Mobile EEG suggests that alpha-band oscillations support the retrieval of the egocentric direction of landmarks around a navigator

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Abstract

Remaining oriented while navigating is a key aspect of survival for many mobile organisms. Previous work suggested that the parietal lobes play a key role in helping navigators determine directions to landmarks relative to themselves. Recent evidence suggests that alpha-band oscillations are crucial for spatial attention and may track egocentric direction as well. We used mobile EEG to integrate these disparate lines of research and test our novel "alpha window hypothesis" that alpha-band oscillations support the retrieval of egocentric directional information around navigators oriented within a real-world environment. Time-frequency-based machine learning analysis revealed significant classification accuracy of the target's egocentric direction within the 8-12 Hz frequency range, thus supporting the alpha window hypothesis. Our results provide a pivotal advancement in our understanding of the neural mechanisms of directional memory by extending previous research that used neuropsychology, fMRI, and EEG into the domain of a dynamic, situated, embodied spatial memory task.

Keywords: egocentric direction; spatial navigation; orientation; memory; alpha oscillations; mobile EEG

Introduction

Remaining oriented while navigating, such as remembering the directions to landmarks, is a key aspect of survival for many mobile organisms. The loss of spatial memory has devastating effects on an individual's ability to live an independent life. One of the hallmark impairments of Alzheimer's Disease is spatial disorientation, which disrupts navigation and wayfinding (Lithfous et al., 2013). A critical component of spatial memory and orientation is egocentric knowledge—the ability to encode the locations of landmarks relative to oneself. Lesion studies in humans highlight the parietal cortex's role in egocentric coding (Driver & Mattingley, 1998; Iachini et al., 2009). A landmark study by Bisiach & Luzzatti (1978) demonstrated that patients with right parietal cortex damage retained an intact allocentric representation of familiar landmarks, but they systematically omitted the recall of landmarks on the left side of their egocentric space, depending on their imagined heading in the environment. Thus, early findings supported the role of the parietal lobes in egocentric memory retrieval.

Functional magnetic resonance imaging (fMRI) studies have provided additional evidence to support the parietal cortex's role in egocentric memory retrieval. Schindler & Bartels (2013) investigated BOLD activity evoked during an egocentric directional memory task using a combination of desktop-based virtual reality (VR) and fMRI. Participants first learned the locations of eight objects placed at equal distances in the corners of an octagonal virtual room. During the test phase, while lying in an fMRI scanner, they imagined the direction of target locations based on a given (virtual) heading. Classification analysis of the fMRI data revealed that researchers could decode the imagined egocentric direction based on blood-oxygen-level-dependent (BOLD) activity in the parietal cortex. These findings extend previous lesion-based studies, demonstrating that the parietal cortex is actively engaged in egocentric directional coding during spatial memory retrieval. Put together, this evidence firmly establishes the parietal cortex as a key neural substrate for egocentric directional memory.

While previous research on egocentric directional memory has primarily relied on behavioral and neuropsychological methods with relatively high spatial resolution, less is known about the temporal dynamics of directional coding in the human brain. Electroencephalography (EEG), which directly measures electrical activity of the brain (e.g., postsynaptic potentials) at the scalp, offers excellent temporal resolution (Cohen, 2014). Due to the excitability of neurons, neural activity recorded via EEG fluctuates at specific frequencies, known as neural oscillations, which can reveal mechanistic insights to the level and type of neural communication that is happening at the time of recording. Low-frequency oscillations have been hypothesized to reflect synchronized firing across brain regions, suggesting inter-region communication, whereas high-frequency oscillations reflect less synchronized activity, often associated with localized processing (Ward, 2003). Given extensive research linking cognitive functions to distinct oscillatory patterns, studying neural oscillations can provide valuable insights into how the electrical activity of the brain supports higher-order cognitive processes (Başar et al., 2004; Buzsáki, 2006; Buzsáki & Draguhn, 2004; Klimesch, 1999; Ward, 2003).

Alpha-band oscillations (8–12 Hz) play a crucial role in various cognitive functions, particularly attention (Klimesch, 1999, 2012; Ward, 2003), potentially making them relevant for spatial navigation. Recent EEG studies explored the relationship between alpha oscillations and spatial attention. Foster et al. (2017) found that alpha activity tracked the locus of covert spatial attention on a computer screen. Schönberger et al. (2010) examined allocentric and egocentric navigation-like movement by manipulating optic flow in a computerized task, revealing increased occipito-parietal alpha activity during egocentric navigation. Together, these findings suggest that alpha-band oscillations encode spatial attention and may specifically track egocentric direction.

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While these studies have advanced our understanding of spatial attention, recent theories emphasize the fundamental role of body-based cues (e.g., head and body rotations) in spatial memory (e.g., Taube et al., 2013). Thus, studying spatial memory in navigators who are physically embedded within their environment is crucial. However, the studies reviewed so far have relied on 2D computerized paradigms, often requiring participants to remain stationary or even lie still in an fMRI scanner. Mobile EEG presents an exciting opportunity to study spatial memory in more naturalistic settings, allowing participants to make full-body rotations and physically orient themselves within an environment (Gramann et al., 2014; Makeig et al., 2009; Park et al., 2018). Building on this prior research, we used mobile EEG and a real-world egocentric spatial memory task to investigate the relationship between alpha-band activity and egocentric directional coding.

In the present study, we integrated and extended the disparate lines of research from the neuroscience of human directional memory (Bisiach & Luzzatti, 1978; Schindler & Bartels, 2013) and spatial attention (Foster et al., 2017) using mobile EEG and a real-world spatial memory task to test the hypothesis that alpha-band oscillations provide a mechanism for supporting the retrieval of the egocentric direction of a target around the participant's body while they are situated within the environment. We term this the "alpha window hypothesis" to indicate that the role of alpha oscillations in human spatial cognition would extend beyond viewed space to include locations around a participant's body, and we emphasize the similarity to the "parietal window hypothesis" (Byrne et al., 2007; Schindler & Bartels, 2013).

We designed a real-world egocentric pointing task based on the eight-objects paradigm used by Schindler and Bartels (2013)[1]. Participants first learned the locations of 8 objects that were evenly spaced around them in a circle (Figure 1). Then, at the beginning of each block, participants saw a heading cue, indicating which object they should face. Within this heading direction, participants then saw a pointing cue (which object they should point to with a joystick), a 1500 ms delay with a fixation cross (planning and maintenance phase), and a response cue. Participants repeated pointing trials for all of the other possible objects in the room before they were cued to change their heading direction. We used a time-frequency-based machine learning analysis to determine whether patterns of oscillations across electrodes carried information about the egocentric direction during a delay period (i.e., the memory retrieval and response planning phase). Specifically, the alpha window hypothesis predicts that the pattern of power across electrodes between 8-12 Hz should carry information that is sufficient to classify the direction of the target relative to the navigator during the delay period as they prepare their response (i.e., between 1-2 seconds after the cue onset; for similar logic in a spatial attention paradigm, see Samaha et al., 2016).

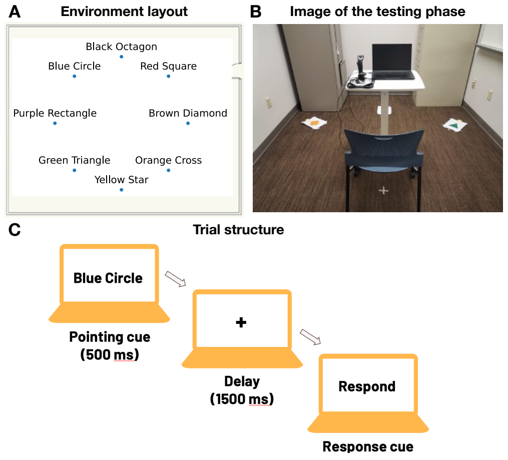

Figure 1: Visualization of the egocentric pointing task in which participants learned the positions of eight objects in a room and pointed to the positions of objects while facing a certain direction. (**a**) Visualization of the eight-objects paradigm in the room. The entrance of the room was located at one side of the wall. Eight pictures of different shapes were located at eight directions relative to the center of the room. Each picture was separated by 45° and had equal distance relative to the center of the array. (**b**) A picture of the actual experimental setup. (**c**) Visualization of a single pointing trial after participants were situated towards one object. All instructions appeared on the screen of a laptop. The joystick was placed on participants' lap throughout the testing phase.

Method

Participants

Drawing on previous studies using time-frequency-based decoding of spatial attention (Samaha et al., 2016), we estimated that detecting an equivalent effect size with 80% power at an alpha level of 0.001 would require a minimum of 15 participants (using the R package pwr). Likewise, similar work used equivalent sample sizes (15 participants in each of 3 experiments in Foster et al., 2016; 16 in Exp. 1 of Foster et al., 2017). We recruited twenty-six healthy participants from our institution's student pool. We removed seven participants from the analysis because they either did not complete at least 400 trials of usable data[2] or due to technical issues during the experiment or other excessive noise in the data, resulting in the inclusion of 19 participants' data in this paper (n=19, 12 female, 7 male, ages 18-22). We recruited participants through our institution's SONA system and online advertisement. Each participant either received Psychology course credits or monetary compensation ($10 per hour). We conducted all procedures in accordance with the Institutional Review Board at Colby College.

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[1] Note that our approach here also extends the 2D version of the paradigm used by Foster et al. (2017).

[2] Note, we included one participant with 395 trials, since they were only 5 trials under our original cutoff.

Procedure

The study contained a learning phase and a testing phase for each participant to complete independently. A written consent form was obtained at the beginning of the study, and a thorough debrief was given at the end of the study.

The Learning Phase. Participants freely navigated in a room for a duration of their choice (see Figure 1a, 1b). In the room, participants learned the location of eight pictures of shapes situated in eight directions relative to the center of the room. Each picture displayed a single geometric shape in a unique color, accompanied by a written description of the shape (e.g., "Black Octagon"). After participants indicated that they had memorized the array of objects, researchers capped the participant and started the EEG recording prior to beginning the testing phase.

The Testing Phase. Participants sat on a chair (with wheels) at the center of the room. Instructions were given through a laptop located on a rotating table in front of the participants (see Figure 1a, 1b). We created our laptop-based task in PsychoPy (Pierce et al., 2019). Participants first rotated both the chair and the table to face one object (e.g., "Turn to the Brown Diamond"), and pressed the space bar when they had finished moving. Then, they performed a pointing trial that contained a pointing cue, a delay period, and a response cue (see Figure 1c). The pointing cue was presented for 500 ms, indicating the object that participants would have to point to for that trial (e.g., "Blue Circle"). Then, a fixation cross representing the delay period was presented for 1500 ms. Participants were instructed before the task began that this delay period was their "thinking time;" that is, the time they should use to retrieve the direction of the object relative to their current facing direction. Finally, a response cue ("Respond") appeared on the screen. Participants had an unlimited response window to indicate the direction of the pointing object by moving the joystick and pressing the trigger button on the joystick. The testing phase contained 8 blocks in total, and each block asked the participants to rotate and face all eight objects. There were two pointing trials for each object in each heading, resulting in 1024 pointing trials for 8 blocks (i.e., 8 headings x 8 objects x 2 repetitions of each object per heading x 8 blocks). Participants could take breaks between blocks for an unlimited period of time. The pointing task took participants between 90 and 120 minutes to complete, including breaks.

EEG Recording & Preprocessing

During the testing phase, mobile EEG was recorded from 64 active electrodes (consistent with the 10/20 International System) within an EASYCAP, as well as one horizontal EOG channel. Two bipolar EOG electrodes were placed left or right of each eye, and a ground electrode was placed on the participant's right earlobe. The impedance levels of the electrodes were generally below 20 kΩ. The EEG signal was digitized at a rate of 500 Hz using the BrainVision LiveAmp 64 amplifier, and recorded to the LiveAmp memory card. Each recording was between 1-2 hours long.

We used custom-written Python code, the Python-MNE package (version 1.3), and scikit-learn to conduct preprocessing, time-frequency analysis, and classification analysis (Gramfort, 2013). We bandpass filtered the data between 0.1 and 50 Hz using a 4th order Butterworth filter. We identified noisy or otherwise bad electrode channels on a subject-by-subject basis and interpolated them using a weighted average of nearby electrodes. We interpolated 1-2 electrodes for a few participants. We conducted independent component analysis (ICA) to remove components that contained eye movement and blink artifacts for every participant. We manually inspected the independent components that accounted for the greatest amount of variance and removed them if the activity was concentrated towards the front of the scalp or near the eyes. Then, we conducted annotated automated muscle artifacts rejection following the tutorials on the Python-MNE official website[3]. Specifically, the function marked time spans of raw data containing muscle artifacts for later rejection. We then epoched the data from -1.5 prior to 4 seconds after pointing cue onset. We conducted a second run of ICA for all participants to check the rejection of eye and muscle movement artifacts from the data. We then baselined the data according to -0.5 to 0 seconds before the pointing cue onset.

Time-frequency-based Classification Analysis. To determine which frequency bands contain information about egocentric direction, we conducted separate classification analyses at each frequency for a time-frequency-based classification analysis (Figure 2). We were interested in testing the alpha window hypothesis of egocentric directional memory retrieval, which predicts that there would be increased classification accuracy at alpha-band frequencies (8-12 Hz). We computed a time-frequency decomposition of the data using linearly spaced frequencies from 4 to 50 Hz in steps of 1 Hz (as in Foster et al., 2016, 2017) using complex Morlet wavelets with 6 cycles. For each of these frequencies, we trained and tested a separate classifier on the power across all electrodes for each time point. As such, we calculated a classification accuracy for each time point and frequency combination, resulting in a time-frequency classification matrix that we used to create a 2-dimensional plot. We used a linear SVM with the dual parameter set to True because we had more features than trials. Similar to previous EEG papers, we used a 3-fold cross-validation procedure and averaged the power within each condition and split of the data to obtain cleaner time-frequency patterns. We z-scored the time-frequency patterns to zero mean and unit variance within each split of data. We then averaged the classification accuracy across the N-fold-cross-validation procedure to obtain mean classification accuracies at each time and each frequency for each participant.

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[3] https://mne.tools/dev/auto_examples/preprocessing/muscle_detection.html

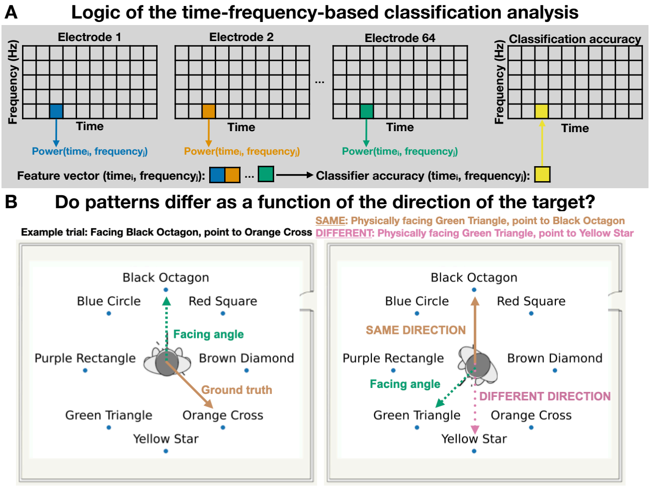

Figure 2: Logic of the time-frequency-based classification analysis. (a) For each of the 46 linearly spaced frequencies, we trained and tested a separate classifier for each time point on the power at that frequency across all electrodes. (b) Each classifier was trained to predict the egocentric direction across all facing directions.

Data Analysis

Behavioral Data Analysis. We conducted behavioral data analysis for participants' task performance and reaction time after the response cue onset to ensure that participants were responding as quickly and accurately as possible, which would suggest that they used the delay period to think about the direction of the target object and to plan their responses. We calculated task performance by the median absolute angular error between joystick pointing direction and the actual direction of the cued object (Figure 3). We compared the averaged median absolute angular errors to chance performance (90 degrees) using a one sample t-test to determine group-level performance (Figure 4). Reaction time for each participant was measured by their median response time in moving the joystick after seeing the response cue onset (Figure 4).

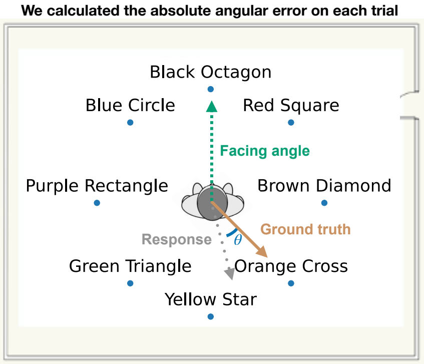

Figure 3: Calculation of the absolute angular error on each trial. We subtracted the ground truth angle to the target object based on the participant's current facing direction from the participant's submitted joystick response.

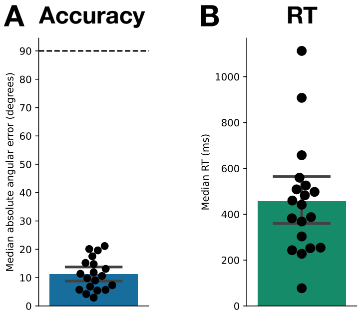

Figure 4: Behavioral results. (a) Participants responded very accurately on the pointing tasks (average median angular error = 11.2 degrees). (b) Participants also responded quickly after the response cue onset (average median reaction time = 455.2 ms). Abbreviation: RT = reaction time.

EEG Data Analysis. Based on our hypothesis that alpha-band oscillations carry information about egocentric direction, we predicted that the peak classification accuracy would be between 8-12 Hz, 1.0-2.0 seconds after the pointing cue onset (Figure 5; for similar logic see Samaha et al., 2013). Thus, we calculated the average classification accuracy between 8-12 Hz and 1.0-2.0 seconds after the pointing cue onset, and we compared the resulting classification accuracy to chance (0.5) using a one sample t-test.

Results

Evidence that participants performed extremely well on the spatial memory task. We operationalized directional memory performance as the median absolute angular error between the participant's response and the actual angle across all trials. Participants average performance was significantly better than chance ($t(18)$ = -60.8; p = 2.70 x 10^{-22}); furthermore, their angular errors were very low on average (i.e., an average median error of 11.2 degrees), thus suggesting that participants were dynamically engaged in the task and that they had precise memories of the layout of the objects from all of the vantage points in the environment (see Figure 5A). We also found that participants responded quickly after the "respond" cue (i.e., on average within 455.2 ms; see Figure 5B), thus suggesting that they used the delay period to retrieve the direction and actively plan their responses. Altogether, these results suggest that participants performed extremely well on our task and thus substantiate our use of the delay period for studying the neural representations supporting directional memory retrieval.

Evidence that alpha-band oscillations play a key role in coding the egocentric direction of a retrieved location around a participant's body. Based on our alpha window hypothesis that alpha-band oscillations contain information about the retrieval of egocentric directional information around a navigator that is situated within the environment, we predicted that a linear SVM would be able to decode the egocentric direction of the target using patterns of power across all electrodes at the frequencies of 8-12 Hz and 1 to 2 seconds after the pointing cue onset (Figure 5).

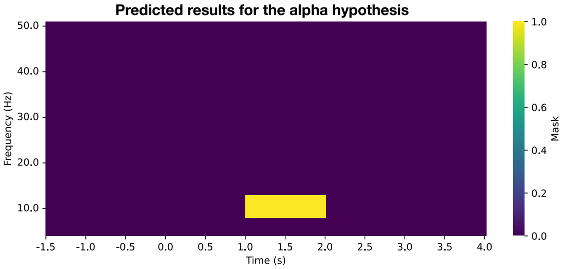

Figure 5: Predicted results for the alpha window hypothesis. If alpha oscillations support the retrieval of egocentric direction, highest classification accuracy will be reached for 8-12 Hz from 1.0-2.0s post pointing cue onset.

We trained separate classifiers on each of the frequencies (from 4-50 Hz in steps of 1 Hz) at each time point (Figure 2). Consistent with our prediction, our time-frequency-based classification analysis revealed an increase in classification accuracy between 8-12 Hz from 1 to 2 seconds after the pointing cue onset (Figure 6A). Moreover, the average classification accuracy between 8-12 Hz and 1 to 2 seconds after the pointing cue onset was significantly greater than chance (M = .56, $t(18)$ = 5.23, p < .001; Figure 6B). Taken together, our results suggest that the alpha-band plays a predominant role in the representation of the egocentric direction of targets during the retrieval and planning phase of our spatial memory task.

Discussion

We proposed and tested the novel "alpha window hypothesis," which posits that alpha-band oscillations support the retrieval of an object's egocentric direction within a real-world environment. Our behavioral analysis revealed excellent response accuracy and fast reaction times, suggesting that participants successfully retrieved the probed direction during the delay period following the pointing cue onset, thus validating our use of this time window in our EEG analysis. Time-frequency classification analysis of EEG data within the 8–12 Hz range revealed significantly above-chance accuracy from 1-2 seconds after cue onset. Together, these findings support the hypothesis that alpha oscillations play a critical role in egocentric directional memory retrieval. Our work extends previous behavioral and neural findings by providing new insights into the temporal and oscillatory dynamics of egocentric directional coding (Bisiach & Luzzatti, 1978; Driver & Mattingley, 1998; Iachini et al., 2009; Schindler & Bartels, 2013; Wang & Spelke, 2000). Specifically, we found evidence of egocentric directional coding using an eight-object paradigm similar to that of Schindler and Bartels (2013). While their fMRI study established a spatial relationship between egocentric directional coding and the parietal cortex, our results reveal a novel temporal link between egocentric directional coding and alpha-band oscillations during retrieval. Additionally, our paradigm resembles the method used by Foster et al. (2016, 2017), which examined alpha-band oscillations in spatial working memory and attention (also see Sutterer et al., 2021). However, our findings extend these studies by demonstrating that alpha-band oscillations also support egocentric directional memory of space around the participant. Taken together, the parallels between our study and those of Schindler and Bartels (2013) and Foster et al. (2016, 2017) suggest that our findings bridge the gap between egocentric directional coding, alpha-band oscillations, and the parietal lobe.

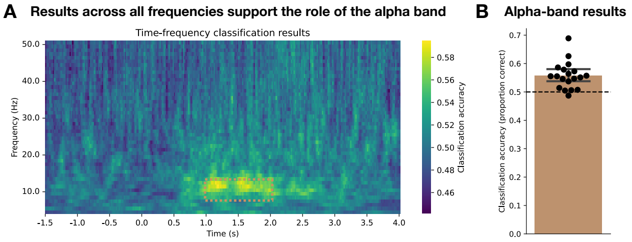

Figure 6: The time-frequency-based classification results support the alpha window hypothesis. (a) Peak classification accuracy for egocentric direction was reached for classifiers trained on the power at frequencies between 8-12Hz from 1-2 s after the pointing cue onset (i.e., note the relatively bright pixels within the brown box indicating our region-of-interest; compare the results in panel A to the prediction in Figure 5). (b) The average classification accuracy for the classifiers trained on alpha-band frequencies 1-2 s after pointing cue onset was above chance (M = .56, (18) = 5.23, p = .000057).

A growing body of research is investigating the specific links between the power at alpha-band frequencies and spatial attention. For example, a recent study by Delaux et al. (2021) examined the relationship between alpha oscillations and landmark-based navigation using high-density mobile EEG. Participants first learned the locations of landmarks in a virtual Y-maze, were placed at different headings, and then navigated to a cued landmark. While this was not a direct pointing task, successful navigation required retrieving the egocentric direction of the target landmark. Delaux et al. (2021) found that task performance was accompanied by alpha-band desynchronization in the posterior cingulate. Alpha desynchronization—characterized by a decrease in alpha power—has been associated with cognitive processes such as focused attention, perception, and inhibitory control (Klimesch, 1999). Prior research suggests that alpha desynchronization in parietal regions plays a crucial role in filtering out irrelevant spatial information, thereby maintaining attention on relevant cues during navigation (Händel et al., 2011; Jensen & Mazaheri, 2010). However, most studies on alpha desynchronization have focused on spatial attention rather than navigation.

Not all researchers agree that alpha-band activity primarily reflects attentional suppression. Foster and Awh (2019) argue that rather than inhibiting distractors, alpha oscillations serve to enhance relevant signals. Future work should seek to determine which of these two explanations—the suppression vs. enhancement account—better explains our findings. More broadly, we build on previous research by bridging an egocentric pointing task (e.g., Frances Wang &

Simons, 1999) with fMRI approaches (e.g., Schindler & Bartels, 2013), providing new insight into possible oscillatory mechanisms. Unlike studies that relied on imagined tasks, stationary participants, or 2D computer-based paradigms, our study marks an important advancement in the field by investigating the neural mechanisms of directional memory while participants are embedded in a real-world environment.

Limitations and Future Direction

An alternative explanation for our findings involves motor planning. Prior research has identified distinct rhythms within the alpha band—low-frequency mu rhythm (8–10 Hz) and high-frequency mu rhythm (10–13 Hz)—which are linked to different movement types, such as finger or foot movement (Pfurtscheller, 2003). While mu rhythm is classically associated with movement planning, execution, and imagery in the sensorimotor cortex, more recent studies suggest its involvement across multiple brain systems (Yin et al., 2016). Given these findings, the observed alpha-band oscillations in our study could reflect either the mental representation of egocentric direction or the planning of joystick movement following the response cue. However, our classification accuracy within 8–12 Hz increased and peaked before the response cue onset—before any actual motor movement occurred. If these oscillations reflect mu rhythms rather than traditional alpha-band activity, they likely indicate a movement planning mechanism rather than pure motor execution. It will be interesting for future research to determine whether the alpha results that we observed here are related to action planning vs. a more imagined component of memory retrieval, both of which would be particularly interesting, especially from the embodied cognition lens.

Future studies could use source localization analyses to determine whether the observed alpha-band oscillations originate from posterior regions (e.g., based on findings from other modalities; Bisiach & Luzzatti, 1978; Schindler & Bartels, 2013) rather than the motor cortex (Yin et al., 2016). If so, this would further support the role of alpha oscillations in egocentric directional processing. In the current dataset, we made a minor error in electrode placement for a subset of participants. According to the standard 10-20 system, the EEG cap should be centered on the scalp based on the Cz electrode. However, for nine of the nineteen participants, we mistakenly used the reference electrode (FCz) as the centering point, causing slight misalignment in electrode placement. While this error resulted in minor shifts in recorded signal locations, it is unlikely to have significantly impacted our classification results because our analysis focused on the patterns of power across all electrodes rather than their precise anatomical origins. Nonetheless, we hope that future studies will aim to replicate our findings, which could also allow the use of source-localization techniques to determine whether the observed alpha effects originate from the parietal cortex.

A limitation of any EEG study is the possible influence of movement-related artifacts; thus, we took multiple steps to try to minimize muscle artifacts in our design. First, we asked participants to sit comfortably in a chair and to avoid tensing their muscles as they performed the task. Thus, although we used a mobile approach, we can consider it to be somewhat of a hybrid approach here (i.e., participants physically changed their heading direction, but remained seated for the pointing trials). Second, we used MNE's automated muscle artifact detection function to reject time spans and we validated this process with a second round of ICA, which did not reveal any clear remaining muscle-related components (see Methods). Third, we instructed participants to remain still during the delay period and to only move the joystick after viewing the response cue. While the vast majority of participants followed these instructions on the vast majority of trials, the experimenters observed that some participants occasionally began moving the joystick after seeing the pointing cue rather than waiting for the response cue. Although experimenters reminded participants to avoid early movement and monitored them throughout the session, complete prevention was challenging due to the high number of trials, short trial durations, and participant fatigue.

While these critical steps helped ensure data quality, future studies could consider alternative response methods that minimize movement, such as using a keyboard or an imagined version of the egocentric pointing task (e.g., Schindler & Bartels, 2013), where participants mentally simulate facing and pointing without actual movement, eliminating potential motor confounds in alpha-band activity. However, we note that such designs would preclude the calculation of measures such as angular error and may actually decrease the demands on spatial memory retrieval. Moreover, other future research should consider going in the opposite direction and employing a fully mobile approach to increase task immersion and ecological validity (Gramann et al., 2014; Graumann et al., 2022; Makeig et al., 2009; Park et al., 2018). Thus, although we cannot completely rule out the possibility that there are still muscle artifacts in our data and while motor planning could contribute to the observed alpha-band activity, our findings align with a growing body of research linking alpha oscillations to spatial processing beyond motor-related functions.

Conclusion

Our study provides, to our knowledge, the first evidence for our novel alpha window hypothesis that alpha-band oscillations support the maintenance and retrieval of the egocentric direction of landmarks around the navigator. Mobile EEG recordings during an embodied spatial memory task uniquely allowed us to study the neural underpinnings behind directional memory while participants were situated within a real-world environment. Going beyond previous literature that implicated alpha band oscillations in spatial attention, we found that the power at alpha-band frequencies can be used to decode the retrieved direction of landmarks relative to the navigator. These findings suggest that a common mechanism underlies both visuospatial attention and egocentric directional memory.

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