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A GUIDED TASK FOR COGNITIVE BRAIN-COMPUTER INTERFACES

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ABSTRACT: Brain computer interfaces are an important tool to enable communication for patients suffering from amyotrophic lateral sclerosis. Yet most existing devices use cognitive functions that are impaired in later stages of the disease. Systems based on higher cognitive processes provide new possibilities for this field. However, many patients in the target group suffer from memory impairments. As many higher cognitive processes involve memory, this could be an interference. The present study investigates the differences between a currently existing cognitive paradigm using autobiographic memories and a new paradigm using a guided imagery story. Both are developed to be used in patients and try to target the same processes, with the new paradigm being less dependent on memory functions. Assessment of EEG- and behavioral data in healthy subjects results in two working paradigms for brain computer interface control. Higher classification accuracies and more favorable behavioral ratings are achieved by the previously existing paradigm.

INTRODUCTION

Patients suffering from the neurodegenerative disorder amyotrophic lateral sclerosis (ALS) can use brain computer interfaces (BCIs) for communication [1] [2]. Most of these BCIs are based on EEG or single-unit features from somatosensory or motor areas of cortex [3]. This is problematic for ALS patients as with the progress of the disease neurons in motor cortex, especially giant pyramidal neurons, degenerate [4]. Another class of BCIs makes use of visual evoked potentials to detect an attended or in this case preferred stimulus [3]. As this class relies on eye movement, and oculomotor dysfunction - especially dysfunction of effective pursuit - is common in ALS [5], it is also not suitable for late-stage ALS patients. Therefore, particularly for patients that reach the completely locked in stage, different classes of BCIs are needed. Until now there are no reliable BCIs for those patients available [6]. One approach are BCI systems that are based on higher cognitive functions. Hohmann et al. introduced a system that allows answering of binary questions by either thinking about a positive experience or focusing on ones breath [7] or, in a more recent version, doing mathematical calculations [8]. Making use of positive memories, however, includes a possible interference: Retrieval of autobiographic memories needs both self-referential processing and memory retrieval processes [9]. As those systems are designed to serve as communication devices for ALS patients the impact of the disease on memory processes is an important factor. A study by Mantovan et al. (2003) showed episodic memory deficits in ALS patients without dementia, with subjects having problems both in encoding and in retrieval [10]. When performing a battery of neuropsychological tests on a patient sample, nearly half of the sample showed cognitive impairments including memory, changing of judgement and reasoning and verbal fluency, as well as behavioral discontrol [11]. Those ALS patients who show cognitive impairment measured by a verbal fluency test also show frontal lobe dysfunction, as indicated by abnormalities in a PET scan [12]. Further, patients exhibit white matter changes in temporal regions, including motor pathways as well as non-motor areas including association fibres to the frontal lobe and anterior cingulate gyrus, that are accompanied by deficits in executive functions and memory [13]. In cognitively unimpaired ALS patients white matter changes were not as strong but still present [13].

These findings encourage the idea to create a BCI for which memory processes are less relevant, as well as motor and oculomotor functions, to make it usable for ALS patients in all stages of disease even when memory functions are impaired.

The system introduced by Hohmann et al. is likely to target up- and down regulation of parietal nodes in the default mode network (DMN). ALS patients even in late stages showed to be capable of modulating activity in the target region without prior training [7]. This is supported by the argument that in locked-in state patients connectivity in the DMN is not significantly different from the one in controls [14]. The DMN is associated with remembering the past, especially autobiographic remembering [15], and is also seen as the seat of self-referential processing in the brain [16] [17]. As a brain system for internal mentation the DMN is most active during spontaneous cognition including mental processes that create fantasy, imagination, daydreams and thoughts. It also takes part in self-relevant mental simulation, which means imagination of scenarios or hypothetical events [15]. Self-related thoughts correlate with an increase in spectral power mainly in the α-band (8-13 Hz), showing spatial patterns consistent with DMN modulation [16] [2]. It is proposed that the DMN consists of two systems: a sys-

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tem related to associations and memory retrieval, and a system related to self-relevant thoughts and self referential judgments [15]. Anatomically, the posterior cingulate cortex (PCC) is described as a critical node of the DMN [18] and the Precuneus (pC)/PCC node as possible side of interaction of the two proposed subsystems [19].
Considering these properties of the DMN, a scenario that could very well up-regulate the DMN is a guided imagery story. It is directed to the self and includes imagination and fantasy without being bound to autobiographic memory. Yet, for creating a binary BCI with external stimulation, this stimulation has to be presented simultaneously to enable subjects to make a decision. Some existing auditory BCI systems with simultaneous stimulation on both ears work with event related potentials like the N1 and P3 component and reach high accuracies even in online scenarios [20]. Studies working on decoding of auditory streams from EEG data like the one by O'Sullivan and colleagues additionally show that subjects are very well capable of following a story on one ear, when getting presented a different one on each ear [21].
In the present study this ability of selective attention is used for an auditory BCI targeting DMN activity. The task introduced by Hohmann et al., including positive memories and a math task [8], is compared to a new task including a guided imagery story and math tasks, both read to the participants simultaneously. During guided imagery a participant has to imagine for example being on a field in the sun or walking through the forest, experiencing the different tones and smells. The former will be referred to as "Memory" paradigm and the later as "Imagery" paradigm. The goal of this study is twofold: First, to find out whether the "Imagery" paradigm is suitable for a BCI system targeting DMN modulation, and second, which of the two paradigms shows a better classification performance.

MATERIALS AND METHODS

Experimental Paradigm: Participants were placed in a chair 1.25 m away from a 17" LCD screen with a resolution of 1280x1024 pixels and a 60 Hz refresh rate and were provided with Phillips SHB9250 headphones. The background of the screen was black, with a white fixation cross in the center. Subjects were briefed on the experimental procedure and the different tasks and their comprehension was assured. They performed four experimental blocks with brief intermissions in which they rated each block. Each experimental block consisted of thirty trials, in which participants were asked questions (fifteen correct and fifteen incorrect) in pseudo randomized order. The questions were binary general knowledge questions designed to be as easy as possible (e.g. "Is Christmas celebrated in December?" or "Is Berlin the capital of Italy?"). Participants indicated their answer to the questions by performing a certain task. After each question an instruction was given to remind the subject which task means "yes" and "no" (cf. Figure 1). One

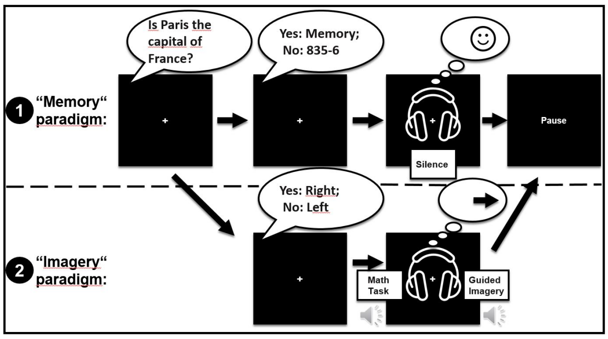

Figure 1: Example trial for the "Memory" and "Imagery" paradigm.

block lasted about 15 minutes. In two of the four blocks the task was to remember a positive experience or to subtract a number between three and nine continually from a higher number (between 800 and 850) for either "yes" or "no". The concerning numbers were named in the instructions and the task was performed in silence ("Memory" paradigm).
In the other two blocks subjects were instructed to indicate their answer by focusing on the sound on one ear while ignoring the sound on the other ear. On the right side a guided imagery story was read (based on stories published on www.hierfindichwas.de and www.planetsenior.de, accessed September 2016) and on the left side mathematical calculations (addition or subtraction of two digit numbers) were asked. The two different sounds were presented simultaneously over the whole task time ("Imagery" paradigm).
Each trial began with five seconds rest, followed by the question and instructions. The time to indicate the answer by performing the instructed task was 17 seconds, to be sure to not cut any of the auditory recordings, which were approximately 15 seconds long. The task for either "yes" or "no" stayed constant within one block but changed between blocks. The resulting different blocks with different paradigms and instructions were alternated and counterbalanced across participants. Questions remained the same for each block. After all four blocks participants got a questionnaire with all 30 general knowledge questions asked during the experiment to ensure they knew the correct answers.

Experimental Data: The study was conducted at the Max Planck Institute for Intelligent Systems in Tübingen, Germany. Ten healthy subjects (German native speakers, 5 female, 5 male) with a mean age of 34.4 $\pm$ 11.2 years took part in the experiment. All of them reported to have unimpaired hearing abilities. They received 12 Euro per hour for their participation. All participants signed a consent form to confirm their voluntary participation in ad-

Table 1: Questions (originally in German)

1) How easily could you concentrate on the task?
2) How exhausting was it to concentrate on the task?
3) How stressful was performing the task?
4) How tiring was performing the task?
5) How successful could you follow the instructions?

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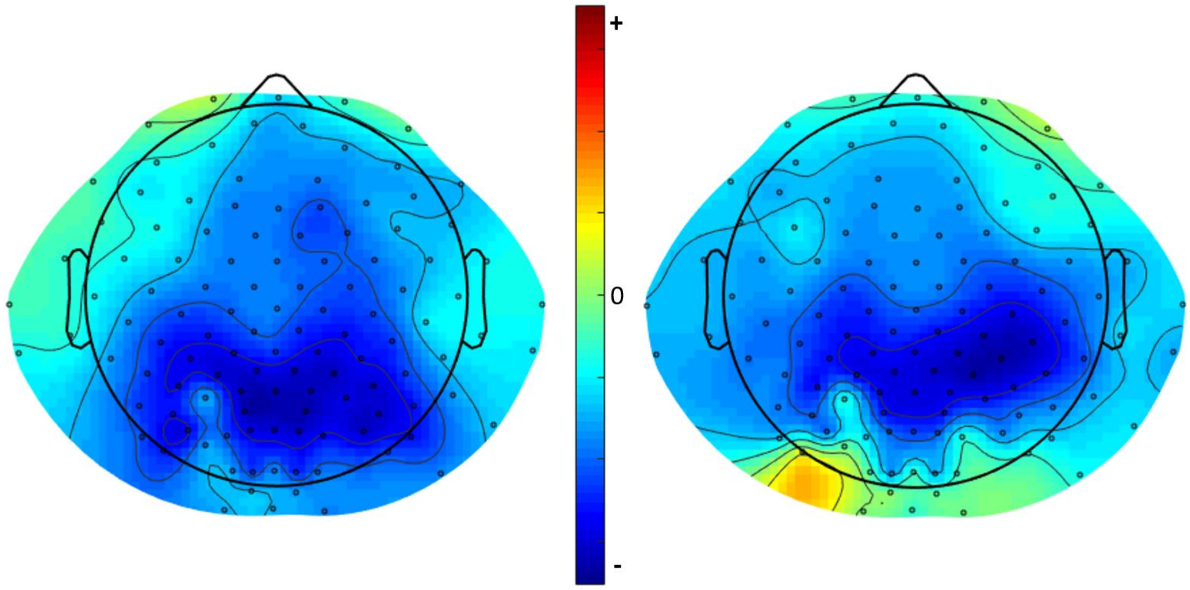

Figure 2: Left side: Encoding model for "Memory" paradigm. Right side: Encoding model for "Imagery" paradigm. Dark colors show the areas most relevant for classification, with the transfer learning algorithm, in arbitrary units.

vance, after being fully informed about the procedure. The study was approved by the ethics committee of the Max Planck Society. For EEG recordings a 124-channel system with a sampling frequency of 500 Hz with actiCAP active electrodes and a BrainAmp amplifier (provided by BrainProducts GmbH, Gilching, Germany) was used. Electrode placement was according to the extended 10-20 system with the left mastoid electrode as the initial reference. All recordings were converted to common average reference previous to analysis. The BCI2000 toolbox was used to implement the application [22]. Behavioral data was obtained by handing a pen and paper questionnaires to participants after each block of the experiment. The questions asked to participants are listed in Table 1. All answers could be indicated on a seven point Likert-scale, with one being the most favorable and seven the most unfavorable answer.

Data Analysis: The 17 seconds per trial in which subjects could indicate their answer to the given questions were used for EEG analysis. As previous studies [16] [7] showed that the α-frequency range is the range of most significance for modulations of the DMN, analysis was restricted to this frequency band. We used the Discrete Fourier Transform with a Hann window to compute the log-bandpower of the α-frequency band (8–13 Hz) at every channel in every trial. As the α-frequency range is not very susceptible to muscular or oculomotor artifacts, preprocessing only included the removal of electrodes that showed malfunctioning for at least one participant, reducing the feature space from 124 to 117. For obtaining optimal decoding with the relatively small number of trials recorded, we used a transfer learning technique further described by Jayaram et al. [23]. It allows to simultaneously learn decoders for all subjects while still accounting for inter-individual differences, using a linear regression model. We employed a nested cross-validation procedure, with leave-one-subject-out cross-validation for learning priors over decoders and ten-fold cross-validation to estimate decoding accuracy on each individual subject. To spatially depict the resulting encoding model, we multiplied the priors obtained by the transfer learning algorithm with the covariance matrix of the extracted features, both averaged over subjects [24]. This was plot as a topography to illustrate the areas most relevant for classification.

RESULTS

EEG Data: On average subjects achieved a decoding accuracy of 75.5% (SD 20.1%) in the "Memory" paradigm and 64% (SD 14.7%) in the "Imagery" paradigm. The encoding models used by the transfer learning algorithm for each paradigm are shown in Figure 2. Individual decoding accuracies can be seen in Table 2. Both paradigms classify significantly better than chance ($p < 0.001$) when tested with a permutation test with 1000 permutations of class labels. On an individual level

Table 2: Individual Accuracies

Subject	"Memory"	"Imagery"	Differences
S1	50%	63.3%	-13.3%
S2	70%	65%	5%
S3	96.7%	90%	6.7%
S4	95%	40%	55%
S5	51.7%	53.3%	-1.6%
S6	90%	51.7%	38.3%
S7	95%	83.3%	11.7%
S8	46.7%	61.7%	-15%
S9	73.3%	61.7%	11.6%
S10	86.7%	70%	16.7%
Mean	75.5%	64%	11.5%

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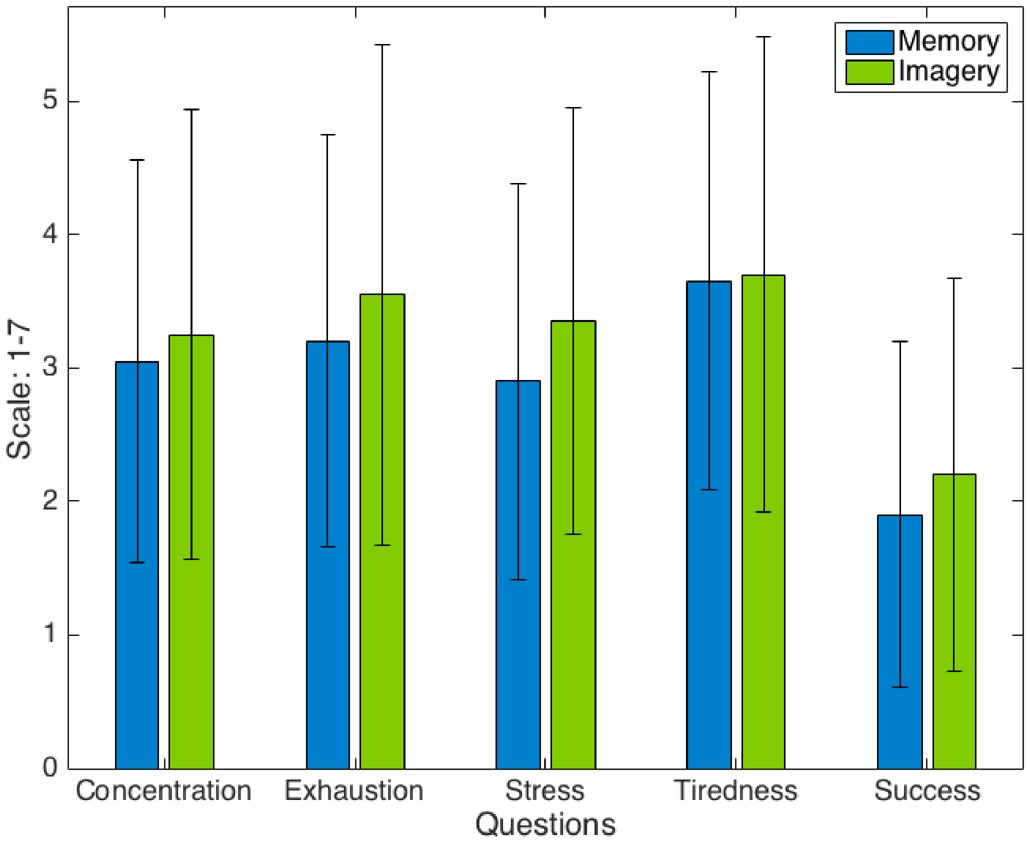

Figure 3: Mean values and standard deviations of rating data, showing a different perception of the two paradigms.

there was a high variability and some subjects did not succeed using one or the other or both paradigms while others were highly successful (Table 2). When comparing the two different paradigms in a paired permutation test with 10^4 permutations, the "Memory" paradigm achieved a better performance ($+11.5\%$), yet this difference was not significant ($p = 0.126$).

Behavioral Data: Mean rating values of each question of the pen and paper questionnaire are shown in Figure 3. Participants indicated by their ratings that they found it more difficult and more exhausting to concentrate on the "Imagery" task as well as more stressful and tiring. They also rated to have been more successful in performing the "Memory" task. Over all, the "Memory" paradigm achieved lower mean rating values (2.94, SD 0.07) compared to the "Imagery" paradigm (3.21, SD 0.59). A paired sample t-test revealed this difference to be significant ($p = 0.0167$).

DISCUSSION

Results of EEG- and behavioral data of the "Memory" paradigm and the "Imagery" paradigm lead to further support for the "Memory" paradigm to be a well functioning BCI system and introduced the "Imagery" paradigm as a new approach for classification based on DMN modulation. The "Memory" paradigm showed a better performance and was also more liked, based on participants' ratings. This pattern of results shows to be robust even when using a different approach of data preprocessing to completely omit including possible residual muscular artifacts: When performing artifact correction using an independent component analysis approach [25], instead of using the unfiltered EEG signal, the mean accuracy for classification in the "Memory" paradigm was 73.2% (SD 18%) and for the "Auditory" paradigm 60.3% (SD 8.2%). The areas weighted as being most relevant for classification by the encoding model of the transfer learning algorithm show a spatial distribution that is consistent with bandpower modulation in the pC/PCC [2]. The pC/PCC node interacts strongly with the rest of the DMN [19] and, regarding the proposition that the DMN consists of a system related to associations and memory retrieval and a system related to self-relevant thoughts and self referential judgements [15], the key role of communicating between those systems is assigned to the PCC/pC node [19]. Even though both tested paradigms appear to target the region of the PCC/pC node, there is the possibility that each of them triggers a different system of the DMN, with the "Memory" paradigm triggering system one and the "Imagery" paradigm triggering system two. This possible explanation is supported by the finding that the individual accuracies of both paradigms are not highly correlated (Pearson's $\rho = 0.315$).

A potential explanation for the differences in decoding accuracy across paradigms is provided by the over all dif-

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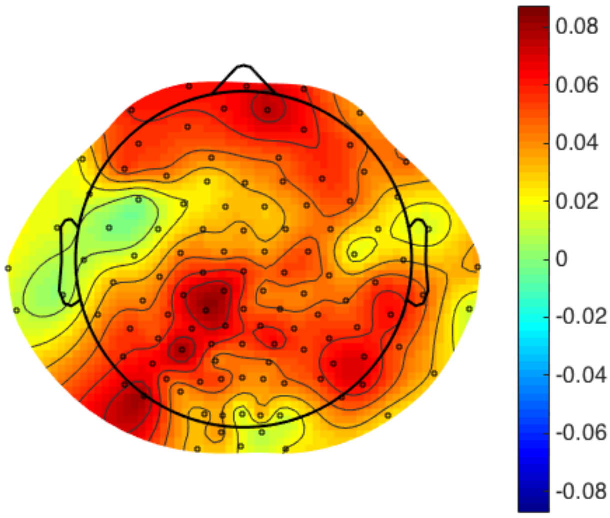

Figure 4: Baseline difference of α-power between paradigms over all participants. Approximate overlap of areas with largest differences and areas most relevant for classification.

ferences in α-power during baseline periods within each trial. The mean value of the α-log-power over all subjects and channels was -1.789 (SD 0.32) and -1.831 (SD 0.31) for the "Memory" and "Imagery" paradigm, respectively. This over all difference showed to be significant ($p = 0.031$) when tested with a paired permutation test with 10^4 permutations. The distribution of the differences over the scalp can be seen in Figure 4. These findings can be related to the research of Blankertz et al., who detected that for BCI systems based on sensorimotor rhythms (SMRs) strength of idling SMR in EEG is predictive for BCI performance.

They calculated this predictor with the maximum elevation in power spectral density compared to a noise floor over a sensorimotor area in resting state. The higher this maximum, the better the performance as it opens the possibility for a bigger difference when SMRs are attenuated [26]. Related to the current study this could mean that the over all lower α-power in the "Imagery" paradigm leaves less space for big differences due to task dependent modulations. The areas having the largest differences (Figure 4) also approximately correspond to the areas most relevant for classification. As stress is correlated negatively with α-band power [27], and participants rated the "Imagery" paradigm as more stressful, this could be the origin of the detected difference.

Nevertheless, the finding of a new paradigm working with binaural auditory stimulation supports the development of more auditory BCI systems. They could be an attractive alternative to vision based BCIs for ALS patients because, as Hill and colleagues report [20], even if vision remains intact, listening is less exhausting for most patients. Additionally, eye movements are getting more and more tiring with progressing disease. The high accuracies throughout studies support acoustic BCIs as promising tools [20] [28]. However, what should be kept in mind regarding this development is the opinion of the users. For example binaurally presented beep sounds are judged as unpleasant by participants [20] and also in the present study participants rated the paradigm presenting binaural acoustic stimuli as less appealing than the "Memory" one. Yet, the results presented here correspond to the performance and opinion of a sample of healthy subjects with no memory impairment. Until tested on an ALS patient sample, it is not clear if this pattern of results will be replicated in this special group of subjects with completely different preconditions. It is important for future research to pay attention to crucial differences between populations to be able to transfer results to target groups and develop assistive devices that can improve patients everyday life.

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