Identifying Changes in Brain Activity Caused by Motor Imagery Exercise Through EEG

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Introduction

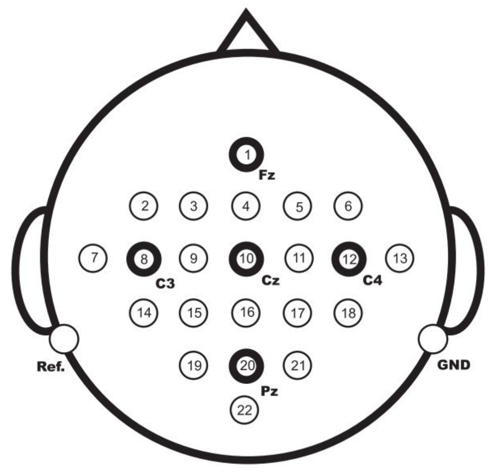
Motor imagery is the process of imagining the movement of different body parts and has shown potential in stroke recovery, resistance training, and muscle preservation during immobilization. Stroke affects nearly 800,000 individuals in the United States annually, with costs exceeding $53 billion per year (Tsao et al., 2022), highlighting the significance of stroke recovery for both patients and the community.

The human brain contains approximately 80 to 100 billion neurons that communicate through electrical charges and chemical signs. Since these processes are not directly observable, technological methods are necessary to track brain activity. Current active imaging methods include Positron Emission Tomography (PET) and Functional Magnetic Resonance Imaging (fMRI). While these methods have promising results, their overall utility is limited when considering costs and potential side effects.

In contrast, Electroencephalography (EEG) is an accessible and easy-to-use method that measures brain activity using small metal discs placed on a subject's scalp (*EEG*, 2022). Primarily used for diagnosing epilepsy and seizures, EEG records changes in brain signals with high temporal resolution over time. By providing data focused on the entire activity of the brain rather than isolated snapshots, more precise results can be established. Additionally, EEG allows patients to move during the scanning process, making it less intimidating and more comfortable. Due to its simple preparation and cost-effectiveness, unlike fMRI and PET, the scan can be done frequently. Thus, EEG is an ideal candidate for monitoring the impact of motor imagery on the brain over time, ensuring that motor imagery training programs induce the desired brain activity for optimal stroke recovery.

We hypothesize that brain activity changes in response to motor imagery over time, possibly reflecting brain adaptations and mental fatigue. We discovered that brain changes tend to happen in the alpha (8-12 Hz) and delta (1-4 Hz) bands, with specific changes depending on the type of motor imagery performed. Additionally, these changes tend to occur in certain brain regions, potentially indicating fatigue in those areas (Talukdar et al., 2019). Furthermore, changes in synchrony/desynchrony between brain regions have been observed, aligning with previous findings during motor imagery (Pfurtscheller et al., 2006). These findings indicate potential mechanisms through which motor imagery exercises can be monitored for efficacy and act as a source of rapid feedback for stroke patients using motor imagery to improve motor recovery following a stroke.

Figure 1 (below). Electrode placement diagram. 22 electrodes were placed on the scalp, plus one on the right ear as a ground and one of the left ear as a reference. Electrode Cz represents the vertex electrode.



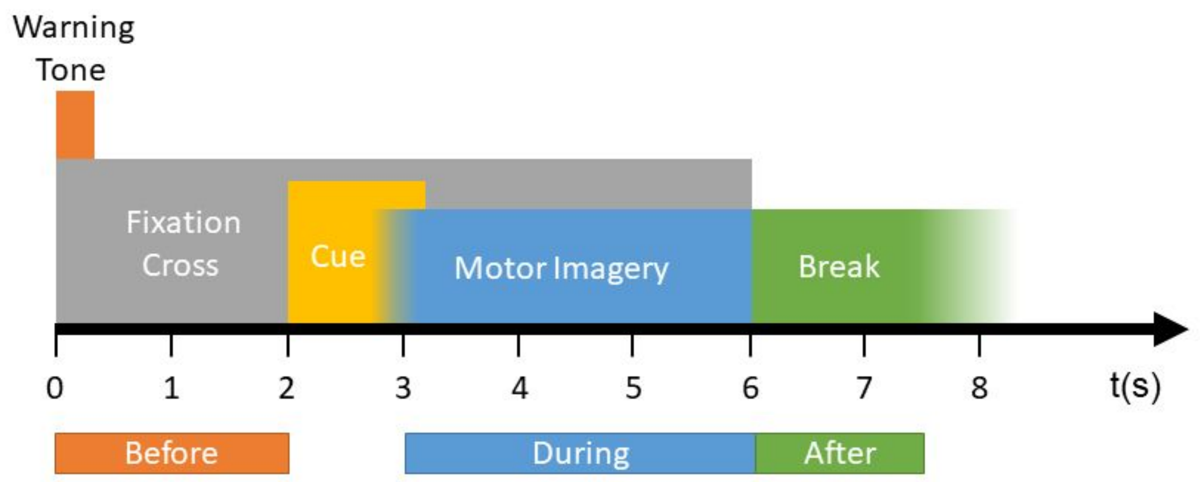


Figure 2. Timing scheme of motor imagery trials. Before was defined as being the time period from the warning tone (0 s) to the visual cue for motor imagery (2 s). To account for the delay in beginning motor imagery, the During period was defined from 3 s to 6 s, when the fixation cross disappeared. The break lasted a variable period, but was always at least 1.5 seconds in duration, so the After period was defined as 6 s to 7.5 s.

Materials & Methods

The data used in this study was originally released as part of a brain-computer interface competition (Brunner et al., 2008) and is being repurposed for studying how the brain changes and adapts over time in response to performing motor imagery.

The 9 subjects in this study, 56% male and 44% female, ranged from the ages of 17 to 24 with an average age of 23. To measure the EEG signals from the brain during these trials, 22 electrodes were placed on the scalp 3.5 cm apart, as shown in Figure 1. Electrode Cz represents the vertex electrode. All signals were recorded monpolarly and were sampled with 250 Hz, and band-pass filtered between 0.5 Hz and 100 Hz. The sensitivity of the amplifier was set to 100 µV.

During each trial, a computer screen displayed an arrow instructing the subjects to perform a motor imagery task corresponding to the left hand, right hand, foot, or tongue until the arrow disappeared. This task was repeated multiple times with short breaks in between (Figure 2). Two sessions were held for each subject, each with 6 runs, and each run comprised 48 trials. Each motor imagery task involved moving a different body part, activating different regions of the brain and affecting the EEG signals recorded. All 9 subjects performed all 4 motor imagery tasks multiple times in random order.

To analyze the changes over time, the 48 trials were divided into three tertiles: Tertile 1 (T1) included the first 16 trials, Tertile 2 (T2) included the middle trials, and Tertile 3 (T3) consisted of the last 16 trials.

Motor imagery trials were broken down into Before, During, and After periods (Figure 2). The Before period spanned from 0 s to 2 s, starting from the warning tone until just before the motor imagery cue was presented. The During period began at 3 s, allowing a 1-second gap after the cue for the subject to initiate motor imagery, and continued until 6 s, just before the fixation cross disappeared, indicating the end of motor imagery. The After period was determined to be from 6 s to 7.5 s. The period of the break was variable but was always at least until 7.5 s. The rebound was calculated as bandpower from the After period minus that of the During period.

The relative difference measure (RDM) was calculated between all possible pairs of electrodes within a single trial in order to represent the synchrony/desynchrony between electrodes (Homölle & Oostenveld, 2019). RDM was calculated using raw EEG data according to the following equation, where double vertical bars indicate the Euclidean norm of the vector:

$$RDM\,(u^{ref},\, u) = \left\| \frac{u^{ref}}{\|u^{ref}\|} - \frac{u}{\|u\|} \right\|$$

Band power was calculated in MATLAB by using the *bandpower* function to find the average band power for the corresponding frequencies for each electrode. Alpha was defined as 8-12 Hz, Beta 14-28 Hz, Delta 1-4 Hz, and Theta as 4-7 Hz. In cases where band power was normalized, normalization was performed by dividing the band power from the second and third tertiles (T2 and T3) by the band power of the first tertile (T1), reflecting a multiplicative change in band power from the first 16 motor imagery trials.

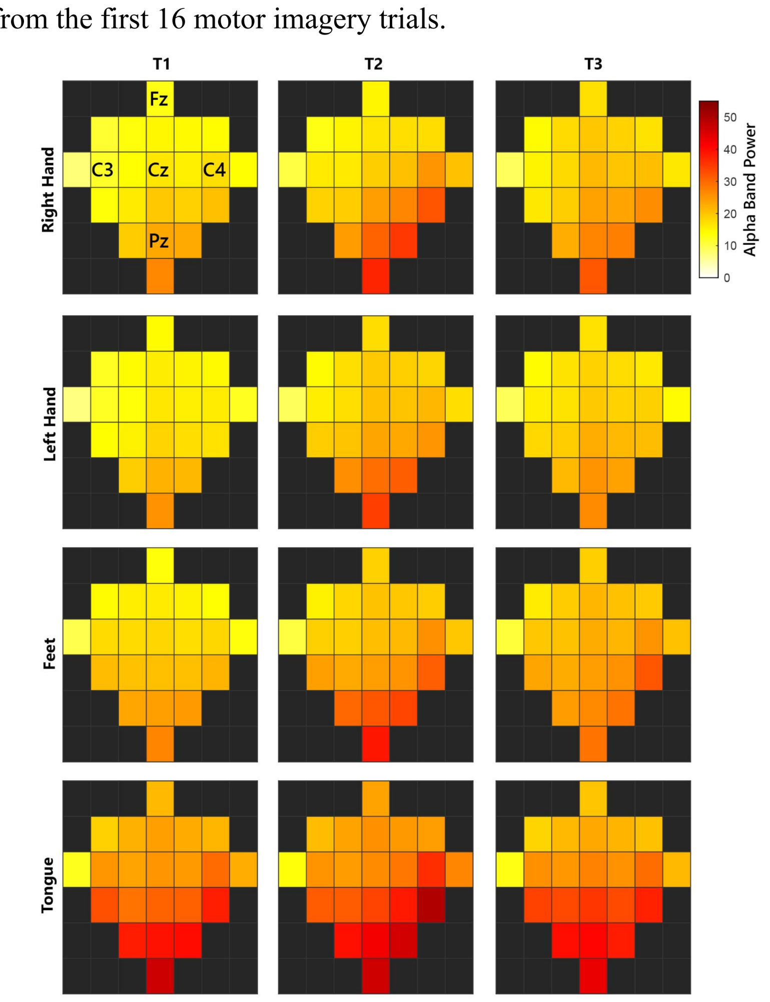


Figure 3. Changes in EEG power for individual electrodes over time during motor imagery. The tongue and right hand motor imagery tended to have the most changes in power over time, especially the more occipital-right electrodes. This shows that changes in band power vary depending on location in the brain. Fz, C3, Cz, C4, and Pz represent the positions of the corresponding electrodes in the electrode placement diagram (Figure 1).

Results

First, we examined changes in alpha band power over time, specifically for motor imagery of the right hand, as all subjects were right-handed. The alpha band was chosen because changes in alpha band power during motor imagery have been previously reported (Pfurtscheller et al., 2006). The After stage showed a significant increase in activity, especially in the third tertile (T3), while the other stages exhibited minimal changes. The Rebound showed a substantial decrease in activity in T1 and T2, but T3 did not display significant changes.

This analysis was then expanded to all other motor imagery categories (Figure 3). The tongue and right-hand motor imagery showed the most significant changes in alpha band power, particularly in the occipital-right electrodes. This indicates that alpha band power changes vary depending on the brain region. Figure 4 depicts the data, with each line connecting two nodes representing one subject. The most significant changes from baseline (T1) occurred in the alpha (Figure 4A) and delta bands (Figure 4C). In the alpha band, the feet motor imagery had a significant change from T1 in T3, whereas, in the delta band, there was a significant change in power during tongue motor imagery but not feet motor imagery, suggesting that different forms of motor imagery will impact different power bands differently. In the beta band (Figure 4B), the only significant change seen was during T3 feet motor imagery, potentially influenced by a single outlier. No significant changes were seen in the theta band (Figure 4D) for any form of motor imagery across all time points.

In order to examine changes in synchrony/desynchrony between electrodes after motor imagery, we calculated relative different measures (RDMs) in the alpha band across all three tertiles (Figure 5). RDMs in the alpha band were calculated during and after motor imagery of moving the right hand, the left hand, the feet, and the tongue, respectively. The mean of four trials per tertile for each of the nine subjects was calculated. The RDMs from the time period during motor imagery were subtracted from the time period following motor imagery. For all forms of motor imagery, RDMs uniquely shifted over time depending on the type of motor imagery being performed. The tongue, overall, favored increased synchronization following motor imagery in all three tertiles. However, the right hand had a strong preference for synchronization in the second tertile, while the left hand favored synchronization in T1 and T3. For the feet, synchronization increased with each tertile. These findings demonstrate that different motor imagery types lead to distinct changes in activity synchrony over time.

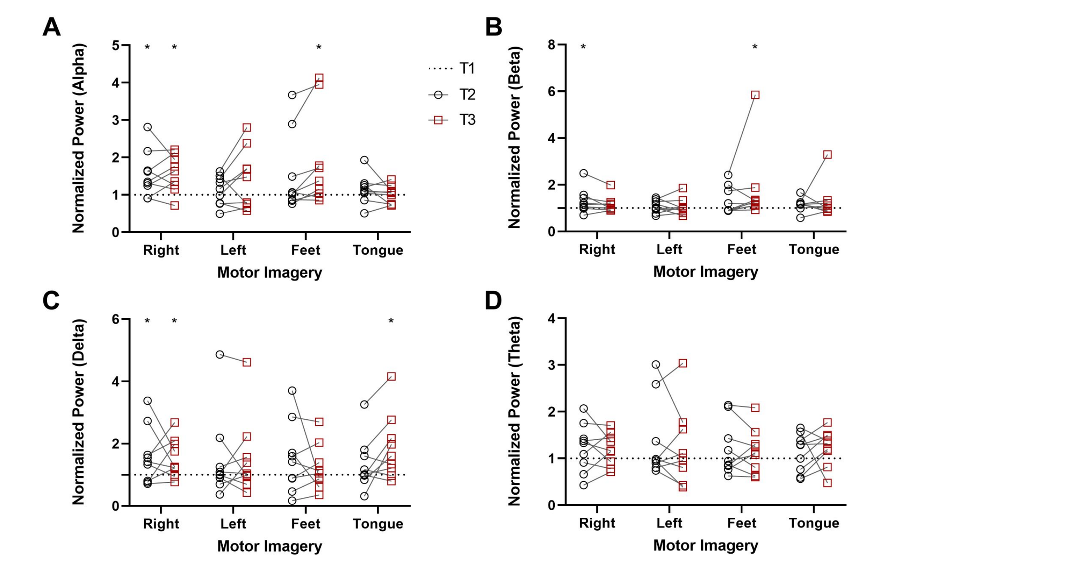


Figure 4. Changes in normalized EEG power across multiple bands during motor imagery. Each two nodes connected by a line represents one subject. The most significant changes from baseline (T1) occurred in the (A) alpha and (C) delta bands. In the alpha band, the feet motor imagery had a significant change from T1 in T3, whereas in the delta band, there was a significant change in power during tongue motor imagery but not feet motor imagery, suggesting that different forms of motor imagery will impact different power bands differently. In the (B) beta band, the only significant change seen was during T3 feet motor imagery, but that may be due to the influence of a single outlier. In the (D) theta band, no significant changes were seen for any form of motor imagery across all time points. *=p<0.05 (Wilcoxon signed-rank test).

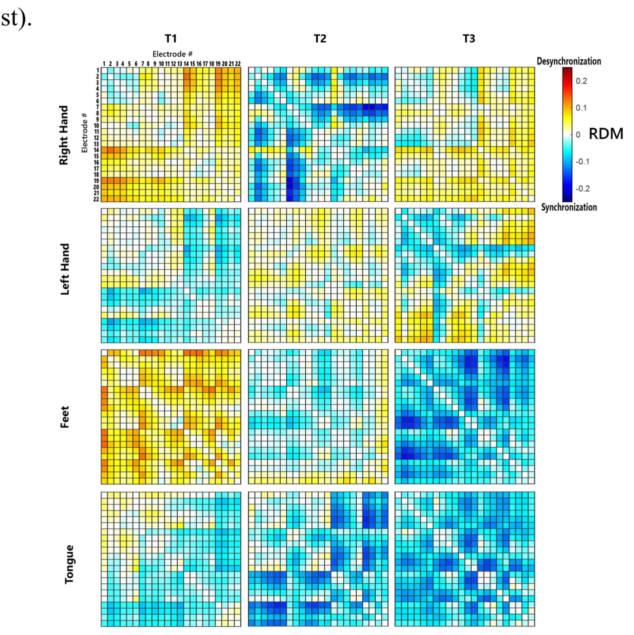


Figure 5. Mean relative difference measure (RDM) between different electrodes during motor imagery over three tertiles. RDMs in the alpha band (8-12 Hz) were calculated during and after motor imagery of moving the right hand, the left hand, the feet, and the tongue, respectively. The mean of four trials per tertile for each of the nine subjects (n = 9) was calculated. The RDMs from the time period during motor imagery was subtracted from the time period after motor imagery. RDMs changed between tertiles depending on the type of motor imagery being performed. For all forms of motor imagery, RDMs uniquely shifted over time depending on the type of motor imagery being performed.

Conclusions

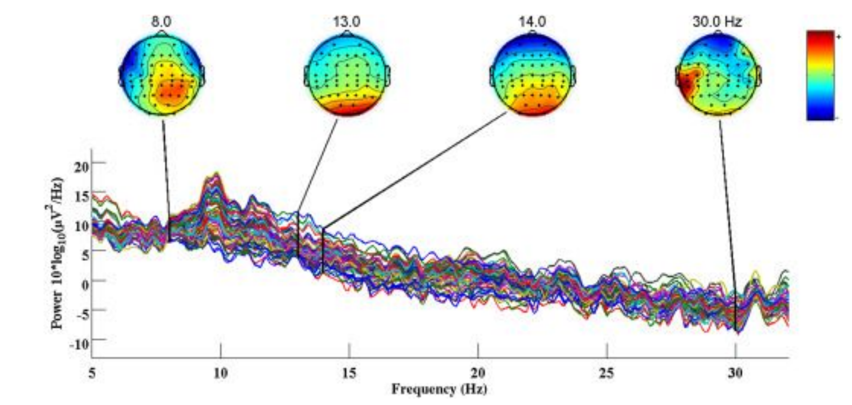
Overall, we discovered that brain activity changes during repeated motor imagery practice. This could be one factor in why attempts to classify brain activity for brain-computer interfaces have been mostly unreliable (Chu et al., 2020). In order to improve decoding for it, incorporations of changes that correlate with mental fatigue may be necessary.

Some limitations of this study were the low number and the young age of the subjects. Brains are highly diverse, so a larger number of subjects should be studied to find more reliable differences in brain activities. Furthermore, if we are to apply this information to guide recommendations for stroke recovery via motor imagery exercise, an older group of subjects, which has the most risk of stroke, should be studied. The subjects in this study also never reached a stable plateau with band power that we could detect, which could indicate that the duration of motor imagery was not long enough to reach a fully mentally exhaustive state. However, like with exercises, complete exhaustion may not be necessary for recovery (Carrasco & Cantalapiedra, 2016).

Additionally, all subjects were right-handed, so the information gained from this study might not apply to left-handed subjects. We observed more changes in power in response to right-hand motor imagery, possibly because all were right-handed (Figure 3, 4). This study should be replicated with left-handed subjects in order to map out the changes in brain fatigue in response to repeated motor imagery. If different areas of brain fatigue differentiate by handedness, it suggests that handedness may have to be considered when designing a motor imagery exercise.

The subjects in this study received no form of feedback on the effectiveness of their motor imagery. Although they showed many features common to mental fatigue (Talukdar et al., 2019), receiving feedback from an experimenter or simple app observing their EEG signals in real-time might have improved their motor imagery. Additionally, such feedback mechanisms could be useful to ensure that damaged brain areas are being sufficiently used in a way that optimizes stroke recovery. Further research should first determine the brain activity patterns that best recover damage from stroke. Then, EEG can be used to monitor and provide feedback to improve rehabilitation.

These findings contribute to our knowledge of motor imagery by indicating potential methods through which motor imagery exercises can be monitored. Different types of motor imagery cause different patterns of brain activity that change over time. EEG may be a practical and effective source of rapid feedback for physicians and patients using motor imagery to improve motor function following a stroke.



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