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BRAIN-COMPUTER INTERFACING WITH EMOTION-INDUCING IMAGERY: A PILOT STUDY

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ABSTRACT: Using neural correlates of intentionally induced human emotions may offer alternative imagery strategies to control brain-computer interface (BCI) applications. In this paper, self-induced emotions, i.e., emotions induced by participants performing sad or happy related emotional imagery, are compared to motor imagery (MI) in a two-class electroencephalogram (EEG)-based BCI. The BCI setup includes a multistage signal-processing framework allowing online continuous feedback presentation in a game involving one-dimensional control of game character. From seven participants, the highest online classification accuracies are 90% for emotion-inducing imagery (EII) and 80% for MI. Offline and online results analysis showed no significant differences in MI and EII performance. The results suggest that EII may be suitable for intentional control in BCI paradigms and offer a viable alternative for some BCI users.

INTRODUCTION

Brain-computer interfaces (BCIs) offer means to communicate and control computer-based applications without movement, including entertainment [1], [2] (e.g. BCI games), rehabilitation [3] and assistive technologies. BCIs are built around decoding the person's intent by direct measurement of brain activity [4], usually measured through electroencephalography (EEG). One of the challenges in BCI is that there are limited options for control strategies available to the users: some strategies, e.g., motor imagery, are challenging for some users and require training [5], [6], and other strategies (evoked potentials) often require gaze control and are dependent on external stimuli. As a non-negligible portion of subjects have been shown to be unable to learn how to control a motor imagery (MI) BCI [5], within a limited duration of training there is a need for investigation of alternative imagery strategies for such users.

Emotion is being investigated as a potential BCI control strategy. The differences observed in brain responses to different emotional stimuli or recall of emotional events may enable a multi-class BCI [7]. Positive emotions (e.g., happy, joy) are associated with less relative alpha power in left frontal cortical regions than the right, whereas for negative emotions (e.g., sad, disgust) less relative alpha power is observed in the right frontal cortical area [8], [9], and similar hemispheric asymmetry activation was reported in functional imaging [10]. Besides the differences in brain activity associated with different emotions, for emotion to be useful in active independent BCIs, where the user issues a command as opposed to waiting on a stimulus to evoke a brain response, the BCI user is required to imagine or recall emotional situations. Chanel et al. [11] reported an accuracy of 71.3% in two-class classification of self-induced emotion, in their study, the participants were self-paced in the task of self-inducing emotion. In similar study, Chanel et al [12] achieved an accuracy of 63% in a three-class (negative emotion, positive emotion, and neutral) and 80% for two-class classification. In their study, the participants were asked to recall emotional events in an 8 s trial. Furthermore, Iacoviello et al. [13] achieved a classification accuracy of 90.2% for imagery induced by remembering unpleasing odor versus relaxed state. Sitaram et al. [14], in fMRI-based study, presented performance feedback to participants who were recalling sad, happy, and disgust emotions, and achieved an accuracy of 60% in a three-class classification with feedback presentation. Only a few of previous work have applied emotion-inducing imagery with real or pseudo-real time feedback presentation. In a typical BCI system, the user should be provided with interaction feedback.

In the preliminary study on EII [15], participants controlled a video game character using sad and happy imageries, and their performance suggested that the use of emotion-inducing imageries in BCI should be investigated. Here, imageries of self-induced emotional states are investigated as an alternative to MI, using a standard MI BCI paradigm and setup with healthy human participants. Performance results of imageries induced by sad versus happy events compared to results of left versus right hand movement imageries during the one-dimensional control of a video game character are reported.

MATERIALS AND METHODS

Participants: Seven healthy volunteering participants (1 female and 6 men, mean age 29, SD = 6) were recruited at Ulster University. Each participant, individually participated in one EEG recording session,

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and after the session the participant was asked, in an informal interview, what he/she thought about his/her performance in task execution during the session. Six of the participants had previously participated in at least one motor imagery BCI study, and one of these six participants was known to have a good performance in MI. The remaining participant was participating in active BCI paradigm for the first time. All the seven participants had not previously participated in EII BCI training prior to the study.

Experimental Setup: Each EEG recording session included four runs: two EII runs and two motor imagery runs. Each type of imagery consisted of one training run and one online feedback run as shown in Fig. 1. The order of runs was randomized between participants i.e., either EII or MI was performed in the first two runs. The recording session utilized a computer game paradigm called NeuroSensi, in which a light, representing a neuronal spike, traversed the left or right graphical axon (see Fig. 2) on the computer screen, cued the participant to perform one of two imageries i.e., left versus right hand movement, or sad versus happy emotion-inducing imagery. In feedback runs, the game objective was to collect the spike by moving the game character (a graphical representation of neuron's cell body and dendrites as shown in Fig. 2). Points are awarded for moving the game character in the right direction and positioning the character as close as possible to the axon when the spike reached the end of the axon. Additional points are awarded for collecting more than three spikes consecutively without failure. These bonus points are accompanied with background neurons firing and propagating several spikes for about 1 s (after task execution). The continuous feedback, i.e., movement of the game character, was controlled by the BCI. Each run included 60 trials randomly ordered for two class tasks, 30 trials for each class. Before starting EII runs, the participant was instructed to identify two mnemonic or fictitious emotional events: one event he/she thought would make him/her happy and another events that would make him/her sad. To avoid possible emotional stress into the participants, they were instructed to refrain from using extremely sad events. During EII training runs, participants were asked to imagine or recall the sad event when the spike was cued on the left axon, and to imagine or recall the happy event when the cue appeared on the right hand side axon. In the case of motor imagery tasks, the participant was asked to imagine right hand movement when the cue was on right, and left hand movement when the cue appeared on the left side.

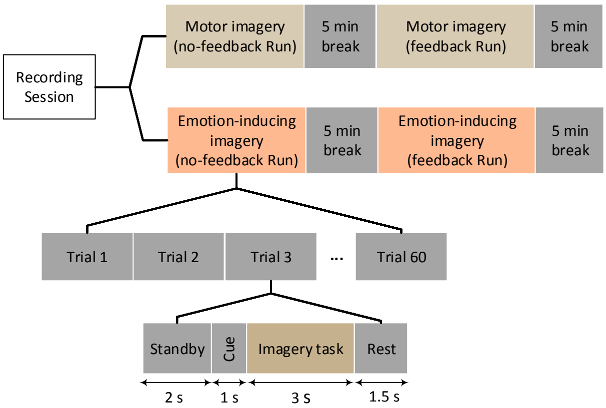

Figure 1. The structure of recording session. Each recording session had 4 runs of imagery tasks, each run with 60 trials (see details in text).

EEG data were sampled at 125 Hz from 16 channels (Fp1, Fp2, F3, Fz, F4, T7, C3, Cz, C4, T8, P3, Pz, P4, PO7, PO8, and Oz) setup in 10-20 system. EEG data were visually inspected for strong artefacts (e.g., eye-blinks) and then processed through a multistage signal processing framework which includes neural-time-series-prediction-preprocessing (NTSPP), spectral filtering (SF) in subject specific frequency bands and common spatial patterns (CSP) as previously used in [1], [16]. This signal processing framework is illustrated in Fig. 3.

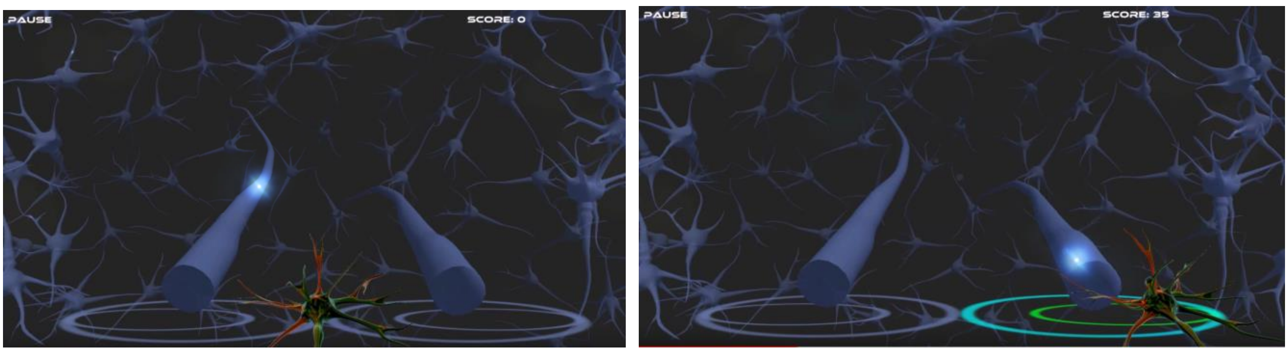

Figure 2. The screenshots of the BCI game used in cueing and feedback presentation. The neuron character is fixed in the middle of the two axons during no-feedback run (screenshot on the left), and it moves horizontally to collect the spike during the feedback run (screenshot on the right).

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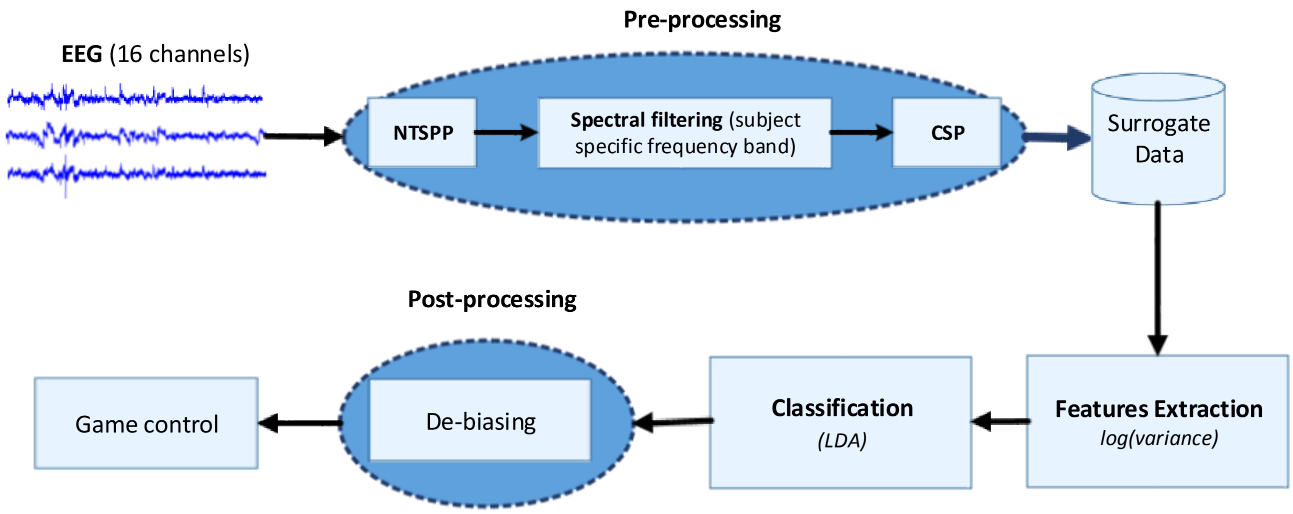

Figure 3. BCI setup used to preprocess EEG, extract and classify EEG features correlating to imageries; in the feedback session, the classifier's output is de-biased to adapt the feedback.

Time-Series-Prediction: In the NTSPP framework different prediction networks are trained to specialize in predicting future samples of different EEG signals. Due to network specialization, features extracted from the predicted signals are more separable and thus easier to classify. The number of time-series available and the number of classes governs the number of specialized predictor networks and the resultant number of predicted time-series from which to extract features

$$P = M \times C \tag{1}$$

where P is the number of networks (which is equal to number of predicted time-series), M is the number of EEG channels and C is the number of classes. For prediction,

$$\hat{x}_{ci}(t+\pi) = f_{ci}\left\langle x_i(t),\ldots,x_i(t-(\Delta-1)\tau)\right\rangle \tag{2}$$

where t is the current time instant, Δ is the embedding dimension and τ is the time delay, π is the prediction horizon, f_{ci} is the prediction model trained on the i^{th} EEG channel, x_i, i=1,..,M, for class c, c =1,..C, and $\hat{x}_{ci}$ is the predicted time series produced for channel i by the predictor for class c. NTSPP adapts to each subject autonomously using self-organizing fuzzy neural networks (SOFNN) [17].

Spectral Filtering: Prior to the calculation of the spatial filters, X can be preprocessed with NTSPP and/or spectrally filtered in specific frequency bands. The bands are selected autonomously in the offline data processing stage using a heuristic search and are subsequently used to band pass filter the data before CSP is applied. The search space is every possible band size in the 8 - 28Hz range. The high frequencies are not considered since they are likely to be contaminated with scalp electromyogram (EMG) [18], especially in the case of frowning associated with emotion-inducing tasks. These bands encompass the alpha, beta bands which are altered during sensorimotor processing [17], [19], [20] and for emotional state detection these bands or sub-bands within these bands are often used [21], [22].

Common Spatial Patterns (CSP): CSP is used to maximize the ratio of class-conditional variances of EEG sources. CSP is applied by pooled estimates of the covariance matrices, Σ_1 and Σ_2, for two classes, as follows:

$$\Sigma_c = \tfrac{1}{I_c}\sum_{i=1}^{I_c} X_i X_i^t \quad (c \in \{1,2\}) \tag{3}$$

where I_c is the number of trials for class c and X_i is the $M\times N$ matrices containing the i^{th} windowed segment of trial i; N is the window length and M is the number of EEG channels – when CSP is used in conjunction with NTSPP, M=P as per (1). The two covariance matrices, Σ_1 and Σ_2, are simultaneously diagonalized such that the Eigenvalues sum to 1. This is achieved by calculating the generalized eigenvectors W:

$$\Sigma_1 W = (\Sigma_1 + \Sigma_2) WD \tag{4}$$

where the diagonal matrix D contains the Eigenvalue of Σ_1 and the column vectors of W are the filters for the CSP projections. With this projection matrix the decomposition mapping of the windowed trials X is given as

$$E = WX \tag{5}$$

Features Extraction and Classification: Features, $\bar{\omega}$, are derived from the log-variance of preprocessed/surrogate signals within a 2 second sliding window:

$$\bar{\omega} = \log(\mathrm{var}(E)) \tag{6}$$

The dimensionality of $\bar{\omega}$ depends on the number of surrogate signals used from E. The common practice is to use several (between 2 and 6) eigenvectors from both ends of the eigenvector spectrum, i.e., the columns of W. Using NTSPP the dimensionality of X can increase significantly. CSP, can be used to reduce the

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dimensionality therefore combining NTSPP with CSP leads to increased separability while maintaining a tractable dimensionality [16]. Linear discriminant analysis (LDA) is used to classify the features at the rate of the sampling interval.

An inner-outer cross-validation (CV), with 5 outer folds, is performed to find the optimal subject-specific frequency. In the outer fold, NTSPP is trained on up to 10 trials randomly selected from each class (2 seconds of event related data from each trial). The trained networks then predict all the data from the training folds to produce a surrogate set of trials containing only EEG predictions. The 4 training folds from the outer splits are then split into 5 folds on which an inner 5-fold cross validation is performed for best subject specific frequency selection. After the subject specific frequency band selection, NTSPP-SF-CSP is then applied on the outer fold training set, where a feature set is extracted. The LDA classifier is trained at every time point across the trials and tested for that point on the outer test folds. The average across the five-folds is used to identify the optimal number of CSPs (between 1-3 from each side of W) and the final time point of maximum separation which are then used to setup the final classifier using all the training data, to be deployed online. The Fig. 3 illustrates the BCI setup used in this study.

In the online processing, the classifier's output translation to the game character movement was de-biased to account for class bias behaviour and improve feedback stability. This de-biasing was carried out by continuous removal of the mean from the continuous classifier output, where the mean was calculated with a 35s window on the most recent classifier output.

Additionally, EEG dynamics throughout tasks execution were also explored through event-related (de)synchronization (ERD/S) analysis. The ERD/S was computed as power change respective to the baseline power as in [23] within the subject's selected frequency band after applying independent components analysis and wavelet transform on the data for further artefacts removal [24].

RESULTS

Offline cross-validation classification accuracy (CA) for each run, along with online single-trial CA results for feedback runs, online results, and sample results from event-related (de)synchronization analysis are reported in Fig. 4, Fig. 5, Fig. 6, and Fig. 7 respectively. Wilcoxon signed rank tests showed no significant differences between EII and MI ($p > 0.05$), although the EII training accuracies exceed the MI accuracies for most of the participants. ERD/S analysis showed EII tasks separability in the temporal and frontal channels; this can be seen in sample topographic maps for subject 2 in Fig. 7. The online classification results in Fig. 5 show decrease in accuracies for most of the participants compared to what was achieved in offline analysis for the feedback run. However, in each of the considered BCI strategies, there was one participant who achieved good online performance: one experienced participant achieved 81% in MI and another achieved 90% in EII online performance. The performance in the remaining participants is 64.18 ± 4.75% and 62.09 ± 2.03% for EII and MI respectively.

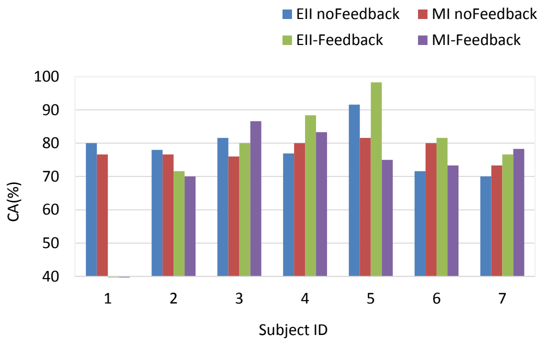

Figure 4. The LOOCV classification accuracy for feedback and no-feedback runs. There were no feedback runs for subject 1.

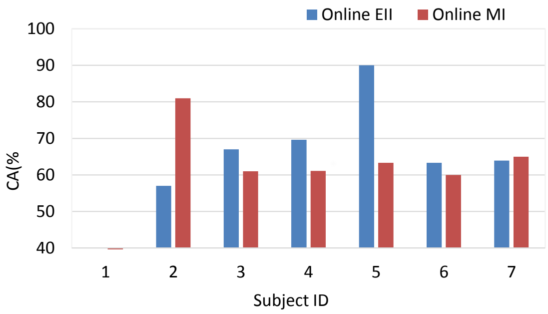

Figure 5. Online task classification accuracies for emotion inducing imagery and motor imagery during feedback runs. Note that there were no feedback runs for subject 1.

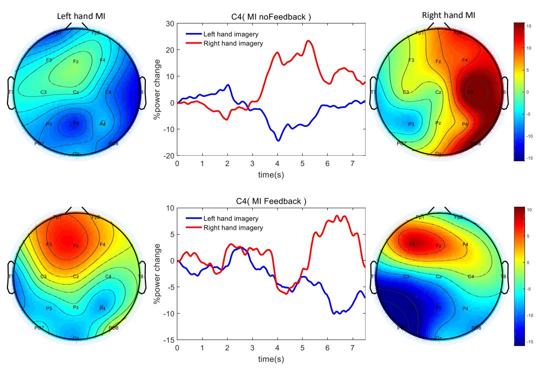

Figure 6. Topographic maps of band power changes (ERD/S) in [8–13] Hz band during motor imagery task execution for subject 2, and time-course ERD/S observed from channel C4.

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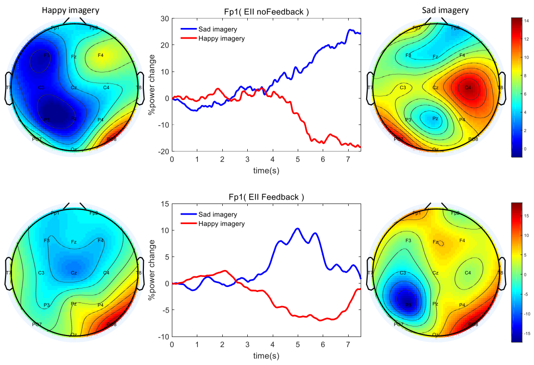

Figure 7. Topographic maps of band power changes in [8–20] Hz band during emotion inducing tasks execution for subject 2, and and time-course ERD/S from channel Fp1.

DISCUSSION

The objective of this pilot study was to investigate the discriminability of EEG during emotion inducing imagery, to investigate if emotion-inducing imageries could be used to control a video game using a BCI and to compare performances of EII with the extensively studied motor imagery based control strategies. The results suggest that emotions, which normally influence the way we live [25], may be intentionally modulated and actively translated in a BCI control paradigm. Consequently, the study shows some of the first evidence to support the use of emotion inducing imagery as a replacement to motor imagery. This study was based on one off-line training session and online training session for both MI and EII. Although participants were limited by the amount of training, their classification accuracies exceed chance level which was 50%. It usually requires several training sessions to achieve good accuracy in motor imagery performance, so further validation with multiple sessions training and on a larger sample of participants is required to determine if emotion imagery could be used by BCI users who do not perform well with motor imagery. Subject 2 who achieved high online performance in MI is familiar with motor imagery based BCI and had achieved good accuracies in the past. The participant with highest accuracy in online EII (subject 5) reported in the post-session interview that meditation practice was the key technique used in executing tasks for EII; meditation has been shown to improve BCI performance [26], [27]. Subject 2 also reported regular meditation practice.

Two participants showed acceptable online performance, whereas for the other participants' online performance is diminished with respect to the calibration run (the run without feedback). Even though a reduction in accuracy was observed in the online runs, the baseline accuracy (1 s before cue) were significantly lower that the peak accuracy during the task execution ($p < 0.05$) for all the participants indicating that above chance performance was achieved. In addition, as this is single session and participants experienced on-screen feedback for the first time (except subject 2) along with distractors in the games (game score updates and bonus firing spikes), this likely had an impact on participants' concentration, cognitive load [28] and maintaining focus and consistency between the runs. With additional sessions the BCI and participants' performance may be more robust.

CONCLUSION

Emotion induced by imagining fictional events or recalling mnemonic emotional events with a continuous feedback in a BCI setup was investigated in this preliminary study, using a setup normally used for motor imagery. The comparison between online control of a game in single session with either motor imagery and emotion-inducing imagery showed that the performance difference is insignificant, suggesting that emotion-inducing imagery may be used as an alternative to motor imagery. The reported results are from seven participants, each with one EEG recording session, so more analysis with a larger sample of participants and multiple training sessions is currently being carried out to thoroughly compare motor imagery and emotion inducing imagery BCI. Besides validating the comparison, there is a need to assess the effect of multiple training sessions on EII performance.

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