we employed in this study is the DECAF dataset [11]. This dataset contains the MEG brain signals of 30 volunteers while they were watching 40 music video clips. These music clips were projected onto a screen placed in front of the subject inside the MEG acquisition room with 20 frames/second and at a screen refresh rate of 60 Hz. The magnetoencephalographic data were recorded in a magnetically shielded room with 1KHz sampling rate and in a controlled illumination using a Electa Neuromag device that outputs 306 channels (102 magnetometers and 204 gradiometers).

EEG dataset: The EEG dataset, we employed in this study is the DEAP dataset [10]. This dataset contains the EEG brain signals of 32 participants while they were watching 40 music video clips. These music clips were projected onto a screen placed about a meter in front of the subject at a screen refresh rate of 60 Hz. The electroencephalographic data were recorded in controlled illumination, at a sampling rate of 512 Hz, using a Biosemi ActiveTwo system that outputs 32 channels.

B. Annotating Music Clips

The definition of the musical genre is very subjective so that one song may belong to different genres according to different individuals. As a result of such arbitrariness in the definition of the musical genre, many researchers have shown that even major music taxonomies are very inconsistent [22], [1], [23], [3].

To deal with such a difficulty and given the few number of total samples in our employed datasets (40 excerpts of music clips), in this study, three human annotators were asked to watch the music video clips and classify each music clip into one of the two categories; The first category include the following genres: Pop, Dance, Disco and Tech-no. We refer to this category as the *POP* category. The second category include the following genres: Rock and Metal. We refer to this category as the *ROCK* category. The music genre of each clip was picked based on the majority voting between the annotators. To evaluate the consistency of the annotation across subjects, we measured the Cohen's Kappa agreement between annotators' labeling. The obtained average κ across observers ($69.8\% \pm 5\%$, $p - value < 0.001$) indicates a *substantial* agreement [24] between the annotators. We refer to the majority voting labels as the ground-truth labels. Table II presents the name of the music clips together with their ground-truth labels.

C. Feature Extraction

MEG features: Using the MATLAB Fieldtrip toolbox [25] and following [11], the MEG trials are extracted and pre-processed as follows: 1) Upon down-sampling the MEG signal to 300 Hz, High-pass and Low-pass filtering with cut-off frequencies of 1 Hz and 95 Hz are performed respectively. 2) Then, the spectral power of the 102 combined-gradiometer sensors of the MEG trials is estimated with a window size of 300 samples. 3) MEG features are calculated by averaging the signal power over four major frequency bands: theta (3:7 Hz), alpha (8:15 Hz), beta (16:31 Hz) and gamma (32:45 Hz). The output of this procedure for each trial is a matrix with the following dimensions: 102 (number of the MEG combined-gradiometer sensors) $\times$ 4 (major frequency bands) $\times$ 60 (length of a music clip in seconds).

EEG features: We used the publicly available pre-processed EEG data [10]. These pre-processing steps include: EEG signal down-sampling to 128 Hz, EOG artifacts removal and bandpass frequency filtering (4 - 45 Hz). Then, for every trial, the spectral power of each channel is estimated with a window size of 128 samples. EEG features are calculated by averaging the signal power over four major frequency bands: theta (3:7 Hz), alpha (8:15 Hz), beta (16:31 Hz) and gamma (32:45 Hz). The output of this procedure for each trial is a matrix with the following dimensions: 32 (number of the EEG sensors) $\times$ 4 (major frequency bands) $\times$ 60 (length of a music clip in seconds).

MCA features: For each second of the music video clips, low-level audio-visual features are extracted. These low-level Multimedia Content Analysis (MCA) features include: Mel-frequency cepstral coefficients (MFCC), spectral flux, zero crossing rate, pitch, energy, formants, silence ratio, lightning key, shadow proportion, visual details, colour variance, motion, and etc (see [11] for more details).

D. Classification Procedure

In the classification experiments we adopted an svm classifier under the leave-one-clip-out cross-validation schema to decode the brain/multimedia feature descriptors into our target genre classes. The feature descriptors are calculated as follows:

MEG-based, EEG-based and MCA-based descriptors: MEG/EEG/MCA descriptor of each trial is calculated by averaging the computed MEG/EEG/MCA features over the length of the music video clip (60 seconds). Hence, the length of each MEG descriptor is 408 (4 bands $\times$ 102 combined-gradiometer sensors), the length of each EEG descriptor is 128 (4 bands $\times$ 32 EEG sensors) and the length of each MCA

descriptor is 166 (number of multimedia features) respectively.

MEG+MCA fusion: For each subject, the MEG descriptors and MCA descriptors are concatenated and a feature vector of the length 408+166=574 is created as a result of such fusion.

EEG+MCA fusion: For each subject, the EEG descriptors and MCA descriptors are concatenated and a feature vector of the length 128+166=294 is created as a result of such fusion.

Note that the fusion MEG and EEG descriptors is not feasible, since the subjects in these two datasets are not the same (DEAP contains 32 subjects whereas DECAF contains 30 subjects).

IV. EXPERIMENTAL RESULTS

As explained in section III-D, for the sake of compatibility, the same svm classifier under the leave-one-clip-out cross-validation schema was employed to classify the extracted feature descriptors (MEG, EEG and MCA) into our genre classes (i.e. Pop and Rock). The ground-truth labels are used as the target labels in the classification procedure (see section III-B). Such evaluation, provides us with a fair comparison of our features descriptors (MEG, EEG and MCA). This procedure is performed in the two following scenarios:

Subject-level analysis

At subject level, the classification procedure was employed on the brain data of each subject separately. Thus, the classification of the MEG-descriptors and EEG descriptors are repeated 30 times and 32 times respectively (corresponding to the number of subjects in each dataset). For each subject, the 40 MEG/EEG descriptors (corresponding to the 40 music clips) are used as samples. Given the unbalanced number of samples for each genres, both accuracy and F-measure are reported as the metrics to compare the classification performance. These metrics are averaged over all subjects.

Table I compares the results of music genre classification using MEG, EEG and MCA descriptors with chance level (0.51). The chance level is computed by feeding random numbers with normal distribution into the classification procedure for 100 times. In both MEG and EEG case, the distribution of the obtained classification accuracies is better than chance level. This difference implies the existence of genre related information in the recorded brain activity. In the case of EEG descriptors, this difference is significant ($p-value < 0.001$). Furthermore, combining brain features (EEG descriptors and MEG descriptors) of each subject with MCA descriptors provides higher accuracy (0.75 and 0.82) than employing only EEG/MEG descriptors. Such brain-multimedia features fusion also outperforms the result of MCA descriptors suggesting the existence of complementary

music genre related information in the brain signals.

TABLE I
COMPARISON BETWEEN THE ACCURACY OF MEG, EEG AND MCA
DESCRIPTORS WITH RANDOM INPUTS IN THE SINGLE-SUBJECT LEVEL
SCENARIO.

Feature-Space	Accuracy	F-measure
Random	0.51 ± 0.10	0.60 ± 0.09
MCA	0.70	0.73
EEG	0.60 ± 0.10	0.66 ± 0.09
EEG+MCA	0.75 ± 0.05	0.78 ± 0.05
MEG	0.54 ± 0.10	0.62 ± 0.09
MEG+MCA	0.82 ± 0.04	0.86 ± 0.03

Population-level analysis

To evaluate the efficacy of MEG/EEG descriptors at the population level, for each video clip, we computed the majority vote over predictions of the single-subject classification across all subjects. The results are summarized in table II. In case of EEG descriptors, the population level accuracy (75%) is higher than the single subject-level accuracy (60%) and it is also higher than the classification accuracy of only MCA descriptors (70%). In case of MEG descriptors, the population-level analysis does not perform well. Nevertheless, in single-subject level analysis, as explained in previous section, the average obtained results are better than chance level. However, the fusion of brain features and multimedia features (MEG+MCA and EEG+MCA) outperforms the results of only MCA features in population-level scenario. This, confirms the existence of complementary genre related information in brain signals and multimedia contents.

V. CONCLUSION

In this paper, we presented an approach for classification of music video clips into two broad genres (pop and rock) using brain signals. For the sake of simplicity, a simple SVM classifier has been employed to perform the music genre prediction using the extracted brain features. We evaluated our approach on two neuroimaging datasets (EEG and MEG). Regardless of the limitation of such datasets that is few and noisy samples, our results shows the possibility of user-centric classification of music clips into two broad genres only based on brain signals. This is one of the first studies that employs brain signals for music genre classification. As our future plan, we will replicate the experiments using portable brain recording devices (e.g. Emotiv sensors). Furthermore, we plan to extend this work by employing other classification algorithms with different features extraction strategies in order to improve our classification results.

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TABLE II
MOVIE CLIP TITLES, GROUND-TRUTH LABELS, AND PREDICTED LABELS OF DIFFERENT FEATURE DESCRIPTORS.

ID	Music Clip Title	Ground-Truth	MCA	MEG	MEG+MCA	EEG	EEG+MCA
1	Emiliana Torrini: Jungle Drum	POP	ROCK	POP	POP	POP	ROCK
2	Lustra: Scotty Doesn't Know	ROCK	POP	POP	POP	POP	POP
3	Jackson 5: Blame It On The Boogie	POP	ROCK	POP	POP	POP	ROCK
4	The B52'S: Love Shack	POP	POP	POP	POP	POP	POP
5	Blur: Song 2	ROCK	ROCK	POP	ROCK	POP	ROCK
6	Blink 182: First Date	ROCK	ROCK	POP	POP	POP	ROCK
7	Benny Benassi: Satisfaction	POP	ROCK	POP	POP	POP	POP
8	Lily Allen: Fuck You	POP	ROCK	POP	POP	POP	ROCK
9	Queen: I Want To Break Free	POP	POP	POP	POP	POP	POP
10	Rage Against The Machine: Bombtrack	ROCK	POP	POP	POP	POP	POP
11	Michael Franti : Say Hey (I Love You)	POP	POP	POP	POP	POP	POP
12	Grand Archives: Miniature Birds	POP	POP	ROCK	POP	POP	POP
13	Bright Eyes: First Day Of My Life	POP	POP	POP	POP	POP	POP
14	Jason Mraz: I'm Yours	POP	POP	POP	POP	POP	POP
15	Bishop Allen: Butterfly Nets	POP	POP	POP	POP	POP	POP
16	The Submarines: Darkest Things	POP	POP	POP	POP	POP	POP
17	Air: Moon Safari	POP	POP	POP	POP	POP	POP
18	Louis Armstrong: What A Wonderful World	POP	POP	POP	POP	POP	POP
19	Manu Chao: Me Gustas Tu	POP	POP	POP	POP	POP	POP
20	Taylor Swift: Love Story	POP	POP	POP	POP	POP	POP
21	Diamanda Galas: Gloomy Sunday	ROCK	POP	POP	POP	POP	POP
22	Porcupine Tree: Normal	ROCK	POP	POP	POP	POP	POP
23	Wilco: How To Fight Loneliness	POP	ROCK	POP	POP	POP	POP
24	James Blunt: Goodbye My Lover	POP	POP	POP	POP	POP	POP
25	A Fine Frenzy: Goodbye My Almost Lover	POP	POP	POP	POP	POP	POP
26	Kings Of Convenience: The Weight Of My Words	POP	ROCK	POP	POP	POP	POP
27	Madonna: Rain	POP	ROCK	POP	POP	POP	POP
28	Sia: Breathe Me	POP	POP	POP	POP	POP	POP
29	Christina Aguilera: Hurt	POP	POP	POP	POP	POP	POP
30	Enya: May It Be (Saving Private Ryan)	POP	ROCK	POP	POP	ROCK	ROCK
31	Mortemia: The One I Once Was	ROCK	ROCK	POP	ROCK	POP	ROCK
32	Marilyn Manson: The Beautiful People	ROCK	ROCK	POP	ROCK	ROCK	ROCK
33	Dead To Fall: Bastard Set Of Dreams	ROCK	ROCK	POP	ROCK	ROCK	ROCK
34	Dj Paul Elstak: A Hardcore State Of Mind	ROCK	ROCK	POP	ROCK	ROCK	ROCK
35	Napalm Death: Procrastination On The Empty Vessel	ROCK	ROCK	POP	ROCK	ROCK	ROCK
36	Sepultura: Refuse Resist	ROCK	ROCK	POP	ROCK	POP	ROCK
37	Cradle Of Filth: Scorched Earth Erotica	ROCK	ROCK	POP	ROCK	ROCK	ROCK
38	Gorgoroth: Carving A Giant	ROCK	ROCK	POP	ROCK	POP	ROCK
39	Dark Funeral: My Funeral	ROCK	ROCK	POP	ROCK	ROCK	ROCK
40	Arch Enemy: My Apocalypse	ROCK	ROCK	POP	ROCK	ROCK	ROCK
-	Accuracy	-	70%	57.5%	87.5.6%	75%	72.5%

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