Highlights

•	Neural	trajectories	in	the	hippocampus	exhib-
	ited gre	ater variabil	ity	durir	ng a working n	nemory
	(WM) t	ask compare	d to	thos	e in the entorhi	nal cor-
	tex and	amygdala re	gio	ns.		

• The distance of neural trajectories between encoding and retrieval states in the hippocampus was memory-load dependent during a WM task.

 Hippocampal neural trajectories fluctuated between the encoding and retrieval states in a taskdependent manner during both baseline and sharpwave ripple (SWR) periods.

• Hippocampal neural trajectories shifted from encoding to retrieval states during SWR period.

Hippocampal neural fluctuations between memory encoding and retrieval states during a working memory task in humans

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Abstract

Working memory (WM) plays a critical role in many various cognitive functions, but the intricate neural mechanisms that support its operation remain elusive. Specifically, while the hippocampus and sharp-wave ripple complexes (SWRs) - brief, synchronous neural oscillation observed in the hippocampus - are recognized for their roles in memory consolidation and retrieval, their involvement in WM tasks has not yet been defined. Current research suggests that during WM tasks Here we show that during a WM task, multiunit activity patterns in the hippocampus display distinctive dynamics, particularly during SWR periods. This study analyzed a dataset derived from intracranial electroencephalogram recordings made conducted in the medial temporal lobe (MTL) of nine individuals with epilepsy during an eight-second Sternberg task. We applied Gaussian-process factor analysis to determine low-dimensional neural representations, or 'trajectories,' within the MTL regions while performing the WM task. The results indicate revealed significant variations in the hippocampus' neural trajectories compared to those in the entorhinal cortex and amygdala. Additionally, the distance of the trajectory between the encoding and retrieval phases was dependent on memory load. Importantly, hippocampal trajectories during the retrieval phase demonstrated variations fluctuations between encoding and retrieval stages based on task type, particularly showing shifts transient shift from encoding to retrieval states during SWRs. These findings underline the hippocampus's essential function in performing WM tasks and propose an intriguing a hypothesis for future research: the functional state of the hippocampus transition from encoding to retrieval during SWRs.

Keywords: working memory, memory load, hippocampus, sharp-wave ripples, humans

1. Introduction

Working memory (WM) significantly influences everyday life, and the neural bases of this cognitive process continue to be the subject of intensive research. One key focus of this research is the hippocampus, a structure integral to memory functions [1] [2] [3] [4] [5] [6] [7] [8] [9]. A thorough deeper understanding of the hippocampus's role in working memory is essential not only crucial for advancing our knowledge of cognitive processes CHECKME>and fostering advancements

in cognitive training and interventions < CHECKME ENDS but also potentially for enhancing cognitive abilities.

Current evidence suggests that a transient, synchronized oscillation, called sharp-wave ripple (SWR) [10], is associated with several cognitive functions. These include memory replay [11] [12] [13] [14] [15], memory consolidation [16] [17] [18] [19], memory recall [20] [21] [22], and neural plasticity [23] [24]. This association suggests These associations suggest that SWR may be a erucial part fundamental computational manifestation of hippocampal processing that contributes contributing to working memory

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performance as well. However, research on the effects of SWRs on working memory is relatively scarce [25], and is predominantly limited to rodent models engaged in navigation tasks, where the timing of memory acquisition and recall is not clearly defined.

Recent studies have found low-dimensional representations in the hippocampal neurons during WM taskscan explain WM task performances. Specifically, the firing patterns of place cells [26] [27] [28] [29] [30], found in the hippocampus, have been identified within a dynamic, nonlinear three-dimensional hyperbolic space in rats [31]. Additionally, grid cells in the entorhinal cortex (EC), which is the main pathway to the hippocampus [32] [33] [34], exhibited a toroidal geometry during exploration in rats [35]. However, these studies are limited by their focus on spatial navigation tasks in rodents, affecting the temporal resolution of WM tasks CHECKME>such as . To illustrate, the timing of information acquisition and recall<CHECKME ENDS. The when an animal acquires information is ambiguous in these settings. Therefore, the applicability of these findings to human subjects and beyond navigation tasks still needs to be confirmed tasks beyond navigation still requires confirmation.

Considering these aspects, the present study aims to investigate factors, this study investigates the hypothesis that hippocampal neurons display distinctive patterns of activity or show unique 'neural trajectories' in low-dimensional spaces, particularly during SWR periods, in response to WM tasks. To test this hypothesis, we used employed a dataset of patients performing an eight-second Sternberg task (1 s for fixation, 2 s for encoding, 3 s for maintenance, and 2 s for retrieval) with high temporal resolution. Intracranial electroencephalography (iEEG) signals within the medial temporal lobe (MTL) were recorded for these patients [36]. To examine low-dimensional neural trajectories, we utilized Gaussian-process factor analysis (GPFA), an established method for analyzing neural population dynamics [37].

2. Methods

2.1. Dataset

The dataset employed used in this studywas publicly available and consisted of, which is publicly available, comprises nine epilepsy patients performing a modified

Sternberg task [36]. This task encompassed includes four phases: fixation (1s), encoding (2s), maintenance (3s), and retrieval (2s). During the encoding phase, participants were presented with a set of four, six, or eight alphabet letters, defined as the set size. They FIXME>were required to<FIXMEascertain. They were then tasked with determining whether a probe letter shown displayed during the retrieval phase had appeared before previously appeared (the correct choice for the response for Match IN task) or not (the correct choice for the response for Mismatch OUT task). Intracranial electroencephalography (iEEG) signals were captured with a 32 kHz sampling rate within a 0.5-5,000 Hz frequency range, using depth electrodes in medial temporal lobe (MTL) regions: the anterior head of the left and right hippocampus (AHL and AHR), the posterior body of the hippocampus (PHL and PHR), the entorhinal cortex (ECL and ECR), and the amygdala (AL and AR), as depicted in Figure 1A and Table 1. The iEEG signals were subsequently downsampled to 2 kHz. Correlations between variables such as set size and correct rate were examined (Figure ??S1). Multiunit spike timings were determined via a spike sorting algorithm [38] using the Combinato package (https: //github.com/jniediek/combinato)(Figure 1C).

2.2. Calculation of neural trajectories using GPFA

Neural trajectories, also referred to as 'factors' (Figure 1D), in the hippocampus, EC, and amygdala were determined using GPFA [37] applied to the multiunit activity data for each session, performed with the elephant package (https://elephant.readthedocs.io/en/latest/reference/gpfa.html). The bin size was set to 50 ms, without overlaps. Each factor was z-normalized across all sessions, and the Euclidean distance from the origin (O) was then computed (Figure 1E).

For each trajectory within a region such as AHL, geometric medians (g_F for fixation, g_E for encoding, g_M for maintenance, and g_R for retrieval phase) were calculated by determining the median coordinates of the trajectory during the four phases(Figure 1D). An optimal GPFA dimensionality was found to be three using the elbow method obtained by examining the log-likelihood val-

ues through a three-fold cross-validation approach (Figure 2B).

2.3. Identifying SWR candidates from hippocampal regions

Potential SWR events within the hippocampus were detected using a widely used method [39]. LFP signals from a region of interest (ROI) like AHL, were re-referenced by deducting the averaged signal from locations outside the ROI (for instance, AHR, PHL, PHR, ECL, ECR, AL, and AR)(see Figure 1A). The re-referenced LFP signals were then filtered with a ripple-band filter (80–140 Hz) to determine SWR candidates, marked as SWR⁺ candidates(see Figure 1B). SWR detection was carried out using a published tool (https://github.com/Eden-Kramer-Lab/ripple_detection) [40], with the bandpass range adjusted to 80–140 Hz for humans [21] [22], unlike the initial 150–250 Hz range typically applied to rodents.

Control events for SWR⁺ candidates, labeled as SWR⁻ candidates, were detected by randomly shuffling the timestamps of SWR⁺ candidates across all trials and subjects. The resulting SWR⁺/SWR⁻ candidates were then visually inspected (Figure 1).

2.4. Defining SWRs from putative hippocampal CA1 regions

Potential SWRs were differentiated from SWR candidates in putative CA1 (cornu Ammonis 1) regions. These regions were initially defined as follows: SWR+/SWR- candidates in the hippocampus were projected into a two-dimensional space based on overlapping spike counts per unit using a supervised method, UMAP (Uniform Manifold Approximation and Projection) [41](Figure 4A). Clustering validation was performed by calculating the silhouette score [42] from clustered samples(Table 2). Regions in the hippocampus, which scored above 0.6 on average across sessions (75th percentile)(Figure 4B), were identified as putative CA1 regions, resulting in the identification of five electrode positions from five patients(Table 3).

SWR⁺/SWR⁻ candidates in these predetermined CA1 regions were categorized as SWR⁺/SWR⁻, and thus they no longer retained their candidate status. The duration and ripple band peak amplitude of SWRs were

found to follow log-normal distributions (Figure 4C & E). Each time period of SWR was partitioned relative to the time from the SWR center into pre- (at -800 to -300 ms from the SWR center), mid- (at -250 to +250 ms), and post-SWR (at +300 to +800 ms) times.

2.5. Statistical evaluation

Both the Brunner–Munzel test and the Kruskal-Wallis test were executed using the SciPy package in Python [43]. Correlational analysis was conducted by determining the rank of the observed correlation coefficient within its associated set-size-shuffled surrogate using a customized Python script. The bootstrap test was implemented with an in-house Python script.

3. Results

3.1. iEEG recording and neural trajectory in MTL regions during a Sternberg task

Our analysis employed a publicly accessible dataset [36], which comprises LFP signals (Figure 1A) from MTL regions (Table 1) recorded during the execution of a modified Sternberg task. We extracted SWR+ candidates from LFP signals that were filtered in the 80–140 Hz ripple band (Figure 1B), originating in all hippocampal regions (refer to Methods section). Meanwhile, SWR⁻ candidates, control events for SWR⁺ candidates, were defined at the same timestamps but distributed across different trials (Figure 1). The dataset also encompassed multiunit spikes (Figure 1C), recognized via a spike sorting algorithm [38]. Employing GPFA [37], we applied this to 50-ms windows of binned multiunit activity without overlaps to determine the neural trajectories, or factors, of MTL regions by session and region (Figure 1D). We normalized each factor per session and region, for instance, session #2 in AHL of subject #1. We then calculated the Euclidean distance from the origin(O) (Figure 1E).

3.2. Hippocampal neural trajectory correlation with a Sternberg task

Figure 2A exhibits a distribution of median neural trajectories, comprising 50 trials, within the three main factor spaces. Utilizing the elbow method, we established the optimal embedding dimension for the GPFA model as three (Figure 2B). The trajectory distance from

the origin (O) — represented as $\|g_F\|$, $\|g_E\|$, $\|g_M\|$, and $\|g_R\|$ — in the hippocampus surpassed the corresponding distances in the EC and amygdala (Figure 2C & D).

Similarly, we computed the distances between the geometric medians of four phases, namely $\|g_Fg_E\|$, $\|g_Fg_M\|$, $\|g_Fg_R\|$, $\|g_Eg_M\|$, $\|g_Eg_R\|$, and $\|g_Mg_R\|$. Our findings suggest that the The hippocampus showed larger distances between phases than those in the EC and amygdala. ²

3.3. Memory-load-dependent neural trajectory distance between encoding and retrieval states in the hippocampus

Regarding memory load in the Sternberg task, we observed a negative correlation between the correct rate of trials and the set size, which denotes the number of letters to be encoded (Figure 3A).³ Concomitantly, a positive correlation was noted between the response time and set size (Figure 3B).⁴.

Next, we discovered a positive correlation between set size and the trajectory distance separating the encoding and retrieval phases (log₁₀||g_Eg_R||) (Figure 3C).⁵. However, distances between other phase combinations did not highlight statistically significant correlations (Figures 3D and ??).

3.4. Detection of hippocampal SWR from putative CA1 regions

To enhance the precision of recording sites and SWR detection, we approximated the electrode placements in the CA1 regions of the hippocampus using distinguished multiunit spike patterns during SWR events. SWR⁺/SWR⁻ candidates from each session and hippocampal region were embedded in two-dimensional space using UMAP (Figure 4A).⁶ With the silhouette score as a quality metric for clustering (Figure 4B and Table 2), recording sites demonstrating an average silhouette score exceeding 0.6 across all sessions were identified as putative CA1 regions.⁷ (Tables 2 and 3). We identified five putative CA1 regions, four of which were not indicated as seizure onset zones (Table 1).

Subsequently, SWR⁺/SWR⁻ candidates within these putative CA1 regions were labeled as SWR⁺ and SWR⁻, respectively⁸ (Table 3). Both SWR⁺ and SWR⁻ manifested similar identical durations ⁹ (Figure 4C) due to their definitions and followed a log-normal distribution (Figure 4C). During the initial 400 ms of the retrieval phase, we noted an increase in SWR⁺ incidence was found¹⁰ (Figure 4D). The peak ripple band amplitude of SWR⁺ surpassed that of SWR⁻ and followed a log-normal distribution (Figure 4E).¹¹.

3.5. Transient changes in hippocampal neural trajectory during SWR

We assessed the 'distance' of the <u>neural</u> trajectory from the origin (O) during SWR events in both encoding and retrieval phases (Figure 5A). Observing the increase in distance during SWR, as illustrated in Figure 5A, we categorized each SWR into three stages: pre, mid-, and post-SWR. Hence, the distances from O during those SWR intervals are identified as $\|pre-eSWR^+\|$, $\|mid-eSWR^+\|$ and others.

¹Hippocampus: Distance = 1.11 [1.01], median [IQR], n = 195,681 timepoints; EC: Distance = 0.94 [1.10], median [IQR], n = 133,761 timepoints; Amygdala: Distance = 0.78 [0.88], median [IQR], n = 165,281 timepoints.

²Hippocampus: Distance = 0.60 [0.70], median [IQR], n = 8,772 combinations; EC: Distance = 0.28 [0.52], median [IQR], n = 5,017 combinations (p < 0.01; Brunner–Munzel test); Amygdala: Distance = 0.24 [0.42], median [IQR], n = 7,466 combinations (p < 0.01; Brunner–Munzel test).

 $^{^3}$ Correct rate: set size four (0.99 ±0.11, mean ±SD; n = 333 trials) vs. set size six (0.93 ±0.26; n = 278 trials; p < 0.001, Brunner–Munzel test with Bonferroni correction) and set size eight (0.87 ±0.34; n = 275 trials; p < 0.05; Brunner–Munzel test with Bonferroni correction). Generally, p < 0.001 for Kruskal–Wallis test; correlation coefficient = -0.20, p < 0.001.

⁴Response time: set size four $(1.26 \pm 0.45 \text{ s}; n = 333 \text{ trials})$ vs. set size six $(1.53 \pm 0.91 \text{ s}; n = 278 \text{ trials})$ and set size eight $(1.66 \pm 0.80 \text{ s}; n = 275 \text{ trials})$. All comparisons p < 0.001, Brunner–Munzel test with Bonferroni correction; p < 0.001 for Kruskal–Wallis test; correlation coefficient = 0.22, p < 0.001

⁵Correlation between set size and $\log_{10}(\|\mathbf{g}_{\mathrm{E}g_{R}}\|)$: correlation coefficient = 0.05, p < 0.001. Specific values: $\|\mathbf{g}_{\mathrm{E}g_{R}}\| = 0.54$ [0.70] for set size four, n = 447; $\|\mathbf{g}_{\mathrm{E}g_{R}}\| = 0.58$ [0.66] for set size six, n = 381; $\|\mathbf{g}_{\mathrm{E}g_{R}}\| = 0.61$ [0.63] for set size eight, n = 395.

⁶Consider the AHL in session #1 of subject #1 as a case in point.

The identified regions were the AHL of subject #1. AHR of subject #1.

⁷The identified regions were the AHL of subject #1, AHR of subject #3, PHL of subject #4, AHL of subject #6, and AHR of subject #9

⁸These definitions produced equal counts for both categories: SWR^+ (n = 1,170) and SWR^- (n = 1,170).

⁹These definitions result in equal durations for both categories: SWR⁺ (93.0 [65.4] ms) and SWR⁻ (93.0 [65.4] ms).

 $^{^{10}}$ SWR⁺ increased against the bootstrap sample; 95th percentile = 0.42 [Hz]; p < 0.05.

 $^{^{11}}$ SWR⁺ (3.05 [0.85] SD of baseline, median [IQR]; n = 1,170) vs. SWR⁻ (2.37 [0.33] SD of baseline, median [IQR]; n = 1,170; p < 0.001; Brunner–Munzel test).

The magnitude of

As a result, $\|\text{mid-eSWR}^+\|^{12}$ exceeded that of $\|\text{pre-eSWR}^+\|^{13}$, and $\|\text{mid-rSWR}^+\|^{14}$ was larger than $\|\text{pre-rSWR}^+\|$ in both the Match IN and Mismatch OUT tasks. ¹⁵.

3.6. Visualization of hippocampal neural trajectory during SWR in two-dimensional spaces

Having observed neural trajectory 'jumping' during SWR (Figure 5), we visualized the three-dimensional trajectories of pre-, mid-, and post-SWR events during the encoding and retrieval phases (Figure 6). The distance between these was found to be memory-load dependent (Figure 3).

To provide two-dimensional visualization, we linearly aligned peri-SWR trajectories by setting g_E at the origin (0,0) and g_R at $(||g_Eg_R||,0)$. Subsequently, we rotated these aligned trajectories around the g_Eg_R axis (the x axis), ensuring that the distances from the origin in the original three-dimensional spaces and angles from $\overrightarrow{g_Eg_R}$ are retained in the two-dimensional equivalent.

The scatter plot

Scatter plot visualization of neural trajectories within these two-dimensional spaces revealed defining distinct distributions of peri-SWR trajectories based on phases and task types. A particular notable example of this is visible inCHEKME>one can observe<CHEKMEthe observation that the magnitude of ||mid-eSWR+|| surpasses exceeds that of ||pre-eSWR+|| (Figure 6B), which is consistent with our previous observations (Figure 5).

3.7. Fluctuations of hippocampal neural trajectories between encoding and retrieval states

Subsequently, we examined trajectory investigated the 'direction' of the trajectory in relation to $\overrightarrow{g_Eg_R}$, which was found to be dependent on memory load (Figure 3). The directions of SWRs were defined the SWRs were determined by the neural trajectory at -250

ms and +250 ms from their center, $\frac{\text{i.e.denoted}}{\text{center}}$ as, for example, $\overrightarrow{\text{eSWR}^+}$. We calculated the cosine similarities between $\overline{\text{g}_{\text{E}}\text{g}_{\text{R}}}$, $\overrightarrow{\text{eSWR}}$, and $\overrightarrow{\text{rSWR}}$ in both SWR (SWR^+) and baseline periods (SWR^-) (Figure 7A – D). $\overrightarrow{\text{rSWR}^-}$ · $\overrightarrow{\text{g}_{\text{E}}\text{g}_{\text{R}}}$ exhibited a biphasic distribution. By

rSWR $^{-}$ · $\overline{g_Eg_R}$ exhibited a biphasic distribution. By computing the difference between the distribution of rSWR $^{+}$ · $\overline{g_Eg_R}$ (Figure 7A & B) and that of rSWR $^{-}$ · $\overline{g_Eg_R}$ (Figure 7C & D), we were able to determine the contributions of SWR (Figure 7E & F), which indicated a shift in the direction of $\overline{g_Eg_R}$ (Figure 7E & F: *red rectangles*).

Furthermore, eSWR⁺·rSWR⁺ was less than eSWR⁻·rSWR⁻ strictly in the Mismatch OUT task (Figure 7F: pink circles). In other words, eSWR and rSWR pointed in the opposite direction exclusively in the Mismatch OUT task but not the Match IN task (Figure 7E: pink circles).

4. Discussion

5. Discussion

This study hypothesizes that in low-dimensional spaces during a working memory (WM) WM task in humans, hippocampal neurons form unique trajectories, primarily during sharp wave-ripple (SWR) SWR periods. Initially, multiunit spikes in the medial temporal lobe (MTL) MTL regions were projected onto three-dimensional spaces during a Sternberg task using Gaussian-process factor analysis (GPFA) (Figure 1D — E and D-E & Figure 2A). The trajectory distance distances across WM phases (||g_Fg_E||, ||g_Fg_M||, $\|g_F g_R\|$, $\|g_E g_M\|$, $\|g_E g_R\|$, and $\|g_M g_R\|$) was were significantly larger in the hippocampus compared to the entorhinal cortex (EC) EC and amygdala (Figure 2E), indicating dynamic and responsive neural activity in the hippocampus during the WM task. Also, in the hippocampus, the trajectory distance between the encoding and retrieval phases ($\|g_Fg_E\|$) correlated positively with memory load (Figure 3C—DC-D), reflecting WM processing. The hippocampal neural trajectory transiently expanded during SWRs (Figure 5). Lastly, the hippocampal neural trajectory alternated between encoding and retrieval states, transitioning from encoding to retrieval during SWR events (Figure 7). These findings explain aspects of hippocampal neural activity during a WM task in humans and offer FIXME>new insights

 $^{^{12}1.25}$ [1.30], median [IQR], n = 1,281 in the Match IN task; 1.12 [1.35], median [IQR], n = 1,163 in the Mismatch OUT task

 $^{^{13}1.08}$ [1.07], median [IQR], n = 1,149 in the Match IN task; 0.90 [1.12], median [IQR], n = 1,088 in the Mismatch OUT task

 $^{^{14}}$ 1.32 [1.24], median [IQR], n = 935 in the Match IN task; 1.15 [1.26], median [IQR], n = 891 in the Mismatch OUT task

¹⁵1.19 [0.96], median [IQR], n = 673 in the Match IN task; 0.94 [0.88], median [IQR], n = 664 in the Mismatch OUT task

into SWRs as a state-switching element in hippocampal neural states FIXME.

The distance of the neural trajectory across the phases was significantly longer in the hippocampus compared to the EC and amygdala, even when considering the distance from O in these regions (Figure 2C - EC - EC). This establishes the involvement of the hippocampus in the WM task, corroborating previous studies indicating hippocampal persistent firing during the maintenance phase [3] [4] [5] [6]. However, in the present study applying GPFA to multiunit activity during a one-second level resolution of the WM task revealed that the neural trajectory in low-dimensional space presented a memory-load dependency between the encoding and retrieval phases, denoted as $\|g_E g_R\|$ (Figure 3). These findings support the association of the hippocampus with WM processing.

Our analysis focused on putative Cornu Ammonis (CA)1-CA1 regions (Figure 4), reinforced is supported by several factors. This specific focus results from established observations that SWRs synchronize with interneuron and pyramidal neuron spike bursts [44] [45] [46] [47], potentially within a 50 μ m radius of the recording site [48]. Furthermore, we identified an increased incidence of SWRs during the first 0-400 ms of the retrieval phase (Figure 4D). This finding aligns with previous reports of heightened SWR occurrence preceding spontaneous verbal recall [21] [22], supporting our results under a triggered retrieval condition. The observed log-normal distributions of both SWR duration and ripple band peak amplitude in this study (Figure 4C & E) coincide with the current consensus in this field [39]. Consequently, our decision to limit recording sites to putative CA1 regions likely contributed to improving the precision, or true positive rate, of SWR detection. Although, the trajectory distance increase from O during SWRs (Figure 5) might be artificially inflated towards higher values due to channel selection, this potential bias does not substantially challenge our main findings.

Interestingly, during the retrieval phase, trajectory directions alternated between encoding and retrieval states during both baseline and SWR periods in a task-dependent manner (Figure 7C & D). Additionally, the balance of this oscillation fluctuation transitioned from encoding to retrieval state during SWR events (Figure 7 E & F). These results align with previous

studies on the role of SWR in memory retrieval [21] [22]. Our findings introduce a novel understanding indicating that SWRs occur when the hippocampal representation transitions from encoding to retrieval states. Therefore, these results reveal novel aspects of hippocampal representations, including suggest that (i) neuronal oscillation between encoding and retrieval states occurs during a WM task and (ii) SWR serving as a transition trigger for changing neural states events serve as indicators of the transition in hippocampal neural states from encoding to retrieval during a WM task.

Moreover, our study noted differences specific to the WM-task type between encoding- and retrieval-SWRs (Figure 7E–F). Notably, opposing movements of encoding-SWR (eSWR) and retrieval-SWR (rSWR) were not observed in the Match IN task but were apparent in the Mismatch OUT task. Memory engram theory [49] might explain these observations: the Match In task presented participants with previously shown letters, while the Mismatch OUT task introduced a new letter absent in the encoding phase. This explanation underscores the significant role of SWR in human cognitive processes.

In conclusion, this study demonstrates illustrates that during a WM task in humans, hippocampal activity oscillates fluctuate between encoding and retrieval states and transitions uniquely uniquely transitioning from encoding to retrieval during SWR events. These findings provide significant offer novel insights into the neural correlates and functionality of working memory in within the hippocampus.

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Contributors

Y.W. and T.Y. conceptualized the study; Y.W. performed the data analysis; Y.W. and T.Y. wrote the original draft; and all authors reviewed the final manuscript.

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Declaration of Interests

The authors declare that they have no competing interests.

Data and code availability

The data is available on G-Node (https://doi.gin.g-node.org/10.12751/g-node.d76994/).

The source code is available on GitHub (https://github.com/yanagisawa-lab/hippocampal-neural-fluctuation-during-a-WM-task-in-hum

Inclusion and Diversity Statement

We support inclusive, diverse, and equitable conduct of research.

Declaration of Generative AI in Scientific Writing

The authors employed ChatGPT, provided by OpenAI, for enhancing the manuscript's English language quality. After incorporating the suggested improvements, the authors meticulously revised the content. Ultimate responsibility for the final content of this publication rests entirely with the authors.

Tables

Subject ID	of sessions	AHL	AHR	PHL	PHR	ECL	ECR	AL	AR	SOZ
1	4									"AHR, LR"
2	7									"AHR, PHR"
3	3									"AHL, PHL"
4	2									"AHL, AHR, PHL, PHR"
5	3									DRR
6	6									"AHL, PHL, ECL, AL"
7	4									"AHR, PHR"
8	5									ECR
9	2									"ECR, AR"

 $Table\ 1-\ Electrode\ Distribution\ within\ the\ Dataset$

This figure denotes the placements of electrodes and seizure onset zones. Regions marked with were included in the dataset, while those imprinted with were absent. The abbreviations used are as follows: AHL, left hippocampal head; AHR, right hippocampal head; PHL, left hippocampal body; PHR, right hippocampal body; ECL, left entorhinal cortex; ECR, right entorhinal cortex; AL, left amygdala; AR, right amygdala; SOZ represents the seizure onset zone.

Subject	AHL	AHR	PHL	PHR
1	0.60 ± 0.14	n.a.	n.a.	0.1 ± 0
2	0.21 ± 0.16	0.17 ± 0.21	0.18 ± 0.22	0.20 ± 0.15
3	0.40 ± 0.42	0.83 ± 0.12	n.a.	n.a.
4	0.10 ± 0.00	0.10 ± 0.00	0.90 ± 0.00	0.10 ± 0.14
5	n.a.	n.a.	n.a.	n.a.
6	0.63 ± 0.06	n.a.	n.a.	0.27 ± 0.06
7	0.10 ± 0.00	0.35 ± 0.35	0.37 ± 0.47	0.10 ± 0.00
8	0.13 ± 0.10	n.a.	0.28 ± 0.49	n.a.
9	n.a.	0.85 ± 0.07	0.15 ± 0.07	n.a.

Table 2 – Silhouette score of UMAP clustering for SWR^+ candidates and SWR^- candidates

The silhouette scores (mean \pm SD across sessions per subject) for UMAP clustering of SWR^+ candidates and SWR^- candidates are based on their respective multiunit spike patterns (Figure 4A). The mean scores were 0.205 and the standard deviation was 0.285, calculated for the interquartile range (IQR; Figure 4B).

Subject ID	of sessions	of trials	ROI	of SWRs	SWR incidence [Hz]
#1	2	100	AHL	274	0.34
#3	2	97	AHR	325	0.42
#4	2	99	PHL	202	0.26
#6	2	100	AHL	297	0.37
#9	2	97	AHR	72	0.09
Total = 10	Total = 493	Total = 1170	$0.30 \pm 0.13 \text{ (mean } \pm \text{SD)}$		

Table 3 – Summary of Detected SWR Events

The table provides statistics of presumptive CA1 regions and SWR events. Only the initial two sessions (sessions 1 and 2) from each subject were included in our analysis to reduce sampling bias.

Figures

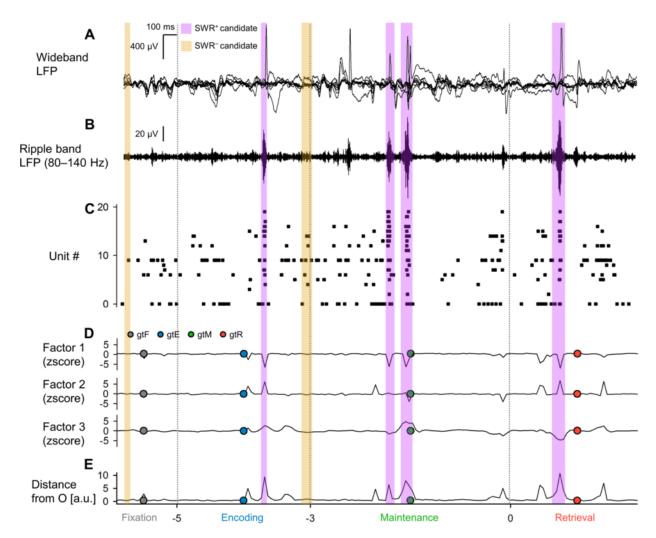
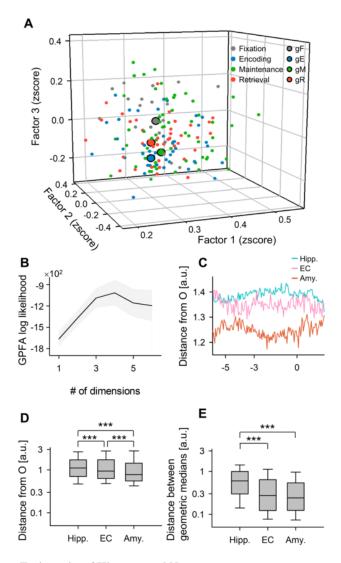


Figure 1 – Local Field Potentials (LFP), Multiunit Activity, and Neural Trajectories in the Hippocampus During a Modified Sternberg Task

A. Representative wideband LFP signals for intracranial EEG recording from the left hippocampal head are presented. The This recording took place while the subject performed a modified Sternberg working memory task, which includes Task stages included fixation (1 s, gray), encoding (2 s, blue), maintenance (3 s, green), and retrieval (2 s, red). B. The corresponding Displays the associated ripple band LFP traces. Note that purple and yellow rectangles indicating, which denote the timings for SWR⁺ candidates and SWR⁻ candidates, respectively (the latter serving as control events for SWR⁺), respectively. C. The A raster plot depicts illustrates multiunit spikes taken from the LFP traces,—These spikes have been sorted using a spike algorithm [38]. D. Neural Shows neural trajectories calculated computed by GPFA[37] based on spike counts per unit with 50-ms bins. Each phase's The geometric median of each phase is marked by the dot circles. E. The Indicates the distance of the neural trajectory from the origin point O.



 $Figure\ 2-\ State-Dependent\ Trajectories\ of\ Hippocampal\ Neurons$

A. Neural trajectories are depicted as a point cloud within the initial-first three-dimensional factors derived from Gaussian Process Factor Analysis (GPFA) [37]. The smaller dots correspond to coordinates of represent 50-ms neural trajectory bins, while and the larger dots with black edges show denote the geometric medians for respective phases each phase in the Sternberg working memory task: fixation ($\|g_F\|$, gray), encoding ($\|g_E\|$, blue), maintenance ($\|g_M\|$, green), and retrieval ($\|g_R\|$, red). B. The figure conveys presents the log-likelihood of the GPFA models versus the count number of dimensions used to embed multiunit spikes found in the medial temporal lobe (MTL) territories regions. In specific Specifically, the elbow method pinpointed identified three as the optimal dimension to be three. C. This panel illustrates displays the distance of the neural trajectories from the origin (O) for the hippocampus (Hipp.), entorhinal cortex (EC), and amygdala (Amy.), plotted against the time elapsed from the probe onset. D. The distance of the trajectory distance from O within the MTL regions is displayed shown. The hippocampus shows has the farthest greatest distance, followed by the EC and the Amygdala. E. The box plot represents illustrates inter-phase trajectory distances within the MTL regions.

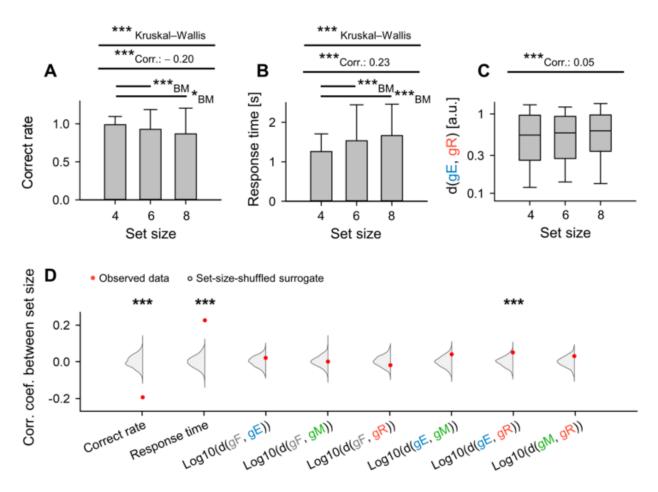


Figure 3 – Dependency of Trajectory Distance on Memory Load: Encoding and Retrieval States in Hippocampus Relationship between Trajectory Distance and Memory Load: States of Encoding and Retrieval in the Hippocampus

A. The Demonstrates the relationship between set size (number of letters that need to be encoded) and correct rate accuracy in the working memory task (coefficient = -0.20, ***p < 0.001). B. The Displays the correlation between set size and response time (coefficient = 0.23, ***p < 0.001). C. The impact Exhibits the influence of set size on the inter-phase distances between the encoding and retrieval phases ($\|g_Eg_R\|$) (correlation coefficient = 0.05, ***p < 0.001). D. Red dots represent Indicates experimental observations of correlations between set size and the following parameters: correct rate accuracy, response time, $\log_{10} \|g_Fg_E\|$, $\log_{10} \|g_Fg_B\|$, and $\log_{10} \|g_Bg_B\|$ represented by red dots. The gray kernel density plots illustrate the corresponding set-size-shuffled shuffled surrogate with set size (n = 1,000) (***p = 0.001).

Figure 4 - Detection of SWRs in Presumptive CA1 Regions Detection of SWRs in Presumptive CA1 Regions

A. Two-dimensional UMAP [41] projection of multiunit displays multi-unit spikes during SWR⁺ candidates (*purple*) and SWR⁻ candidates (*yellow*). **B.** Cumulative A cumulative density plot showing indicates silhouette scores, indicative of reflecting UMAP clustering quality (see Table 2). Note that hippocampal Hippocampal regions with silhouette scores greater than exceeding 0.60 (equivalent to the 75th percentile) were defined are identified as putative CA1 regions. SWR⁺ and SWR⁻ candidates, which were recorded from these putative CA1 regionswere respectively, are classified as SWR⁺ and SWR⁻ respectively (*ns* = 1,170). **C.** The identical Identical distributions of durations are presented for SWR⁺ (*purple*) and SWR⁻ (*yellow*), owing to based on their definitions (93.0 [65.4] ms, median [IQR]). **D.** SWR incidence for both SWR⁺ (*purple*) and SWR⁻ (*yellow*) obtained, relative to the probe's timing, is illustrated as a mean ±95% confidence interval. However, as the intervals may not be visible visibly apparent due to their narrow confined ranges, note be aware that a significant increase in SWR incidence increase was detected during the initial 400 ms of the retrieval phase (0.421 [Hz], *p < 0.05, bootstrap test). **E.** The distributions Distributions of ripple band peak amplitudes for SWR⁻ (*yellow*; 2.37 [0.33] SD of baseline, median [IQR]) and SWR⁺ (*purple*; 3.05 [0.85] SD of baseline, median [IQR]) are delineated manifested (****p < 0.001, the Brunner–Munzel test).

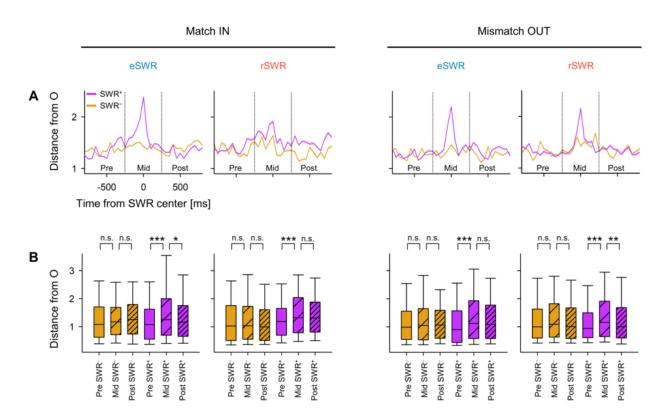


Figure 5 – Transient Alterations in Neural Trajectory During SWR Events

Transient Changes in Neural Pathway

During SWR Events

A. Displayed Presented is the distance from origin (O) of the peri-sharp-wave-ripple trajectory pathway (mean $\pm 95\%$ confidence interval). The intervals may not be apparent obscured due to their narrow-minimal ranges. B. Shown is the The distance from the origin (O) during the pre-, mid-, and post-SWR periods is demonstrated (*p < 0.05, **p < 0.01, ***p < 0.001; the Brunner-Munzel test applied). Abbreviations: SWR, sharp-wave ripple events; eSWR, SWR during the encoding phase; rSWR, SWR while in within the retrieval phase; SWR+, positive SWR event; SWR-, control events for SWR+; pre-, mid-, or post-SWR denote refer to the time intervals from -800 to -250 ms, from -250 to +250 ms, or from +250 to +800 ms, respectively, all relative to the center of the SWR center.

Match IN Mismatch OUT eSWR rSWR eSWR rSWR Pre SWR Mid SWR Post SWR 2 0 (d(gE, gR), 0) → gE to gR direction Pre SWR⁺ Mid SWR⁴ Post SWR

Figure 6 - Visualization of Neural Trajectories during SWR in Two-Dimensional Spaces

The panels display depict hippocampal neural trajectories during SWR as projected onto two-dimensional spaces. A. Hippocampal Shows the hippocampal neural trajectories as point clouds during pre-SWR⁻ (gray), mid-SWR⁻ (yellow), and post-SWR⁻ (black). B. Represents Conveys the equivalents equivalent for SWR⁺ as opposed to rather than SWR⁻. The projection was applied in the following mannerexecuted as follows: First, a linear transformation positioned placed g_E at the origin O(0,0), and g_R at ($||g_Eg_R||$, 0). The point cloud was then subsequently rotated around the g_Eg_R axis (equivalent similar to the x axis) for fitting into adaptation to two-dimensional spaces. Therefore Thus, within these two-dimensional spaces, both the distances from point O and the angles for the g_Eg_R axis are preserved retained as in the original three dimensional spaces in created by GPFA. Abbreviations: SWR signifies denotes sharp-wave ripple events; eSWR denotes refers to SWR during the encoding phase; rSWR indicates signals SWR during the retrieval phase; SWR⁺, marks characterizes an SWR event; SWR⁻ refers to signifies control events for SWR⁺; pre-SWR, mid-SWR, or post-SWR, reference represent the time intervals from -800 to -250 ms, from -250 to +250 ms, or from +250 to +800 ms from the center of the SWR.

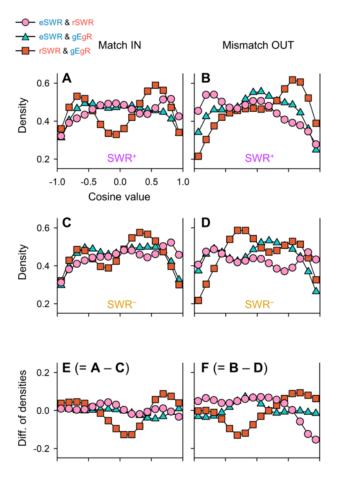


Figure 7 – Directions of Neural Trajectories during SWRs Based on Encoding and Retrieval States

Trajectories Direction during SWRs Based on Encoding and Retrieval States

A-B Kernel Shows the kernel density estimation distributions of \overrightarrow{eSWR}^+ rSWR $^+$ eSWR $^+$ rSWR $^+$ (pink circles) depicted as pink circles), \overrightarrow{eSWR}^+ $\overrightarrow{g_Eg_R}$ eSWR $^+$ $\overrightarrow{g_Eg_R}$ (blue triangles) blue triangles), and \overrightarrow{rSWR}^+ $\overrightarrow{g_Eg_R}$ rSWR $^+$ $\overrightarrow{g_Eg_R}$ (red rectangles) rectangles) in the Match In (A) and Mismatch OUT tasks (B). C-D Present-Illustrates the corresponding distributions of SWR $^-$ instead of those of SWR $^+$ in A and B. E-F Depict Renders the differences in the distributions of SWR $^+$ and SWR $^-$, illuminating detailing the SWR components (E = C - A & F = D - B). Note the The biphasic distributions of rSWR $^+$ geg_R, suggesting rSWR $^+$ egg_R indicates fluctuations between the encoding and retrieval states during the Sternberg task. MoreoverAlso, inverse contradicting directionality between eSWR $^+$ and rSWR $^+$ was observed (pink circles) not in the Match IN task (E)—, but in Mismatch OUT task (F). Lastly, Finally, shifts transition from the retrieval to encoding states are acknowledged apparent in the SWR components in both Match IN and Mismatch OUT tasks (red rectangles red rectangles in E-F).