Analysis of the Interaction of Music and Emotions with the Help of EEG

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***Abstract*—This research paper delves into the intricate relationship between music and emotions, utilizing Electroencephalogram (EEG) data to unravel the underlying neural mechanisms. By analyzing EEG data, we aim to identify specific brainwave patterns associated with various emotional states elicited by music. This study is grounded in the hypothesis that music, a universal medium transcending cultural barriers, evokes a wide spectrum of emotions through distinct neural pathways. Understanding these pathways is crucial for developing advanced emotion recognition systems, enhancing therapeutic approaches in mental health, and improving human-computer interaction interfaces. Our findings contribute to the burgeoning field of affective computing by providing insights into the complex dynamics of music-emotion interaction, highlighting the potential of EEG in capturing the nuanced emotional responses evoked by musical experiences.**

***Index Terms*—Deep learning, electroencephalogram, EEG, music-emotion recognition, feature extraction, TDA**

I. Introduction

The intricate relationship between music and emotions has been a subject of fascination and inquiry across various disciplines, from psychology and neuroscience to musicology and cognitive science. Music, with its universal presence across cultures and its profound ability to evoke emotions, offers a unique window into the complex workings of the human mind. This paper seeks to explore the dynamic interplay between music and emotions, leveraging the advanced technology of Electroencephalography (EEG) to uncover the neural underpinnings of this interaction.

Understanding how music influences emotions and, conversely, how our emotional states affect music perception is pivotal not only for theoretical knowledge but also for practical applications in therapy, education, and entertainment. Despite the considerable body of research on this topic, the mechanisms through which music elicits emotional responses remain only partially understood. The application of EEG in this context presents an opportunity to gain insights into the real-time brain activity that underlies our emotional responses to music.

This study aims to bridge gaps in the current literature by providing empirical evidence on how different musical elements correlate with specific emotional responses at the neural level. By analyzing EEG data collected from participants as they listen to various musical pieces, we intend to decode the complex relationship between musical stimuli and emotional processing.

The paper is organized into several sections: following this introduction, we review existing literature on the interaction between music and emotions, highlighting the contributions and limitations of previous studies. We then detail the methodology employed in our research, including EEG data collection procedures, waveforms, spectrograms and topological data analysis. The subsequent sections present our findings, discuss their implications in light of current theories of emotion and music perception, and consider potential applications of our results.

II. Main body

A. Literature review

1) Music-emotion recognition: Music-emotion recognition (MER) is an interdisciplinary research area that bridges the gap between human affective states and musicology. State-of-the-art (SOTA) approaches in MER have leveraged advancements in machine learning, signal processing, and affective computing to predict emotional states induced by music. A seminal work in this area is by Zhou et al. [2], who provided a comprehensive survey on music emotion recognition, discussing various approaches including content-based and context-based methods.

The use of electroencephalogram (EEG) data in music-emotion recognition introduces a novel aspect of studying the physiological responses to musical stimuli. This approach provides direct insights into the brain's reactions to music, offering a more objective measure of emotional states compared to self-reported methods. A pivotal study by Cui et al. [1] demonstrated the effectiveness of using EEG data for emotion recognition, employing machine learning algorithms to classify emotional states based on brainwave patterns induced by music. Approaches described in this survey often lack interpretability or complexity: in some of them a compatibly primitive and featureless emotion model is used, while in the others the structure of data is not taken into account and somewhat trivial classifiers/regressors (e.g. SVM, Random Forest, linear regression) are used.

For instance, one of the most recent existing approaches includes using a transformer model as an emotion classifier [7]. The drawbacks of this approach are the following: the given task is binary classification, so the model is able to differentiate only two types of emotion. Therefore, it provides only a limited representation of the complicated mechanism of music perception.

Furthermore, in our work we are planning to apply TDA-based methods to the MER task, so works related to this topic should also be considered. For instance, research by Xu et al. [4] explored the use of topological data analysis (TDA) on EEG data for identifying complex emotional responses, showcasing the potential of TDA in uncovering intricate patterns within high-dimensional EEG datasets. Hovewer, this work does not cover the MER-task and focuses on the TDA-EEG relation globally. Another example of TDA-related paper is a work by Zheng et al. [6], which is covering the application of the TDA to the scalp EEG classification and still does not delve into the music-emotion recognition. Thus, we state that the notion to approach the MER-EEG task using TDA is novel, yet promising.

Apart from TDA, it is reasonable to propose a graph-based solution for the stated task. Graph Neural Networks (GNNs) have emerged as a promising tool for analyzing complex, structured data, offering new avenues for advancements in this area. For example, graph-based models such as Graphormer, Ying et al. [5], a novel approach that enhances the performance of Graph Neural Networks (GNNs) by incorporating concepts from Transformers. The key insight of Graphormer lies in effectively encoding the structural information of graphs into the model, and this feature may be efficiently transferred to the task of music-emotion recognition. Besides, it is important to mention the AASIST, Jung et. al [3], a GNN-based solution for antispoofing task, that is able to successfully detect a broad range of different spoofing attacks on the wave-like data. Based on this fact we propose that it is a reasonable idea to extrapolate AASIST from the speech waveforms to the EEG-waveforms.

B. Methodology

1) EEG data: Electroencephalogram (EEG) data is collected through a non-invasive method that involves placing electrodes on the scalp to measure electrical activity generated by brain structures. This activity is recorded as wave patterns that are indicative of various cognitive states, emotions, and neurological conditions. The EEG setup typically consists of a cap fitted with multiple electrodes, each providing a channel of data that captures the brain's electrical signals at different locations. The collected data is then amplified, digitized, and stored for analysis, often in formats compatible with specialized software for EEG analysis. EEG data is characterized by several types of waves, each with distinct frequency ranges and associated with different states of brain activity. These include Delta waves (0.5-4 Hz), associated with deep sleep; Theta waves (4-8 Hz), linked to drowsiness and creative states; Alpha waves (8-13 Hz), present in relaxed but alert states; Beta waves (13-30 Hz), which are seen during focused, cognitive activities; and Gamma waves (¿30 Hz), related to higher mental activity and integration of sensory information. The ability to differentiate between these wave types allows researchers and clinicians to infer the subject's mental state or identify abnormalities. Advances in EEG technology and data analysis methods continue to enhance our understanding of the complex dynamics of brain function, contributing to fields ranging from cognitive neuroscience to clinical diagnostics and neurofeedback therapies. To collect the data, in most cases the 10-20 system is used. The 10-20 system is a standardized method used in EEG studies for the placement of electrodes on the scalp. This system ensures that the electrodes are positioned in a consistent manner across different subjects, facilitating comparability of results. In an experiment, specific electrodes might be chosen based on the brain regions of interest. The 10-20 system enables researchers to systematically study brain activity across these regions, ensuring that data collection is both reproducible and precise, thereby facilitating the analysis of EEG data in relation to cognitive processes or neurological conditions. In our work we use the 10-20 system during the experiment, which we conduct to acquire brain activity related to different kinds of music.

2) Feature extraction: Electroencephalography (EEG) data can be represented and analyzed in various formats, each offering unique insights into brain activity. Two common representations are waveform (time domain) and spectrogram (time-frequency domain). Understanding the advantages and disadvantages of each can help researchers and clinicians choose the most appropriate method for their specific needs.

Both waveform and spectrogram representations of EEG data have their unique strengths and limitations. Waveform analysis offers excellent temporal resolution and simplicity but lacks direct frequency information. Spectrograms provide a rich, comprehensive view of both time and frequency characteristics of brain activity but are more complex and computationally demanding to analyze. The choice between these two approaches depends on the specific goals of the study or clinical assessment, with some scenarios benefiting from combining both methods to leverage their respective advantages.

3) TDA, waveforms, spectrograms: Topological Data Analysis (TDA) is a relatively recent development in the field of data science and machine learning, focusing on understanding the shape (topology) of data. TDA seeks to uncover patterns, structures, and relationships within data that traditional analysis methods might overlook, by examining its geometric properties. This approach can be particularly powerful in complex datasets, such as those generated by EEG recordings, where the underlying structures and connections are not immediately apparent.

When applying TDA to EEG data, the choice between using waveform (time domain) or spectrogram (time-frequency domain) representations depends on the specific aspects of the brain activity one aims to analyze and the inherent characteristics of TDA.

Waveform data preserve the original temporal dynamics of brain activity, which could be crucial for understanding how different regions interact over time. TDA can be used to explore these temporal patterns, identifying recurring shapes or loops in the data that signify periodic or cyclic brain activity. This can be particularly useful for studying event-related potentials (ERPs) or identifying abnormal temporal patterns in neurological disorders. At the same time, the main limitation of using waveforms for TDA in EEG analysis is the high dimensionality and potential noise in the time domain signals. This can make it challenging to extract meaningful topological features without substantial preprocessing.

Spectrograms convert EEG data into a time-frequency representation, providing a comprehensive view of how different frequency bands evolve over time. This additional dimension of frequency can reveal important topological features, such as cyclic behavior in specific frequency bands or interactions between frequencies over time. For TDA, this means more rich and nuanced insights into the brain's dynamic processes, potentially uncovering patterns that are not visible in the raw waveforms. The complexity of spectrograms can be a double-edged sword. While they offer richer information, interpreting the topological features extracted from spectrograms can be more challenging. Additionally, the transformation from time domain to time-frequency domain might introduce artifacts or distortions that could affect the topology of the data.

In practice, it might be beneficial to explore both approaches in a complementary manner. Initial investigations can start with one representation to identify broad patterns or areas of interest, followed by a more detailed analysis using the other representation to delve deeper into specific aspects uncovered by TDA. This dual approach leverages the strengths of both waveform and spectrogram representations, offering a comprehensive understanding of EEG data through the lens of topological data analysis. Therefore, in our work we are going to train the models both on the waveforms and on the spectrograms.

C. Expected results

We anticipate that TDA will unveil unique topological patterns in EEG data that correlate with specific emotional states induced by music. These patterns, when combined with traditional EEG features, are expected to enhance the accuracy and robustness of MER models. Specifically, we predict that: - TDA-derived features will provide significant improvements in emotion classification performance compared to models trained on traditional EEG features alone. - Persistent homology-based features will reveal distinct topological signatures for different emotions, offering new insights into the neural correlates of music-induced emotions. - The integration of TDA features with machine learning models will establish a novel framework for MER, setting a precedent for future research in this domain.

As for the graph approach, the application of graph-based neural networks is expected to efficiently manage the high-dimensional nature of EEG data, effectively capturing the complex spatial-temporal relationships. This would be evident in the reduced computational resources required for training and inference compared to traditional deep learning approaches that do not explicitly model these relationships. Besides, through the analysis of graph-based neural network models, novel biomarkers associated with specific emotional states elicited by music are expected to be identified. These biomarkers could provide new insights into the neurophysiological underpinnings of music-induced emotions.

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