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INVESTIGATING MUSIC IMAGERY AS A COGNITIVE PARADIGM FOR LOW-COST BRAIN-COMPUTER INTERFACES

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ABSTRACT: Many current brain-computer interfaces (BCIs) rely on motor imagery or oculomotor paradigms to transfer information, yet these functions are impaired in people that suffer from late stage Amyotrophic Lateral Sclerosis (ALS). Additionally, patients have limited access to cutting-edge BCI technology for home-use because the necessary, medical grade equipment is expensive and difficult to setup.
We addressed both issues with the current study. First, we devised a novel paradigm that relies on music imagery and mental subtraction. We argue that these are motor-independent abilities that can be reliably executed, without the need for subject training. We find that both tasks can be distinguished after only one experimental session with a 124-channel EEG system, from the band-power in the theta (4-8 Hz) and alpha (8-13 Hz) range. Second, we tested our paradigm in combination with a low-cost EEG system to show that it can be used to develop accessible BCIs for patients in the future.

INTRODUCTION

Background For patients suffering from paralysis, brain-computer interfaces (BCIs) offer the possibility of renewed communication [1, 2, 3]. This is of great importance for people who suffer from amyotrophic lateral sclerosis (ALS), a motor-neuron disease that renders patients completely locked-in during its final stage [4]. However, BCIs for ALS patients suffer from two limitations: The usability of existing paradigms varies greatly, and the required technology is expensive and difficult to set up.
In the final stages of their disease, ALS patients are unable to use most current BCIs that rely on motor-imagery or oculomotor control [5], as these functions decay during disease progression [1, 6]. Recently, efforts have been made to combine motor imagery with higher cognitive tasks including spatial navigation, meditation, mental calculation to improve BCI usage for people with motor-disabilities [7, 8]. Hohmann et al. [9, 12] devised a self-paced strategy that relies on positive self-referential thoughts to modulate activity in the Default-Mode Network (DMN) as an alternative to motor-based strategies. However, it was argued that repeatedly recalling a positive memory may induce fatigue which limits the performance of the BCI over longer time-periods.

Current Work We propose music imagery as another motor-independent task for BCI control. Music imagery fulfils three important criteria: First, it targets a cognitive process that should be immediately accessible to everyone. Second, it is unrelated to motor imagery. And third, it is self-paced and stimulus-independent and should therefore remain accessible to completely paralysed patients. We argue that music imagery is a more concrete task than self-referential thought generation and it may therefore be easier to execute it repeatedly. Music imagery has been found to modulate parietal alpha, similar to positive self-referential thoughts [10].
Based on Hohmann et al. [12], we choose mental subtraction as the opposing task. Mental subtraction is related to an increase in prefrontal theta and a decrease in parietal alpha [13]. With music imagery and mental subtraction we introduce an easy-to-use two-class paradigm that can be performed without the need for motor-abilities.
BCIs are only accessible to patients if they are affordable and easy to set up. To investigate the portability of our paradigm, we tested our paradigm on a low-cost EEG system, in addition to our recordings with a conventional high-density EEG system.

MATERIALS AND METHODS

Experimental Paradigm We conducted a study with 10 healthy subjects that were seated in a chair approx. 1.25 meters away from a 17" LCD screen with a refresh rate of 60 Hz and a resolution of 1280x1024 px. For each trial the instructions were presented in white font on a black background. Between instructions we presented a fixation cross in the middle of the screen.
After the resting phase we recorded two experimental phases, where we employed the high-density EEG and the low-cost EEG for recording. Each experimental phase consisted of two blocks with a brief intermission that each contained 10 trials for the mental subtraction task and 10 for the music imagery task, in randomized order. The order of those two phases was counterbalanced between subjects.
For the music imagery condition, participants were asked to “imagine a favourite song”. In the mental subtraction

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task they were asked to "continuously subtract X from Y" until the end of the trial, where X was a single-digit number and Y was a three-digit number. We excluded 1, 2 and 5 for the single digit number and restricted the range of the three digit number to the interval between $[800, 999]$. Each trial took 35 seconds and began with 5 ± 0.50 seconds pause, after which the instructions were displayed on screen as well as given acoustically by a text-to-speech engine (CereProc Ltd., Edinburgh, United Kingdom). The respective task then had to be executed continuously for the whole trial.

Experimental Data The study was conducted at the Max Planck Institute for Intelligent Systems in Tübingen, Germany. Ten healthy subjects (five male and five female, mean age 24.6 ± 3.6 years) were recruited from the local community and received 12 Euro per hour for their participation. Half of the subjects had previous experience with EEG studies. The experimenter informed them about the procedure with standardised instructions. All participants signed a consent form in advance to confirm their voluntary participation. For the high-density system, a 124-channel EEG was employed. Recordings were conducted at a sampling rate of 500 Hz using actiCAP active electrodes and a BrainAmp amplifier (BrainProducts GmbH, Gilching, Germany). Electrodes were placed according to the 10-5 system with the left mastoid electrode as the initial reference. For the low-cost system, a 14-channel EPOC+ portable EEG system (EMOTIV, San Francisco, U.S.A.) was employed. Recordings were conducted at a sampling rate of 128 Hz. OpenViBE [14] was used to record and store the EEG data. Because of technical issues we excluded the recorded low-cost device data for the first three subjects .

Data Analysis The analysis was performed offline.
To differentiate between the patterns of neural activity related to music imagery and mental subtraction we computed per-trial θ-bandpower features between 4 and 8 Hz as well as α-bandpower features between 8 and 13 Hz for all channels. For each subject the feature matrix contains $trials \times features$, which is one alpha and theta value per channel per trial, so a $40 \times (2 * 124)$ matrix for the high-density system (124 electrodes), and a $40 \times (2 * 14)$ matrix for the low-cost system (14 electrodes). The number of features is twice the number of electrodes since for each electrode there are two bandpower values associated. We used a transfer learning method by Jayaram et al. [15] to account for variation across subjects and the issues arising from large feature spaces. This method fits a linear regression model for each subject individually but penalises deviations in the regression weights from a Gaussian prior distribution. We evaluated the classification performance on one subject in a 10-fold cross-validation procedure, after learning a prior on all others as follows. Afterwards we tested the $H_0 : Accuracies_{BrainAmp} \neq Accuracies_{EPOC+}$ by a paired Student's T-Test.
To investigate the meaningfulness of the weights learned by the transfer learning framework, we multiplied the learned weights with the feature covariance matrix [16]. The resulting matrix can be visualized as a topography map where each value represents the importance the classifier has assigned to this channel based on the modulation by the cognitive strategy.

RESULTS

We achieved a mean classification accuracy of 85% with the high-density system and 77% with the low-cost system (Fig. 1). The paired Student's T-Test yields a significant difference between the classification accuracies from subjects S4 to S10 of the BrainAmp ($M = 0.84, SD = 0.17$) compared to the EPOC+ ($M = 0.77, SD = 0.18$); $t(6) = -2.83$, $p = 0.03$.

After multiplying the weights learned by the transfer learning framework with the feature covariance, we obtained the relevance-map of all 124 features for both the theta and alpha frequency-band (Figure 2).

The channel with the largest weight for the alpha features is PO1 and for the theta features is AFF1. Figure 3 shows the modulation in the power spectrum for both tasks at both of those channels from the BrainAmp recordings.

DISCUSSION

We investigated whether the neural activity during music imagery and mental subtraction could be discriminated without prior subject-training. We found that we can classify both tasks with a mean accuracy of 85% for the high-density EEG system, and 77% for a low-cost EEG system. Additionally, we observed high classification weights for frontal electrodes for the theta band-power features and parietal ones for alpha.
Our results are consistent with previous publications that show frontal activation during a mental subtraction task [17, 18] and parietal activity in the alpha band for music imagery [11]. Therefore the spatial patterns of the relevant features for classification (Figure 2) are in line with our hypotheses and previous research of both tasks.
All except one subject reported the tasks to be very easy. Only subject S4 reported both tasks to be "boring", which might have lead them to not participating very actively over the course of the experiment, causing the decrease in performance as depicted in Fig. 1.
The performance of the low-cost system was significantly lower than the performance of the full-sized system. This may have been caused by the smaller amount of channels, the lesser quality of the electrodes, or non-optimal positioning of the sensors for this paradigm. However, on both the high-density and the low-cost system, we achieved classification performances above 70%, which is considered to be the threshold for building a meaningful communication device. Therefore, we argue that our

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Figure 1: Classification accuracies for both devices (BrainAmp & EPOC+) for all ten individual subjects (S1-S10) in case of the brain amp and the reduced subject set (S4-S10) for the EPOC+. The mean classification accuracy across subjects is 85% for the BrainAmp and 77% for the EPOC+. Chance level (50%) as well as both mean accuracies are indicated with a solid tick on the right of the plot and are labeled accordingly.

results motivate further studies that focus on the development of low-cost EEG devices with better electrode placement with respect to the presented paradigm, or a higher signal quality.

Asking subjects to imagine their favorite song is hard to control, as songs vary in their genre, complexity, the presence of lyrics, and personal relevance. The large variability could have affected the classification performance. To get a better understanding of the effects, it would be interesting to combine this EEG approach with an imaging method like fMRI. This could provide some insight in the related brain-networks which might be for example the dorsal attention network as Scherer et al. [7] hypothesize.

Most importantly, an online BCI study with ALS-patients in all stages of the disease is very important to investigate the feasibility of this cognitive paradigm.

CONCLUSION

We find the neural activity elicited by music imagery and mental subtraction to be distinguishable after only one experimental session. We believe, that our work can be used as a foundation for future development of reliable and accessible systems for paralyzed patients to communicate throughout the whole progress of their disease.

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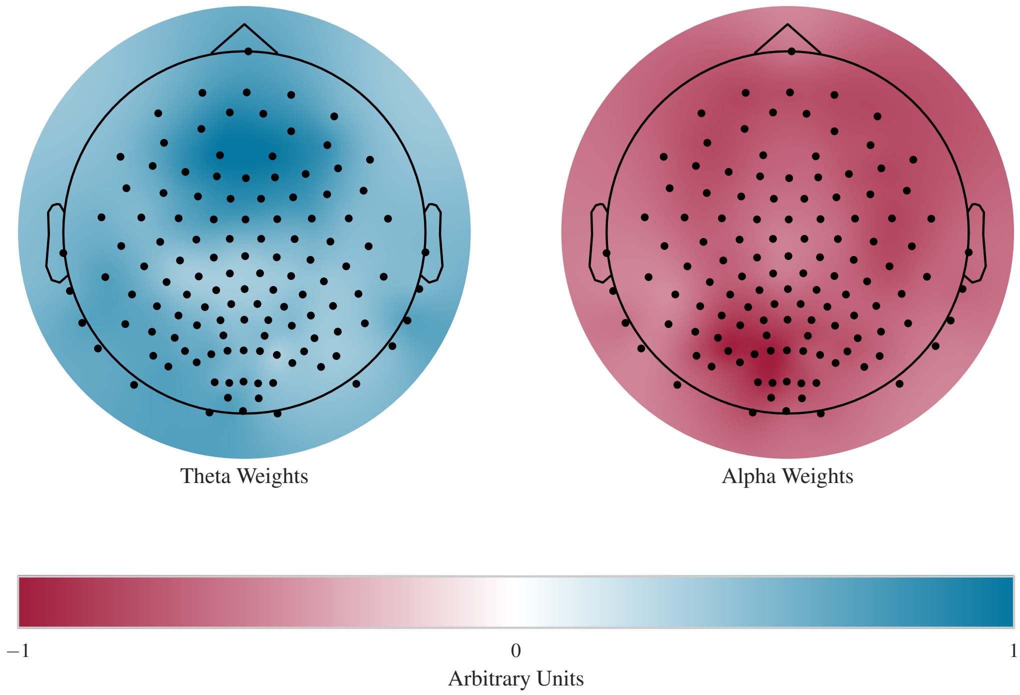

Figure 2: Topography of the weights of the transfer learning classifier based on the BrainAmp recordings. A larger weight represents stronger relevance for the classification. The weights for the theta features are plotted on the left and on the right the weights for the alpha features can be seen.

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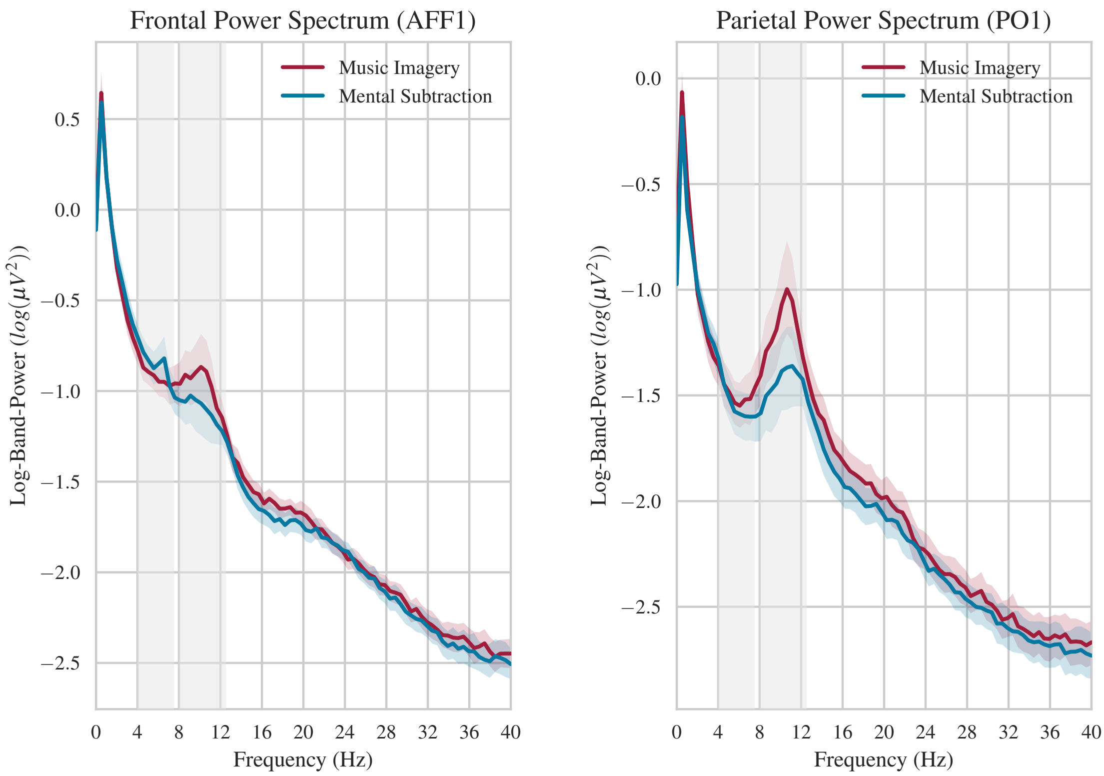

Figure 3: Average power spectral density with a single standard deviation across all 10 subjects for the BrainAmp at the two electrodes with the highest classification weights (AFF1, PO1).

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