Magnetoencephalographic correlates of emotion regulation: topography and classification

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***Abstract*—The most common strategies of emotion regulation are reappraisal and suppression. However, it is still unclear which neural mechanisms underlie them, since a number of studies have identified different patterns of brain activation. In the present study, for the first time, the inter-subject correlation was calculated based on the neural activity captured by magnetoencephalography during free watching of neutral and negative videos, reappraisal and suppression. We also examined sources of activation and attempted to predict the conditions using a neural network. We revealed a greater average inter-subject correlation (a marker of engagement in naturalistic stimuli) regarding watching negative videos in comparison to other conditions, which points to individual differences in emotional processes. Inter-subject correlation of the source activity was higher in the prefrontal cortex during both regulation strategies compared to natural watching of negative videos, which supports the assumption of the involvement of this region in regulation. We were not able to predict the condition of watching by the network, but found that it has a potential to learn and, supposedly, requires more samples in a training dataset. In sum, the inter-subject correlation measures based on magnetoencephalography demonstrated different synchrony of neural activation regarding aspects of emotion regulation, which is worthwhile to investigate in further studies with other naturalistic stimuli.**

Keywords—emotion regulation, magnetoencephalography (MEG), inter-subject correlation (ISC), reappraisal, suppression

I. Introduction

Emotion regulation (ER) involves managing emotions, either by maintaining or altering states experienced at the moment [1]. Cognitive reappraisal, focusing on changing thoughts and attitudes towards a situation, and suppression aimed at inhibiting feelings or expressions are among the most common strategies for ER [2,3]. A number of studies have shown that reappraisal is generally more effective and contributes to long-term well-being, although suppression can also be useful in short-term goal-oriented conditions [4–6]. The difference in the impact of strategies on long-term outcomes can be due to the specific involvement of physiological systems.

In studies focusing on brain activity, predominantly utilizing functional magnetic resonance imaging (fMRI) and electroencephalography (EEG), ER was attributed to the activation of the prefrontal cortex [7–9], as well as the anterior insula and the premotor area [10,11]. In addition, enhanced activity in the lateral temporal lobe and diminished activity in the amygdala were revealed during reappraisal [8,10]. The results of suppression research are contradictory regarding the insula and amygdala, however, correlations with increased activation of the inferior parietal cortex and decreased activation of the temporo-occipital regions have been shown [12].

A less common method of studying ER is magnetoencephalography (MEG), which is mainly implemented for spatio-temporal evaluation. For instance, emotion-related inhibition processes from 100 to 425 ms after stimulus onset were found in the right angular and occipital gyri, the right orbito-frontal gyrus and the left anterior temporal lobe [13,14]. Meanwhile, the high spatial and temporal resolution of MEG makes it valuable for tracking rapid neural responses to emotional stimuli and regulation processes using various types of analyses. One of the promising methods is the inter-subject correlation (ISC) analysis, which identifies neural activity patterns shared across individuals and is suitable for long events and naturalistic stimuli [15]. At the same time most MEG studies regarding emotions utilize images, while implementation of more naturalistic stimuli, like videos, could provide better insights into dynamic processes [16]. Moreover, in an earlier EEG study of ER, the paradigm with clips presentation was already used in combination with ISC: a higher ISC was revealed during regulation processes in comparison to watching negative/neutral video [17].

Our study aimed to explore MEG correlates of ER while subjects watched one-minute negative video clips and used reappraisal or suppression strategies in contrast to watching neutral and negative video without regulation. We hypothesized that neural spatial activation, as well as ISC, would vary regarding emotional valence and regulation conditions. Additionally, in order to explore the possibility of prediction of conditions (free watching or regulation) based on MEG sources data, we applied a convolutional neural network.

II. Methods

A. Sample

Twelve healthy females and six males in the age range between 18 and 24 years (mean age=19.5, SD=1.6), took part in the experiment. None of the participants reported any neurological or psychiatric conditions. All participants signed

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informed consent and were informed about potentially unpleasant content, including blood in the scenes (ethical approval from HSE University № 92, 19.09.2022).

B. Stimuli

For our experimental setup, we selected 36 one-minute videos from our database of affective videos (currently under review). Nine of these videos were emotionally neutral (M=5.13; 1 denoting "very negative" and 9 denoting "very positive"), while the other 27 contained negative content (M=2.78), featuring scenes such as surgeries, suffering animals, starvation, and fights.

C. Procedure

The ER paradigm was based on the approach outlined by Richards and Gross [18], which we had previously tested in earlier studies [19,20]. Each of the 36 videos, presented for 60 seconds, was accompanied by one of three instructions: "just watch", "reappraise", or "suppress", followed by a rest period of 12-18 seconds. During the "just watch" condition, the participants just naturally watched the videos. In the "reappraisal" condition, the participants were asked to watch the videos with emotional detachment, focusing on details and perceiving the content from an objective perspective to minimize emotional load; while in the "suppression" condition the instruction was to control emotional feelings through maintaining a neutral facial expression. After each video, the participants reported the negativity of emotions from 1 for "neutral" to 9 for "very negative".

All neutral videos were shown with the "just watch" instruction, while the negative videos were equally divided between the three instructions. To prevent order effects on the valence ratings [21], each participant watched the videos in a randomized order, with no more than two consecutive presentations of the same condition. Additionally, presentation of the negative stimuli was arranged in such a way that every video was seen under each condition by an equal number of the participants. Thus, our approach takes into account the fact that the same stimulus can cause a different perception of negativity.

D. Data recording

The neural activity data was registered using a 306-channel Neuromag Vector View MEG system (Elekta Oy, Finland) in a magnetically-shielded room at 1 kHz. Throughout the recording session, a band-pass filter (0.1-330 Hz) was applied, and the position of the participant's head was continuously monitored using the HPI coils. Heart rate and ocular movements were obtained to delete artefacts.

E. Data processing

The MEG data was notch-filtered at 50 and 100 Hz. Electrooculography (EOG) signals from two channels, electrocardiography (ECG) signals and empty room signal-space projections (SSP) were applied to eliminate eye-movement and cardiac artifacts [22]. Following these steps, the processed data was segmented into epochs. The MEG preprocessing was performed in the MNE Python [23].

F. Source localization

Various surface reconstructions were created from the individual MRI data using FreeSurfer [24]. We generated reconstruction geometry of 'oct5' with approximately 9.9-mm spacing, resulting in 1026 sources per hemisphere for ISC analysis. The next step involved calculating the forward solution using the boundary-element model. After the alignment and computation of the forward solution, the inverse operator was calculated and applied to the MEG data. The source data were downsampled to 125 Hz to reduce the complexity of calculations.

G. Inter-subject correlation and its topography

ISC was computed separately for each video [25,26]. Three first components were averaged for each subject within each video. Then we averaged ISC within conditions for each subject. Finally, we conducted an analysis of variance with four conditions ("watch neutral", "watch negative", "reappraise", and "suppress") as repeated measures with the Bonferroni correction. To explore the brain topography of ER, for each video clip we computed the mean of three components for each source in every condition. We averaged ISC within conditions for each video and each source. Then we performed a t-test using with 10000 permutations for all pairs of conditions (6 tests with the Bonferroni correction) for each source (with SciPy Python; [27]).

H. Condition prediction

We attempted to predict the four different conditions ("watch neutral", "watch negative", "reappraise", and "suppress") using the localized source data during watching one-minute videos from 18 subjects, totaling 612 entries. Among these objects, the source data of two participants (72 entries) were reserved for testing, while the rest were utilized for training. Each entry was characterized by a matrix of size 2052 × 7500, representing sources over time. We selected a convolutional network EEGNet [28] and conducted training with 50 epochs, assessing loss and accuracy on both training and validation sets.

III. Results

We revealed significant differences in ISC between conditions (F=12.8, η^2=0.05, p<0.001, Fig. 1). Post hoc tests showed the watching negative videos differed from all other conditions: watching neutral videos (t=3.5, p=0.01), suppression (t=4, p<0.001), and reappraisal (t=4.75, p<0.005).

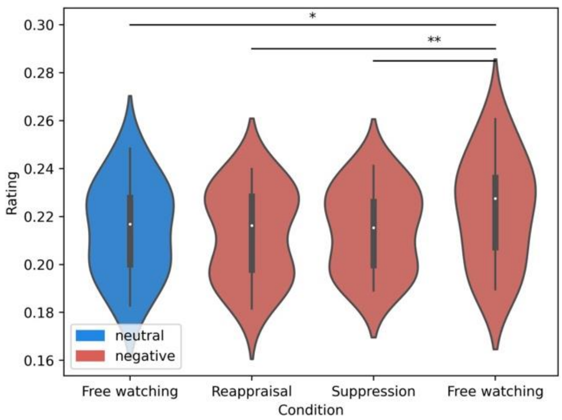

Fig. 1. Inter-subject correlation of source activity during watching neutral and negative videos, suppression and reappraisal, *p=0.01, **p<0.005. The point inside the "violin" represents the median of the data. The black rectangle (box) shows the interquartile range (IQR). Whiskers are within 1.5 * IQR of Q1 and Q3. The bottom line has p<0.005.

A topographic analysis showed significant differences in ISC regarding activation of several brain regions during conditions. Fig. 2 reflects the differences between watching negative videos and suppression. Thus, in the left hemisphere the following areas were detected: middle anterior cingulate gyrus and sulcus, lateral superior temporal gyrus, superior and transverse occipital sulcus. While in the right hemisphere these were: superior frontal gyrus, orbital gyrus, superior parietal gyrus, middle temporal gyrus, central sulcus, intraparietal and transverse parietal sulcus, h-shaped orbital sulcus, postcentral sulcus, superior part of the precentral sulcus, superior temporal sulcus.

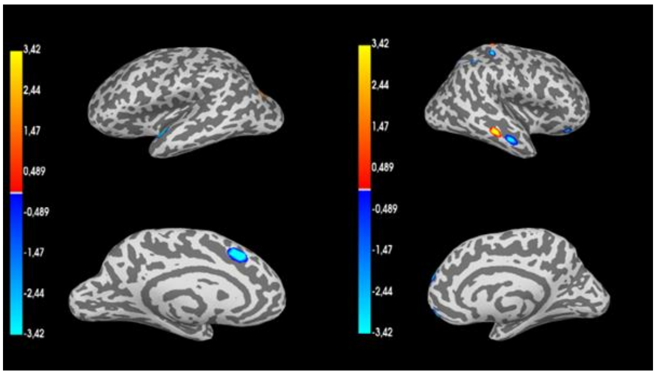

Fig. 2. Topoplots of sources (n=13 sources) where ISC significantly differed between the conditions. The right hemisphere is shown on the right side of the image, the left – on the left side. Yellow represents sources where watching negative > suppression; blue represents sources where suppression > watching negative. Scales indicate t values of permutations tests ($p<0.008$).

Fig. 3 represents the differences between watching negative videos and reappraisal. In the left hemisphere were indicated regions: middle anterior cingulate gyrus and sulcus, cuneus gyrus, supramarginal gyrus of the inferior parietal lobe, posterior lateral fissure, superior circular sulcus of the insula, lateral orbital sulcus, subparietal sulcus, superior temporal sulcus. At the same time, in the right hemisphere these were: middle anterior cingulate gyrus and sulcus, inferior temporal gyrus, anterior circular sulcus of the insula, superior and transverse occipital sulcus, h-shaped orbital sulcus, pericallosal sulcus, superior temporal sulcus.

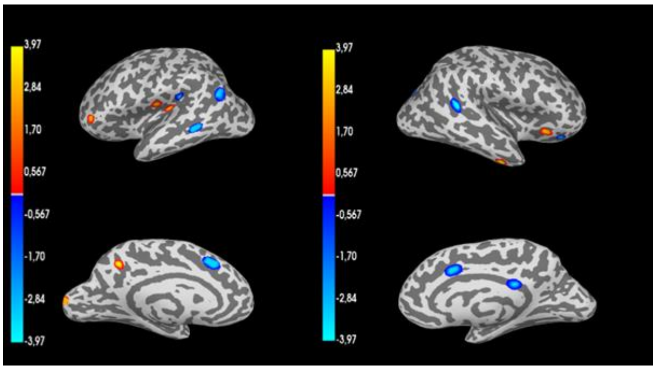

Fig. 3. Topoplots of sources (n=15 sources) where ISC significantly differed between the conditions. The right hemisphere is shown on the right side of the image, the left – on the left side. Yellow represents sources where watching negative > reappraisal; blue represents sources where reappraisal > watching negative. Scales indicate t values of permutations tests ($p<0.008$).

The obtained prediction model utilizing the network EEGNet revealed the ability to learn neural patterns of the conditions on the training data, at the same time the accuracy and Cross Entropy on the test set showed that it was overfitted and cannot yet predict new data with sufficient accuracy. Thus, Fig. 4 shows Cross Entropy Loss on the training and validation data after each epoch. We can see a significant drop in the loss during training, while there is no change in the validation set. Fig. 5 indicates accuracy on the training and validation data after each epoch. The training accuracy is noticeably different from the test accuracy due to overfit of the model.

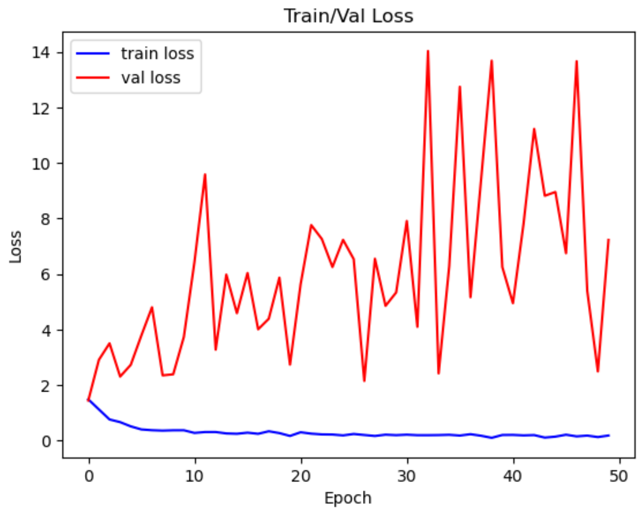

Fig. 4. Cross Entropy Loss on the train and validation data.

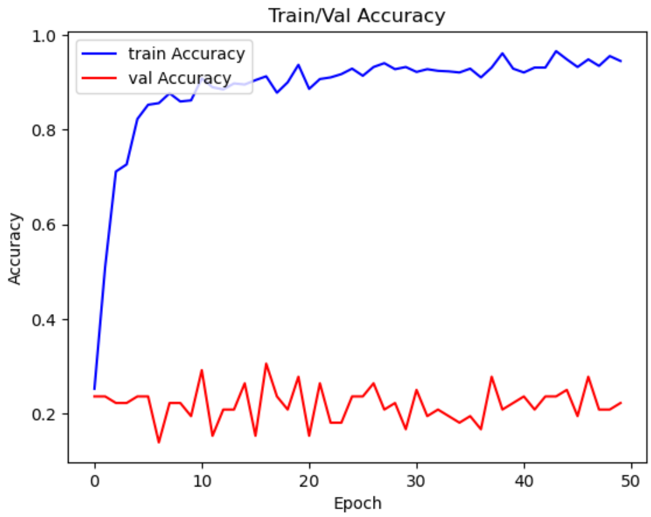

Fig. 5. Accuracy on the train and validation data.

IV. Discussion

According to our hypothesis, the average brain activation resulted in a significantly different and higher ISC in free watching of negative videos in comparison to three other conditions. This can indicate a more uninvolved and distracted perception of nonemotional content [26]. At the same time, a lower ISC was also found in both regulatory conditions, which contradicts the results of a previous study with the same paradigm but using EEG, where synchrony between participants during regulation appeared to be higher than free watching [17]. This disagreement may lie in a higher reliability MEG, which captures differences in neural activation caused by individual differences within regulation in the subjects. In fact, a number of studies emphasize that the choice of a particular regulation strategy, as well as its success, largely depends on the individual characteristics of a person, including personality traits, culture, and context [29,30].

As for the sources of neuronal activity derived from mapping, ISC was significantly greater in the prefrontal cortex during both ER strategies compared to free watching of negative videos. This finding is consistent with results from the previous neuroimaging studies, where it has been shown that higher prefrontal activity is associated with ER process itself, regardless of strategies [9,11]. The obtained result can also be connected with involvement in regulation of cognitive control, which has also been localized in this area [31].

We further tested our MEG data for the ability to predict four conditions (free watching of neutral and negative videos, reappraisal and suppression). We chose a neural network EEGNet that was originally designed on EEG recordings. Applying the neural network to the source data has shown that the training loss decreases, and the accuracy on the training set reaches high levels, which indicates that the neural network can learn. However, it showed low accuracy on the validation set. The possible reason can be the small size of the dataset, that requires further studying with increased training samples.

As one of the limitations, our paradigm of inducing emotions is based on one-minute negative video clips, which is a rather long-lasting stimulus and therefore does not allow to apply a number of common analyses of ER, such as event-related magnetic fields [32]. At the same time long videos, compared to a set of static images presented for several seconds, are closer to emotional triggers in real life. While ecologically valid paradigms can provide a more reliable basis for research on the flow of rapid processes such as ER. Furthermore, realistic stimuli captivate the attention of participants more effectively, resulting in a more targeted focus of perception [33]. In this regard, in future studies it can be potentially beneficial to also examine ISC in various regulation strategies, but with different naturalistic stimuli such as games, recall, and music.

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