Investigating Visual Imagery as a BCI Control Strategy: A Pilot Study

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***Abstract*—Brain-Computer Interface (BCI) technology may provide individuals with motor impairments or even the general population a new way to interact with the world around them. However, current BCI systems using electroencephalography (EEG) can be unreliable and produce large variations in performance. Most studies seek to improve performance by focusing on signal processing and classification techniques. However, it may also be beneficial to investigate different control strategies. For this reason, the main objective of this pilot study was to investigate the use of visual imagery, a control paradigm that has not been much tested for EEG BCI applications. Visual imagery may provide a more intuitive control strategy with a greater number of available classes than other popular imagery-based methods such as motor imagery. Using this paradigm, we have demonstrated above chance binary classification accuracy (59.9%, p < 0.05) during offline decoding of face and scene visual imagery. Furthermore, the participant in this study achieved significantly above chance performance during a three-class, closed-loop BCI interaction (47.2%, p = 0.05). The initial results of this pilot study demonstrate the feasibility of using visual imagery as an alternative EEG BCI control paradigm.**

Keywords—visual imagery, brain-computer interface, EEG

I. Introduction

A brain-computer interface (BCI) is a technology that facilitates communication between the brain and an external device without input from peripheral nerves or muscles[1]–[3]. The BCI instead translates measured brain activity to a control signal that reflects the user's intended action [4]. Such a device could allow an individual with movement impairments[5] or even the general public [6], [7] a new way to interact with the world around them. Electroencephalography (EEG) has been the most popular modality for measuring brain activity in BCI applications due to its high temporal resolution, ease of use, low cost, and portability [4]. However, there are currently various limitations that prevent EEG BCIs from achieving everyday use [4]. To create a BCI suitable for daily use, a control paradigm must first be selected that is easy to use and provides accurate and reliable predictions for the user's intent.

A. *External Stimulation Based Paradigms*

Measuring the neural response to external stimulation is a popular control method that has generally provided high accuracy in decoding user's intent from EEG data [4]. The visual P300 is one of the most well studied control strategies that captures the P300 event-related potential (ERP) that occurs as a response to an infrequently presented visual stimulus [4], [8]. The P300 is identified as a positive peak that usually occurs between 250 and 500 ms after the onset of an event [9]. One application of this paradigm is the popular P300 speller which allows participants to type words or phrases by fixing their gaze on a keyboard whose letters light up at different intervals [10]. By timing the occurrence of the P300 ERP with the changing intensity of one of the letters, the BCI can determine which letter the user intends to type.

A similar paradigm known as the steady state visual evoked potential (SSVEP) presents participants with an array of targets flickering at different frequencies [4]. To select an action, the user is required to maintain their gaze on one of the targets. The intended target can then be decoded by matching the frequency in the user's EEG data from the visual cortex with the frequency of the flickering target [11], [12]. While the use of an external stimulation can provide an accurate and reliable control paradigm, it is not feasible for use in all applications. These techniques require the user to maintain focus on a target stimulation that may not be directly associated with the task at hand. Furthermore, they often cause greater fatigue for participants due to the high level of attention and visual focus required to use the system [4], and they are not well suited for participants with visual impairments or photosensitivity [13].

B. *Motor Imagery Based Paradigms*

Imagery based paradigms provide an alternative strategy that does not require the use of external stimulation. By far the most common imagery technique for BCI applications is motor imagery [4]. The sensorimotor rhythms (SMR) paradigm is one motor imagery technique that is defined as the imagined movements of large body parts such as the hands, feet, or tongue [4]. This imagined movement causes event-related desynchronization in the mu (8-12 Hz) and beta (18-26 Hz) bands of brain activity in the sensorimotor cortex[14]. One major limitation for SMR based paradigms is the lengthy training times required for participants to learn to modulate the specific frequency bands of brain activity [4]. Additionally, SMR requires mapping an action to the imagined movement of a body part in a way that is not always intuitive [15], it is limited by the variety of available classes [16], and it is subject to large inter- and intra-subject variability in participant performance [17].

Imagined body kinematics (IBK) is another motor imagery paradigm that uses the imagined movement of a single body part in a multidimensional space [4]. For example, a user can imagine moving their dominant hand to move a cursor on a computer screen as if they were using a computer mouse. The kinematic information from this paradigm is extracted from the low frequency (less than 1 Hz) components of the recorded brain activity [18]. The use of IBK in BCI applications is limited, but this paradigm may provide a more intuitive control scheme than SMR. However, these motor imagery approaches are susceptible to a phenomenon known as BCI illiteracy in which 15-30% of participants are unable to achieve proper BCI control despite adequate training time [19]. The cause of BCI illiteracy is still unknown, but it could possibly be due to a participant's inability to modulate the specific component of brain activity necessary to control the BCI. An alternative possibility is that participants have difficulty transitioning from the training sessions to the online control sessions due to the nonstationarities in the EEG signal. EEG BCIs are susceptible to large performance variations between sessions due to factors such as fatigue, frustration, motivation, or changes in electrode positions [17].

C. *Visual Imagery Paradigm*

Many previous studies have focused on improving BCI performance through advanced signal processing or classification techniques [20]. However, an often-overlooked solution is to investigate new control strategies [21], [22]. Visual imagery, or the manipulation of visual information from memory [23], could be a useful BCI control paradigm that has yet been relatively untested [24]. The human brain is visual by nature: 90% of the information transmitted by the brain is visual [25], and it can process images 60,000 times faster than text [24], [26]. Visual imagery may also be a more intuitive control strategy than any of the paradigms listed above [16]. For example, if a person would like to use a BCI system to control a light in their house, the user could directly imagine the lamp they would like to turn on instead of gazing at a flickering target or remembering which imagined movement for a limb corresponds to that light. Furthermore, visual imagery could potentially provide a near infinite number of available classes whereas you might be limited to only four or five possible classes with motor imagery [16].

Several studies have shown that various categories of images (e.g., faces, animals, or inanimate objects) can be reliably distinguished using EEG when participants are visually observing (VO) a presented image [24], [27], [28]. However, very few studies have attempted to measure visual imagery using EEG, and those that do have shown mixed success [16], [24], [29]. Bobrov et al. [29] provides the first investigation into the use of visual imagery as a BCI control paradigm. In this study, they were able to reliably distinguish between imagery of faces, imagery of houses, and resting state with an average of 56% classification accuracy (chance 33%) across seven participants. In Kosmyna et al. [24], researchers performed offline classification between two classes of flower vs. hammer during visual observation and imagery. They were unable to achieve above chance accuracy between the two classes during imagery (average classification accuracy 52%, chance 50%), but they were able to distinguish a difference between the trials when participants performed visual imagery vs. rest (77% average classification accuracy; chance 50%) and between visual observation and imagery (71% classification accuracy; chance 50%). Lee et al. [16] was able to demonstrate a high average classification accuracy of around 40% (chance 7.69%; 22 participants) in an offline analysis of 13 visual imagery categories of common words used for patient communication. This included words with concrete properties (e.g., ambulance, clock, or toilet) or abstract properties (e.g., hello, stop, or yes).

It remains unclear why certain categories of images, such as faces and scenes, were able to be distinguished while other categories, such as flowers and hammers, could not. Additionally, because the use of visual imagery is still in its early stages, the aforementioned studies used substantially different task protocols, spatial and spectral features, and classification techniques which made a direct comparison difficult. For this reason, we attempted to recreate the experiments of Bobrov et al. [29] and Kosmyna et al. [24] using similar methodologies for each pair of image categories (flower vs hammer and face vs scene). We also attempted to expand upon this work by using visual imagery of face and scene categories in a closed-loop BCI application.

II. METHODS

A. *Participants and Data Collection*

Due to the state regulations for mitigating the spread of the COVID-19 virus in place at the time of this experiment, only one individual participated in this pilot study (male; right handed; 26 years of age; previous BCI experience; no reported disabilities; corrected-to-normal vision). EEG data was collected using a Brain Products actiCap Xpress Twist with a wireless LiveAmp amplifier (Brain Products GmbH, Gilching, Germany). This headset features 32 dry electrode channels in the standard 10-20 electrode placement system with a 500 Hz sample rate.

B. *Experimental Protocol*

In this experiment, the participant was instructed to perform visual observation and imagery of flower, hammer, face, and scene images. The flower and hammer images used in this experiment were the same images from Kosmyna et al. [24]. The face and scene images were selected by the user from a dataset of recognizable face and scene pictures. The face images included famous actors and actresses, politicians, and athletes.

J.K. completed this work as a Research Intern at Microsoft Research

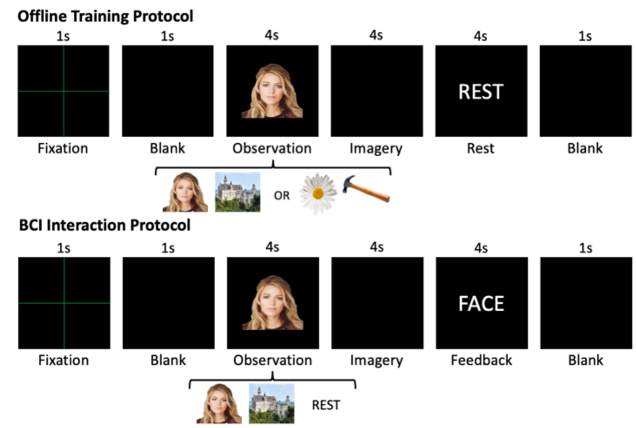

Fig. 1. Experimental task protocol. A. Stimulus presentation and timings during offline training sessions and first 2 runs of the BCI interaction session. B. Stimulus presentation and timings during the final 2 runs of the closed-loop BCI interaction session.

The scene images included famous landmarks or recognizable locales such as a beach or mountain. The full experiment included one offline session using flower and hammer stimuli, three offline sessions using face and scene stimuli, and one online BCI interaction session.

The experimental task followed a similar procedure as the work of Kosymna et al. [24] and is presented in Fig. 1. Each trial of the offline sessions starts with the presentation of a green fixation cross in the center of the screen over a black background for 1 sec followed by a blank screen for 2 sec. Next, one of the images from the two categories appeared for a period of 4 sec. During this time, the participant was instructed to carefully observe the presented image. The image then disappeared for 4 sec and the participant was instructed to imagine the picture that was previously displayed. The word REST was then displayed for 4 sec followed by a blank screen for 2 sec before the next trial began (Fig. 1A). Each offline session was divided into four runs of 20 trials where each image from the two target categories was presented ten times in a random order. After each run, the participant was allowed to take a brief pause before beginning the next run.

In the real-time BCI testing session, we attempted to perform online classification of face and scene visual imagery. The first two runs were identical to the offline sessions to provide us with additional training data to initialize the visual imagery classifier (Fig. 1A). After the second run, the visual imagery classifier was trained using this data along with the data from the previous three training sessions using the face and scene categories. In the last two runs, each trial began with the fixation cross for 1 sec followed by a blank screen for 2 sec. Next, the participant was presented with a visual cue for 4 sec of the target imagery category to perform during that trial. The categories for this session included the selected face or scene images or the word REST. After the cue, the participant performed visual imagery of the target category or rested for a period of 4 sec. Feedback for the predicted category based on their neural data was then presented for 4 sec in the form of the words FACE, SCENE, or REST. Finally, a blank screen was presented for 2 sec before the start of the next trial (Fig. 1B). The last two real-time BCI runs each included six face trials, six scene trials, and six rest trials presented in a random order.

C. EEG Preprocessing and Classification

We tested offline classification during both the visual observation and imagery periods. For the visual observation classifier of flower and hammer, we included the data from the O1, O2, and Oz electrodes surrounding the visual cortex re-referenced to the average of the TP9 and TP10 electrodes over the mastoids. For classification of face and scene, we used the data from electrodes O1, O2, Oz, P3, P4, Pz, P7, and P8. We applied a bandpass filter from 1-40 Hz and a notch filter at 60 Hz to remove powerline noise. The first 0.5s of data from each observation trial was removed to eliminate any transition effects. The remaining 3.5s of data was epoched into three windows of 1.75s with a 50% overlap. The full power spectrum in the 1-40 Hz range was used as features to train a linear Support Vector Machine (SVM) classifier. The classification results were then cross-validated using a leave-one-run-out approach.

For the visual imagery classifier, we included data from all 32 electrodes except TP9 and TP10 that were used to re-reference. Previous literature suggests that information contained in the high gamma band of neural activity may be relevant for visual imagery [16]. For this reason, we applied a bandpass filter from 1-125 Hz with a notch at 60 Hz and 120 Hz to remove powerline noise and its harmonic. The data from each imagery trial was epoched in the same way as the observation classifier. The full power spectrum in the 1-100 Hz range was used as features to train a linear SVM with a leave-one-run-out cross-validation.

During the real-time BCI testing session, the visual imagery data from the first two initialization runs was preprocessed in the same way as the visual imagery classifier above. This data, along with the three previous training sessions, was used to train the linear SVM for real-time use. In the two closed-loop BCI runs, each visual imagery trial was preprocessed and classified in the same way as before; however, only the epoch from the middle of the trial (0.875-2.625s) was used for classification and feedback.

D. Evaluation of Performance

The Participant's ability to control the BCI application is evaluated based on the number of trials where the classification of brain activity matches the cued image category for that trial beyond the level of chance. For the initial offline training sessions, a binary classification of face vs. scene would yield an absolute chance level of 50%. However, the small sample size present in brain signal classification can lead to higher chances of false positives. For this reason, Combrisson and Jerbi [30] have suggested to address this issue by adjusting the chance level as a function of sample size, number of classes, and the desired confidence interval using a binomial cumulative distribution. In this case, each session of the offline training includes a total sample size of 80 observations with 2 classes providing a corrected chance level of 58.8% at $p = 0.05$ and 62.5 at $p = 0.01$. This means that a classifier must obtained at least 58.8% accuracy to be considered significant at $p = 0.05$. The two closed-loop BCI interaction runs consist of a total sample size of 36 observations with 3 classes providing a corrected chance level of 47.2%.

III. Results

A. Recreation of Previous Experiments

Our first objective was to recreate the experiments of Bobrov et al. [29] and Kosmyna et al. [24] using similar methodologies for each pair of image categories (flower vs hammer and face vs scene). For the session using the flower and hammer stimuli, we found a mean classification accuracy of 63.3% (corrected chance 62.5 at p = 0.01) during the visual observation period. When using the face and scene stimuli, we found a mean classification accuracy of 58.7% (corrected chance 58.8% at p = 0.05). These results were similar to those found in Kosmyna et al. [24] who achieved 61% classification accuracy during visual observation.

For the visual imagery classifier, we found a mean classification accuracy of 47.9% for the flower and hammer stimuli and 64.2% (corrected chance 62.5 at p = 0.01) for the face and scene stimuli (Fig. 2). To better understand why it was possible to distinguish between the flower and hammer stimuli during visual observation but not imagery, we repeated this experiment using multiple new flower and hammer images. These new images were of the same size and shape, but with slightly different colors or orientations. Interestingly, the classification accuracy during the visual observation period for this new task fell to below chance level (46.3%). The classification accuracy during the visual imagery period remained around chance at 54.6%. Further discussion of these results can be found in section IV.

B. Classification of Visual Imagery Across Multiple Sessions

For our next experiment, we repeated the session using the face and scene images two additional times to better understand performance variability across sessions. Using the data from the first session during the visual imagery period, we obtained a binary classification accuracy of 64.2% (corrected chance 62.5% at p = 0.01). However, we found that this classification accuracy was relatively variably across sessions (Fig. 3A). The classification accuracy for the second and third sessions were 61.7 and 53.8, respectively. This led to a mean classification of 59.9% over the three sessions which was significant at the corrected chance level of 58.8% at p = 0.05. We also tested a between-session classifier in which the classifier was trained on two sessions and tested on a left-out session. This resulted in a mean classification accuracy of 59.7% which was significant at the corrected chance level.

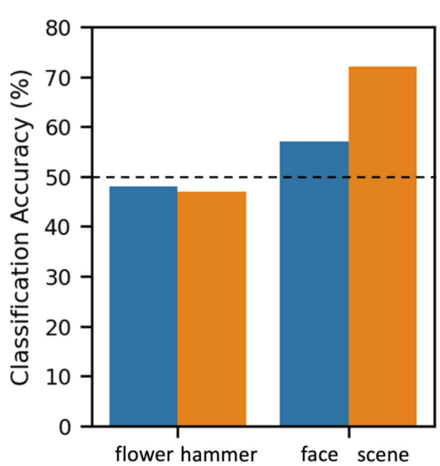

Fig. 2. Classification accuracies for visual imagery of flower vs hammer (47%) and face vs scene (64%) experiments. Dashed line indicates absolute chance level (50%).

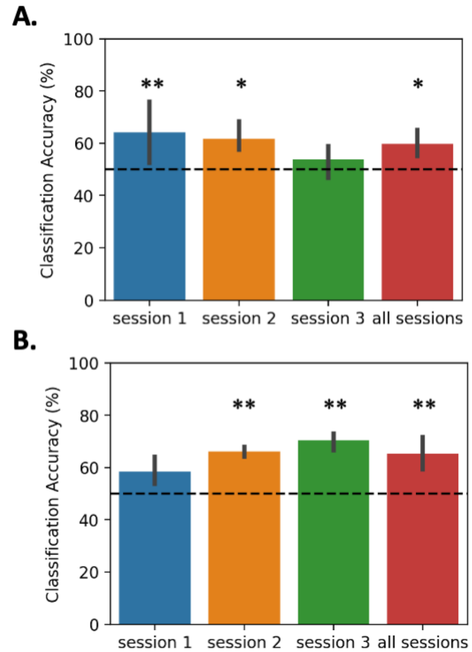

Fig. 3. Offline classification of visual imagery. A. Binary classification accuracy of face vs. scene imagery for session 1 (64.2%, blue), session 2 (61.7%, orange), session 3 (53.8%, green), and between-session accuracy (59.7%, red). B. Binary classification accuracy of visual imagery vs. rest for session 1 (58.3%, blue), session 2 (66.0%, orange), session 2 (70.4%, green), and between-session accuracy (65.2%, red). Dashed lines indicate absolute chance level (50%); * indicates significance for corrected chance level of 58.8% at p = 0.05; ** indicates significance for corrected chance level of 62.5% at p = 0.01. Error bars indicate 95% confidence interval.

We also tested binary classification of visual imagery vs. resting state. To accomplish this, the visual imagery trials for faces and scenes were combined under a single label. Our classifier achieved 58.3% classification accuracy during the first session, 66.0% during the second session, and 70.4% during the third session. This yielded a mean classification accuracy of 64.9% over the three sessions which was significant at the corrected chance level of 62.5% at p = 0.01. A between-session classifier trained on this data yielded 65.2% classification accuracy which was also significant at the corrected chance level of 62.5% at p = 0.01 (Fig. 3B).

C. Real-Time Classification of Visual Imagery

Our final experiment was to evaluate performance during real-time BCI interaction. The classifier was trained on the data from the three offline sessions using face and scene images plus the data from the first two runs of the interaction session. The objective was to discriminate between visual imagery of a face, visual imagery of a scene, or resting state. We were able to achieve a significantly above chance classification accuracy of 47.2% (corrected chance 47.2% at p = 0.05) during the two real-time BCI runs (Fig. 4).

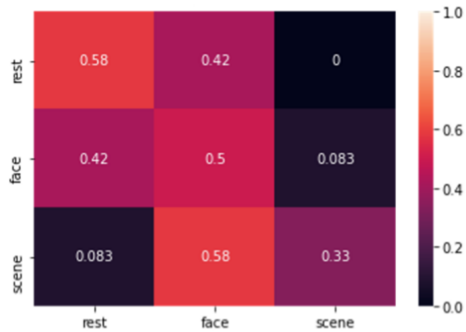

Fig. 4. Confusion matrix of classifier predictions during the closed-loop BCI interaction runs. Overall classification accuracy was 47.2% (corrected chance 47.2% at p = 0.05).

IV. Discussion

The results from our offline analyses during the visual observation and visual imagery periods were similar to accuracy found in previous works [24], [29]. We found significantly above chance classification accuracy during the offline and closed-loop BCI interaction runs for visual imagery using the corrected chance values calculated in accordance with Cobrisson and Jerbi [30]. Interestingly, we also found that our visual imagery classifier remained effective when trained solely on data recorded during different sessions. This allowed us to have a larger pool of data with which to train the classifier for real-time BCI use.

It is interesting why visual imagery of certain categories of images could be reliably distinguished (faces and scenes) while others could not (flowers and hammers). This may be due to a higher representational similarity between the brain activity of flowers and hammers which makes classification difficult [31]. Previous research using functional magnetic resonance imaging [32], single cell recordings [33], magnetoencephalography [34], and EEG [35] have investigated the representational similarity of brain activity during visual observation human faces, human bodies, animal faces, animal bodies, natural objects, and manmade objects. These studies have shown that certain categories (e.g., human and animal faces) are highly distinguishable, while other categories (e.g., natural and manmade objects) show higher similarity in their representational structure. This may explain why we had difficulty in classifying between visual imagery of the flower (natural object) and hammer (manmade object) images.

As for why we were able to classify between these two categories during visual observation, it might be due to the nature of the stimulus presentation. The flower stimulus used by Kosmyna et al. [24] was a large, bright image whereas the hammer was a darker, smaller image displayed against a black background. This may have allowed the classifier to identify between the different intensities of the images, rather than their conceptual representations. This idea is reinforced by our experiment using multiple new flower and hammer images of different colors. This test removed the influence of color and orientation from the stimuli, and we were unable to reliably classify between the categories.

V. Conclusion

This study served as an initial pilot test to investigate the efficacy of using visual imagery as a BCI control paradigm and was conducted under the state regulations for mitigating the spread of the COVID-19 virus. For this reason, the results of this study are limited by the inclusion of only a single subject. Additionally, this study was limited by the quality and amount of data that could be captured using a dry-electrode EEG cap. Dry electrode caps are more susceptible to noise and movement artifacts, and can become uncomfortable after prolonged use [36]. Further work with a larger subject pool, wet-electrode EEG cap, and longer training times is necessary to fully verify the feasibility of using visual imagery as a BCI control strategy. Additional work is also needed to investigate the representational similarity between visual imagery of various object categories measured by EEG. Nevertheless, the results of this pilot study indicate that visual imagery can be used as an effective control paradigm for BCI. Our results yielded significantly above chance classification accuracy in distinguishing between visual imagery of a face and a scene image in an offline analysis. The participant in this study was also able to achieve significantly above chance performance in a real-time visual imagery BCI application with three classes.

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