

Phase coding of competing memories along the hippocampal theta oscillation in human MEG

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Abstract

How can the human brain retrieve unique memories, given the vast amount of overlapping information available in memory? The aim of the present study is to understand what role hippocampal theta oscillations play in this mnemonic selection process.

Computational models propose that phase coding along a slow (theta) oscillation provides an efficient way of separating relevant, to-be-remembered information from overlapping, currently irrelevant information (Lisman & Jensen, 2013; Norman et al., 2006). In the present study, we used a newly developed approach (Kerren, Linde-Domingo, Hanslmayr, & Wimber, 2018) for analysing periodic memory reactivation in non-invasive magnetoencephalographic (MEG) data. We show that to-be-remembered memories are reactivated at a specific phase along a slow (7Hz) hippocampal

oscillation, and that the brain codes competing memories at a different phase of the oscillatory cycle. This is the first demonstration of phase shifts in periodic memory reactivation signals in humans, and provides new insights into how the brain handles mnemonic competition on a millisecond time scale.

Keywords

Episodic memory; interference; competition; classification; hippocampus; theta oscillations.

Introduction

In a previous study, we showed that the neural signatures of memory reactivation rhythmically fluctuate, and that there is a specific phase of an ongoing slow oscillation at which target memories are preferentially reactivated (Kerren et al., 2018). The present study set out to test for a functional role of slow oscillations, and phase coding in particular, in separating overlapping memories. Our predictions



were derived directly from a computational model that uses an oscillating learning algorithm to resolve competition during memory retrieval (Norman, Newman, Detre, & Polyn, 2006; Norman, Newman, & Detre, 2007) This model assigns specific phases or “time slots” along the oscillation to the reactivation of target and competing memories, respectively. During the high inhibition phase, weak nodes representing the target memory are identified and strengthened, while

overly strong nodes representing the competing memories are being identified and punished during low inhibition phase. We here aim to test two basic predictions of this model, namely (a) that target and competitor representations are active at different phases along a slow oscillation; and (b) that across repeated reactivations target features are strengthened while competitor features are weakened.

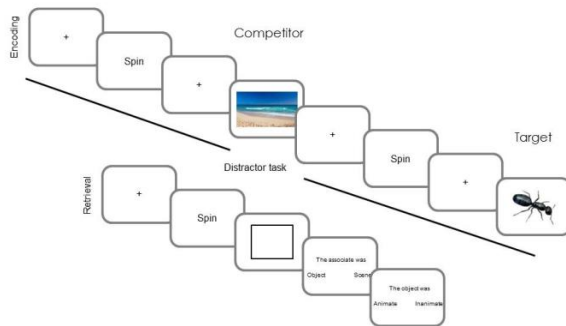


Figure 1. At encoding, participants associated action verbs with pictures of objects or scenes, or both. At retrieval, they were asked to retrieve the most recently encoded association. Thereafter, two questions were asked, in order to evaluate memory performance.

Paradigm

An associative-learning task was used where all (n = 22) participants (but two, where time limits and button error occurred resulting in five blocks) performed 6 experimental blocks (40 encoding trials and 72 retrieval trials per block), each consisting of an associative learning phase, a distractor task, and a retrieval test (Figure 1). A learning trial consisted of a jittered fixation cross (between 500 and 1500ms), a unique action verb (1500ms), a fixation cross (between 1000

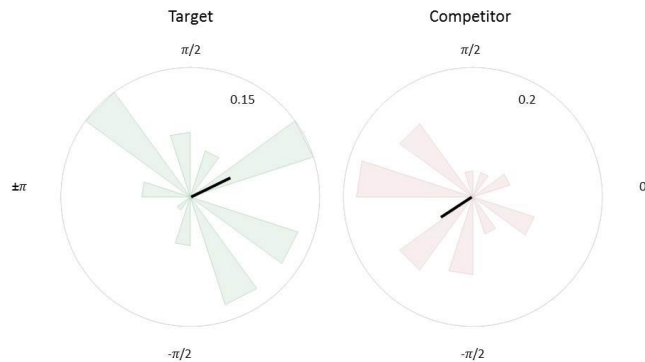
and 1500ms), followed by a picture of an object that was presented in the centre of the screen for a 4 s. Participants were instructed to press a button as soon as they had created a vivid mental image that involved the object and the action verb. In the critical competitive condition (CC), two different images were associated with the same word cue during learning. Two baseline non-competitive (NC) conditions were created where an object was presented with the same word twice (NC1), or was only learned with a single word once (NC2).

A distractor task followed each learning phase. Participants' memory for the 40 verb-object associations learned in the immediately preceding learning phase was then tested in random order. A test trial consisted of a jittered fixation cross (500-1500ms), followed by one of the action verbs as a reminder cue for 1s. Participants were asked to bring back to mind the object that had been associated with this word as vividly as possible, and to indicate successful recall with a button press. The frame flashed once and a blank

screen was on for 4 seconds. The blank screen was followed by two catch questions probing the category and sub-category of the recalled object.

The retrieval phase was repeated 3 times in order to investigate up- and down-regulation across repetitions for the neural representations of target and competing memories, respectively.

Figure 2. Optimal phase for episodic memory reactivation for target and competing memories, respectively. Target memories has a mean angle of 16 degrees, whereas competitors had a mean angle of -153 degrees.



Method

In order to attenuate high frequency noise, a Gaussian window with a full-width at half maximum (FWHM) in the time-domain of 40ms was applied to the signal before classification. A Linear Discriminant Analysis (LDA) was then trained and tested on the MEG sensor patterns (pre-processed signal amplitude on each of the 306 channels, with leave-one-out cross-validation), independently per participant and at each time point of a retrieval trial from 500ms pre-cue up to 2000ms post-cue. Two separate classifiers were trained to detect systematic differences between category-pure

(i.e., non-competitive) trials where participants were recalling animate vs inanimate trials (for object), and indoor vs outdoor scenes (for scenes), respectively. These two classifiers were then tested on the competitive condition, and evidence was plotted separately depending on the category of the target and competitor memory. This LDA approach reduces the data from 306 channels into a single decoding time course per trial per category, and we used these single-trial, time-resolved outputs of the classifier as an index of memory reinstatement of targets and competitors.

To compute the phase of the hippocampal slow oscillation, the raw sensor data were projected into source space using a linear constrained minimum variance (LCMV) beamforming algorithm (Gross et al., 2001; Van Veen, van Drongelen, Yuchtman, & Suzuki, 1997), and a hippocampal mask was used to extract the 7-Hz phase of the hippocampal virtual channels for each trial and time point. Ten phase bins covering the full cycle of this 7-Hz oscillation were created, and evidence for memory reinstatement from our classifiers was then sorted according to these recurrent bins, on each single trial and separately for target and competitor memories.

Results

Sorting classifier evidence by hippocampal theta phase provided evidence that the phase for maximal decoding of target memories is shifted by approximately 170 degrees compared to the phase of maximal competitor decoding (Figure 2). This result confirms the idea that target and competing memories tend to be active at opposing phases of a slow oscillation, derived from the computational model (Norman et al., 2006; Norman et al., 2007).

Conclusion

The present study was aimed at understanding the sub-second brain dynamics supporting the selection of relevant against irrelevant, currently competing memories. By extracting the phase from virtual

hippocampal channels, and relating it to continuous indices of the fidelity of episodic memory reinstatement, we show that the optimal phase for target and competitor reactivation is shifted by approximately 170 degrees. This is the first result showing that the brain is rapidly alternating between mnemonic alternatives, mirroring some recent findings observed in the rodent literature (Kay et al., 2019), and providing support for computational models that are based on an oscillating learning rule (Norman et al., 2006).

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