Inter-Subject Synchrony and Emotional Dynamics in Magnetoencephalographic Signals During Music Stimulation

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ABSTRACT

Music has been present throughout human evolutionary history and is an intimate part of the human form of life which can elicit strong and a wide range of emotions. Recent evidence suggests that during social situations and prolonged natural stimulation, synchronization of individuals' brain activity may occur in a multitude of brain areas during audio and visual stimuli. This study analyzes the Magnetoencephalographic (MEG) based music emotion by combining these two concepts of inter-subject synchrony and music stimulation. The dataset used in this study is already preprocessed using the spatiotemporal signal space separation (tSSS) method and can be immediately used to perform analysis and experiments. Inter-subject correlation analysis and correlation component analysis is used to show that brain responses synchronize among subjects to different parts of music stimulation. Further, Spearman correlation coefficient is computed to verify negative correlation between the standard deviation of subject's emotions and averaged inter-subject synchrony, which consequently means that when brain signals synchronize across subjects, it is due to the same emotional perceptions that the subjects felt to the song.

KEYWORDS

Magnetoencephalographic Signals, Inter-subject Synchrony, Music-Emotion, Correlated Component Analysis

1. INTRODUCTION

Music is an intimate part of the human form of life and it has been well argued that music is a universal and cross-culturally present feature shared by all humans [3, 20]. It has been present throughout hominid evolutionary history [2], and always had a powerful effect on the human brain. Neuroscience of music represents the scientific study of brain mechanisms and cognitive processes underlying music; while the brain induces emotion by a variety of stimuli, music is considered an extraordinary material to elicit strong and a wide range of emotions [9, 19]. Due to the human evolutionary history, unexpected deviations from a regular sound pattern induce powerful emotions in the human brain, like a crack of a branch during a nightly scene might indicate the approach of a predator [7]. This is common in everyday life and modern music as well and often convey important information about the emotions of the subject.

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Copyright 2020, University of Twente, Faculty of Electrical Engineering, Mathematics and Computer Science. Many studies have shown that human emotions are highly contagious. Recent evidence suggests that during social situations and prolonged natural stimulation, synchronization of individuals' brain activity may occur in a multitude of brain areas [13]. These shared emotions are usually elicited by the same stimuli in multiple subjects which can be found using functional magnetic resonance imaging (fMRI) [19], which has relatively lower temporal resolution than modern tools like Magnetoencephalographic (MEG). As stated by Thammasan et al. "Understanding inter-brain synchrony may pave a way towards insights on emotional dynamics when exposing emotional stimuli" [19].

The dataset used for this study has been taken from an institute currently researching in brain-computer interfaces (BCIs). Even though BCIs have been studied for decades with the primary goal to provide assistance for people with severe disabilities [12], the applications for BCIs has grown significantly in recent years. This is because usually BCIs are subject-specific and have time consuming calibrating processes [15], making them difficult to develop. Due to the diversity in individual brain growth, it would be really helpful if some applications of BCI can take advantage of brain synchrony. The results from this study can be used in developing efficient human-computer interfaces because recognizing the emotions and synchrony among users make the users' experience more complete in several target applications.

This study analyzes the MEG based music emotion by combining these two concepts of inter-subject synchrony and music stimulation. Examining the similarity/difference in the response in MEG signals to musical stimuli and studying inter-subject synchrony while also determining if the different brain signals are caused by the different emotional perceptions by the subjects would be the main focus of this study.

2. RESEARCH QUESTION(S)

RQ1: Does the brain magnetoencephalographic (MEG) response synchronize across subjects to the same part of music stimuli (inter-subject synchrony)?

RQ2: If the brain magnetoencephalographic (MEG) response differ across subjects to the same part of music stimuli, is it related to the different emotional perceptions of music by different subjects?

3. BACKGROUND

Music plays an important role in informing broad theories of higher-order cognitive processes. Listening or playing music can elicit multiple senses and a variety of activations in different areas of the brain as shown in figure 1.



Figure 1. Core brain areas associated with musical activity. (Based on Tramo, 2001, updated from Levitin, 2006) [11]

Brain imaging like fMRI, EEG and MEG are usually used to locate brain activity in these regions during attentive music listening. EEG signals are frequently used to analyze brain activity and infer emotional states in the data. Previous research on the topic of inter-subject synchrony has also been done mostly using EEG. MEG is high-standard brain imaging with a highdensity electrode which also allows source localization (pinpointing source of brain activity at a particular instant) and investigation at that source.

Although EEG and MEG signals are different, they share many common features as they are simultaneously generated by the identical brain oscillation. By focusing on these equivalent characteristics, MEG signals can be treated as EEG signals with a greater number of electrodes. By doing this, the same EEG techniques can be utilized to analyze the MEG dataset. This data is then used to infer conclusions about inter-subject synchrony.

Uri Hasson introduced the method of inter-subject correlation (ISC) and in his research states that individual brains 'tick together' when exposed to the same environment [6]. ISC is not technically a measure of activity but a model-free analysis method that is used to detect common stimulus-driven brain activity that is temporally synchronized between subjects [20]. BCIs are very dependent on a users' emotional signals and responses. It is fair to assume that research into stimuli that can induce strong emotions such as music and studying the underlying brain activity during this stimulus will pave new understanding into ISC. The manifestation of structural elements, gestalt and integration of information over extended periods make ISC a suitable approach for music studies [1]. ISC analysis

can be performed using Correlated Component Analysis (CorrCA).

CorrCA was originally developed in the context of neuroimaging studies to extract similar activity in multiple subjects [4]. In this study, we use CorrCA to identify components that are maximally correlated between repetitions which in this case are the subjects to better understand brain synchrony when listening to music.

4. RELATED WORK

Although there isn't much research done on MEG ISC (intersubject correlation) in music-emotion dynamics, many studies have demonstrated that MEG ISC is a viable approach to discover the dynamics of speech [21], movie perception [10] and social interaction [5]. One of the studies on MEG ISC in musicemotion dynamics [20] focuses on the concurrent changes in power spectral density which sacrifices the high temporal resolution of MEG data. Therefore this study and the project that it is based on, uses the application of CorrCA approach [4, 19].

However, the previous preliminary work [19] using the same dataset did not take into account time-course of synchrony with limit inference on emotion. The results of that study showed the correlation between averaged ISC and the annotated valencearousal scores during the song trials. This study will further increase the granularity of ISC by dividing the songs into smaller epochs to determine the exact time of synchrony among the subjects aiming to gain insights on emotion-driven ISC.

5. METHODS

The data in this study is drawn from an existing study of MEGbased music-emotion conducted at Centre for information and Neural Networks (CiNet) [19] with permission for research purpose under the collaboration with University of Twente. CiNet is an interdisciplinary neuroscience technology research institute based in Osaka, Japan researching on a number of neuroscience-related areas including active non-invasive BMI (Brain-Machine Interface) program. MATLAB was used to analyze the data and produce figures and statistics in this study. Along with the descriptions for the participants and stimuli used in this dataset, a visual representation of the experiment that a subject goes through is shown in figure 2.



Figure 2. Visual representation of the experimental protocol for constructing the dataset used in this study

5.1 Participants

The data was collected from 36 healthy adults which consisted of 11 female subjects and 25 male subjects, which had been approved by the ethics committee of CiNet, Suita, Japan [19]. All subjects gave written informed consent to participate in the study.

5.2 Stimuli

In this experiment, a subject participated in six sessions of music listening task; where each session consisted of the listening of four 45-second musical excerpts, each of which was preceded by a 5-second white-noise sound listening for baseline purposes. The participants were expected to elicit four different types of emotions; high-arousal-positive-valence, low-arousal-positive-valence, low-arousal-negative-valence, and high-arousal-negative-valence after listening to the music excerpt. They were asked to annotate their emotion on an arousal-valence model after each song.

5.3 Data Acquisition

360-channeel neuromagnetometers produced by Elekta Neuromag system (Helsinki, Finland) were used to collect the MEG signals of the subjects in a seating position. The machine consisted of 206 planar gradiometer, 103 magnetometer and 51 vertical magnetic sensors at the sampling frequency of 1000 Hz [19]. In this study we merely use 102 magnetometer channels and MEG channels that are band-passed to 0.02-330 Hz.

Head-position-indicator (HPI) coils were used in this experiment to help determine the exact position of the subject's head with respect to the sensor helmet before each stimulus session. This was done to allow future analysis of source localization. However, source localization is not part of this study due to time constraints. [19]

Furthermore, time delay correction has already been done on the dataset to ensure the time alignment along with preprocessing of the data using spatiotemporal signal space (tSSS) method [9] implemented within the Elekta Neuromag Maxfilter system.

5.4 Data Analysis

5.4.1 Preprocessing

The first step would be to start with the data pre-processing and cleaning of the MEG dataset. This can be achieved by using signal space separation (SSS) method [20] or spatiotemporal signal space separation (tSSS) method [18] to suppress external magnetic artefacts on MEG signals which is implemented within the Elekta Neuromag Maxfilter system.

Maxfilter software uses tSSS to clean the MEG data in many ways like, remove noise using the temporal extension; detecting bad channels that are either malfunctioning or too different from the channels around it; realigning interpolated data after a movement of the head, which is possible because of the HPI coils being used during the sessions; and moving the data to a standard space across all subjects. The dataset received is already preprocessed and can be immediately used to perform analysis and experiments.

5.4.2 Inter-subject Synchronization

After noise and irregularities in the data has been cleaned, intersubject correlation analysis can be performed using CorrCA approach [4]. CorrCA is a similar approach to canonical correlation analysis which is just generalized so that it can be applied to multiple subjects. This is used to uncover the projection matrices which maximize correlation between different components of the brain [8], yielding the underlying neural response that was recorded. By looking at the MEG activity during a particular instance in a song and crossreferencing it with all subject data gives a clear view of the existence and extent of inter-subject synchrony during music stimulation.

CorrCA can be performed on datasets with three dimensions such as $T \times D \times N$. Figure 3 shows an illustration of how CorrCA can be done. Neural activity is measured among N subjects using D number of channels/electrodes. T denotes the repeated measures done on the same electrodes. In this study there are 36 subjects, 102 channels and 24 songs/trials.



Figure 3. Overview of how CorrCA is performed during natural stimulation [8]

This algorithm is used to analyze the data and the MATLAB code implemented is taken from Lucas Parra [14] and Nattapong Thammasan [19]. As shown in figure 4, in this study, only the top three correlated components are used to measure ISC. Just like in a previous research, correlated components are going to be separately extracted for each set or trial of data and the top three components are taken to average ISC to maximize the correlated brain activity and produce meaningful results [16].

5.4.3 Music-Emotion

The inter-subject synchrony is then tested in association with the emotional labels of the subjects. By correlating the emotional valence and arousal scores of the subjects during a song might provide insight into the similarity and differences in synchrony.

To achieve this, Spearman correlated coefficient is used which is based on ranked values to prove the hypothesis that the standard deviation of the arousal and valence scores is negatively correlated to the average ISC observed among subjects. Spearman analysis is used instead of other methods because it is non-parametric. The dependent and independent variables being tested for correlation are ordinal rather than linear and don't follow normal distribution.

If the coefficient is negative in the results then it can be concluded that as ISC increased, the SD of emotional scores tend to decrease. This will help answer the second research question by verifying if difference in synchrony is related to different emotional perceptions of the subjects to that song.

6. RESULTS

The MEG brain activity of 36 adults was measured during music stimuli. To examine the variation of synchrony in the MEG signals, each song of 45 seconds was divided into nine epochs of 5 seconds each to determine the exact time of synchronization and increase the granularity of ISC. This would suggest the evidence that ISC varies over time rather than being stable throughout natural stimulation. The 24 songs or trials as referred to in the figures, that were used in this study were grouped into

four types of expected emotion before the experiment; positivevalence-high-arousal, positive-valence-low-arousal, negativevalence-low-arousal, and negative-valence-high-arousal. The analysis was done on these groups of songs separately to produce new findings regarding the role of emotions in ISC.

Each of the figures below represent the correlation between the averaged ISC of top three synchronized components of the brain versus the epoch number in the song which correspond to five seconds each. The figures 4,5,6 and 7 shown below have six line plots each belonging to the group of four different emotional types.



Figure 4. Correlation between epoch number and averaged ISC among songs grouped as expected emotion positivevalence-high-arousal



Figure 5. Correlation between epoch number and averaged ISC among songs grouped as expected emotion positivevalence-low-arousal



Figure 6. Correlation between epoch number and averaged ISC among songs grouped as expected emotion negativevalence-low-arousal



Figure 7. Correlation between epoch number and averaged ISC among songs grouped as expected emotion negativevalence-high-arousal

Furthermore, to find if there is any correlation between the standard deviation of valence-arousal scores the subjects annotated after each song and the averaged ISC scores, Spearman correlation plots are graphed. Figures 8 and 9 illustrate these two plots for valence and arousal separately.



Figure 8. Spearman correlation plot between ISC and SD of valence scores



Figure 9. Spearman correlation plot between ISC and SD of arousal scores

7. DISCUSSION

As shown in figures 4, 5, 6 and 7, higher synchrony can be observed at the beginning of each song. Although the reason behind this is unclear, it can be argued that the subjects were attentive during the first five seconds of listening either because they were trying to recognize the song or reacted to the change from white noise to music. Further research needs to be done to determine the reason for this.

It is also apparent that groups of trials expected to elicit higharousal emotion seem to induce more ISC than groups of lowarousal songs. Some studies have shown that people usually favor positive emotional states [17] and it could be that higher arousal stimuli elicit or trigger stronger emotion than less arousal stimuli. Also, it might be the case that, since arousal is the phycological and physiological state of being awoken or the brain stimulated enough to the point of perception, the evolution history of humans might play a role in this as discussed in the introduction that strong or sudden sounds can induce powerful emotions in one's brain. And this hypothesis is further verified by the fact that some unusual peaks in ISC for example in figure 4 and 7, trials 17 and 20 have sudden increase in ISC during epoch 4 and 6 respectively. During this time, the songs had an unusual sound like intentionally playing an incorrect note or at the very least disrupted the flow of the song by using different music. Even if this is not the case for every sudden increase in synchrony, it is worth studying in future research. It is also worth pointing out that the ISC in high-arousal songs is more fluctuating that stable ISC in low-arousal songs. This finding is again consistent with the assumption that high-arousal songs induce stronger and varying emotions among subjects than lowarousal songs.

Although there was some amount of synchrony among subjects during the experiment, it is hard to say whether it was genuinely due to the emotion state of the subjects or external factors like low-level auditory processing, high-level musical feature perception or a number of other plausible reasons. Therefore, the second part of the study was done to check if the emotions annotated by the subjects correlated to the ISC. Figure 8 and 9 illustrate the Spearman correlation between the standard deviation of the arousal, valence scores and the averaged ISC. As seen from the results, the spearman correlation coefficient is negative in both plots which means that as the values in horizontal-axis increase, the values in vertical-axis tend to decrease. The result proves this hypothesis because as expected, when the SD of emotional scores are low which means the subjects felt relatively the same emotion to the song, the average ISC increased. Hence, the synchrony among subjects was relatively less for a music excerpt, when the emotions of the subjects differed drastically. However, this association is not statistically significant because it's p-value is greater than 0.05 as seen in figures 8 and 9.

8. CONCLUSIONS

The study provides new information regarding inter-subject brain synchronization in response to music stimuli. Inter-subject correlation (ISC) and correlation component analysis (CorrCA) are two approaches that are used in this study to find synchrony in subjects' brain signals over multiple songs or trials. Further, spearman correlation coefficient is used to find how ISC tends to increase or decrease in relation to the standard deviation of emotions among subjects.

Based on the results it can be observed that there is indeed higher ISC in brain activity during certain parts of music stimulation when listening to unusual or unfamiliar sounds. Songs expected to induce high-arousal emotion showed increase in synchrony among subjects which can be interpreted that stimuli that can awaken the perception parts of the brain can lead to higher ISC. It is also observed that synchrony is usually high during the beginning of a song and further research has to be done on this to find the underlying reasons for this incident.

The second part of the results show that when the MEG response of the subjects differs and when synchronization is low, the emotional valence and arousal scores that the subjects reported had higher standard deviation. Hence proving that SD of the emotions felt by subjects is negatively correlated to the synchrony they experienced. Although this is an interesting finding, it is not statistically significant and interpreting and using these results should be done with caution.

Future work can be done on the reliability of these methods and studying the accuracy based on practical experiments. Combining this study's results with source localization can pave a new understanding into the specific brain regions that are synchronized to different types of emotion inducing stimuli. This will not only provide more detailed information of the human brain but also allow conducting new types of analysis that are not possible with other brain signal data.

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