Spatial locations decoded by human hippocampal wide-band signals in a virtual navigational environment

Jiaona TONG[1] , Diogo SANTOS-PATA[2] , Xuanlong ZHU[1] , Chenyang LI[5] , Rui WANG[4] ,
Zhaoxin WANG[1] , Hongjie JIANG[4] , Shaomin ZHANG[5] , Sze Chai KWOK [1,2,3*]

Objective

- Theories on cognitive maps stipulate that hippocampal neural activity is related to the spatiotemporal coding of one's spatial environment.
- We aimed to **decode and determine specific memorized locations and its search trajectories** during memory recall using hippocampal local field potential signals.
- We hypothesized that this memory process might resemble physical path search strategies such as Lévy flight.

Methods

We acquired hippocampal LFPs from 6 epileptic patients and used a deep learning method to decode the encoded locations and search processes in memory. (Fig 1)

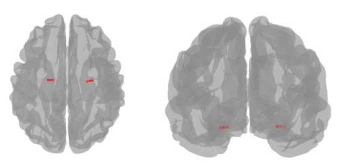


Figure 1. Selected hippocampus channel of subject 1.

We let the patients passively navigate along a circular path in a virtual environment interspersed with 20 equidistant objects and had them perform a recall task in which they had to compare the distance between two choices to a sample shown in the navigated environment. (Fig2)

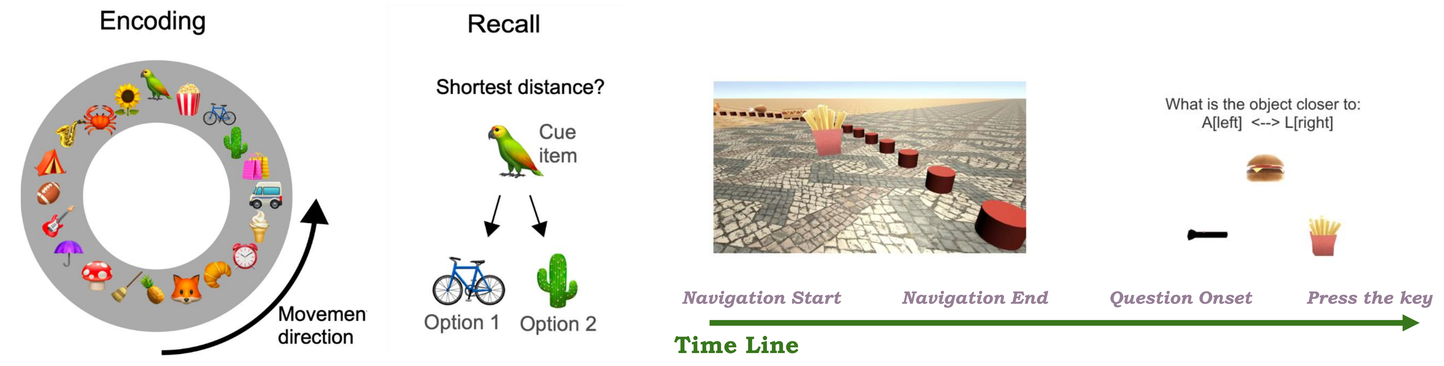


Figure 2. Left: Passive navigation period. **Middle:** Distance judgement task. **Right**: Time line of a trial.

Specifically, the model will transform the wide-band neural data into frequency space via a wavelet transformation, which was fed into a convolutional network for training models to reveal behavioral states in the order of millisecond. (Fig3)

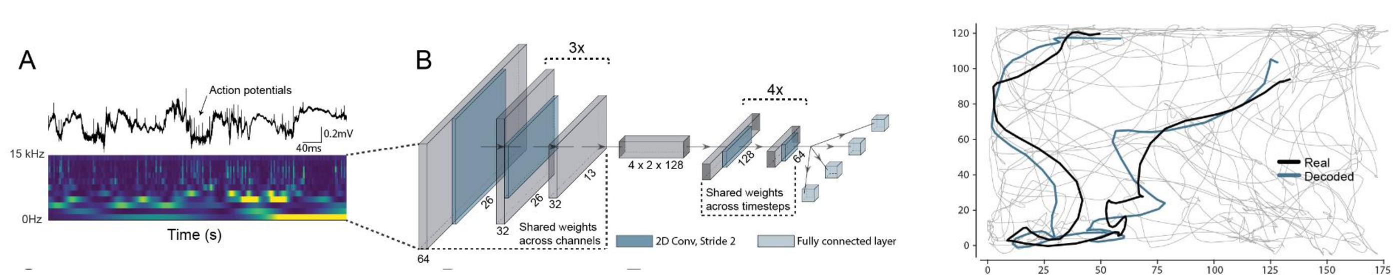
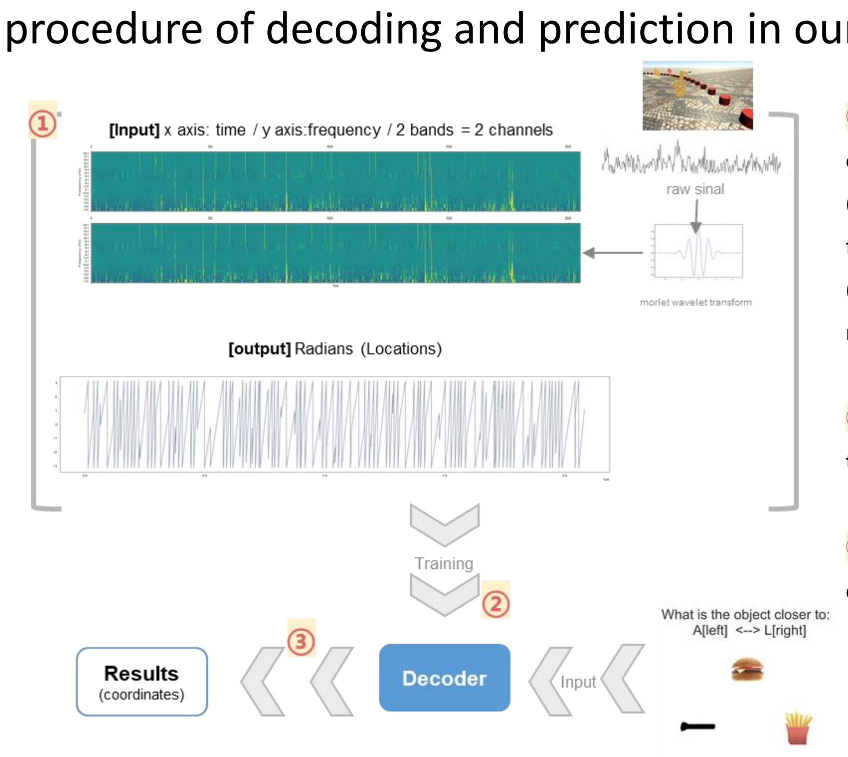


Figure 3. Left: The framework provides a unified way of decoding continuous behaviors or stimuli from neural time-series data. **Right:** (Frey et al., 2021)

The procedure of decoding and prediction in our real case:

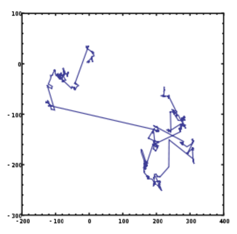


① We take the signal and behavioral data of memory encoding phase (navigation) as the training set.
(1) Transform the wide-band neural data into frequency space via a wavelet transformation.
(2) Fed into a convolutional network for training models.

② The fully trained model of each subject acts as their own location decoder.

③ Decode sEEG signal during memory recall into coordinates by the decoder.

We also fitted the decoded memory search paths with classical Lévy flight distribution -μ $P(l)$ ~ l , where 1＜μ＜3.



The Lévy walk is an optimal searching strategy found widely in nature, from the movement of bacteria to human movements [43–46], especially in foraging strategies. This behavior can be described by

$$P(l) \sim l^{-\mu} \text{ with } 1 < \mu \leq 3, \quad (7)$$

Results

We produced trial-wise decoded memory search maps within the navigational environment (Fig 4 & 5) and found that the decoded locations reliably predict subject's memory performances. (Fig 6)

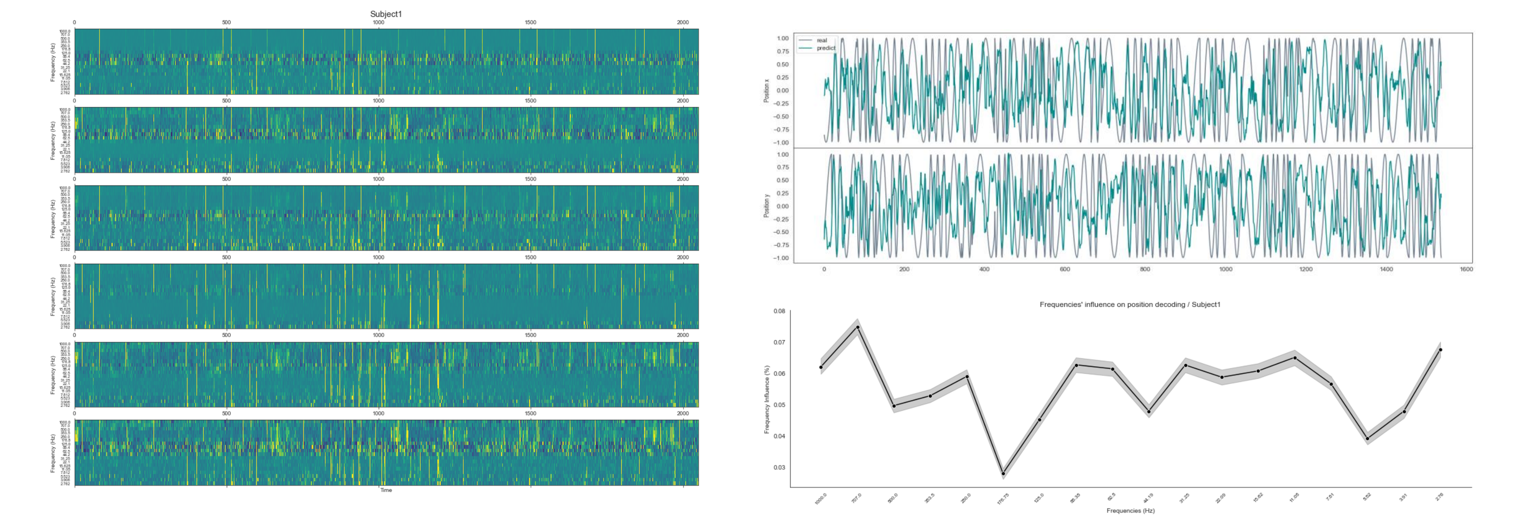


Figure 4. Left: 5 channels' time-frequency plots (wavelet transform) of Subject 1's hippocampal LFP. **Right top:** Decode performance. **Right bottom:** Frequency influence calculated by shuffled data.

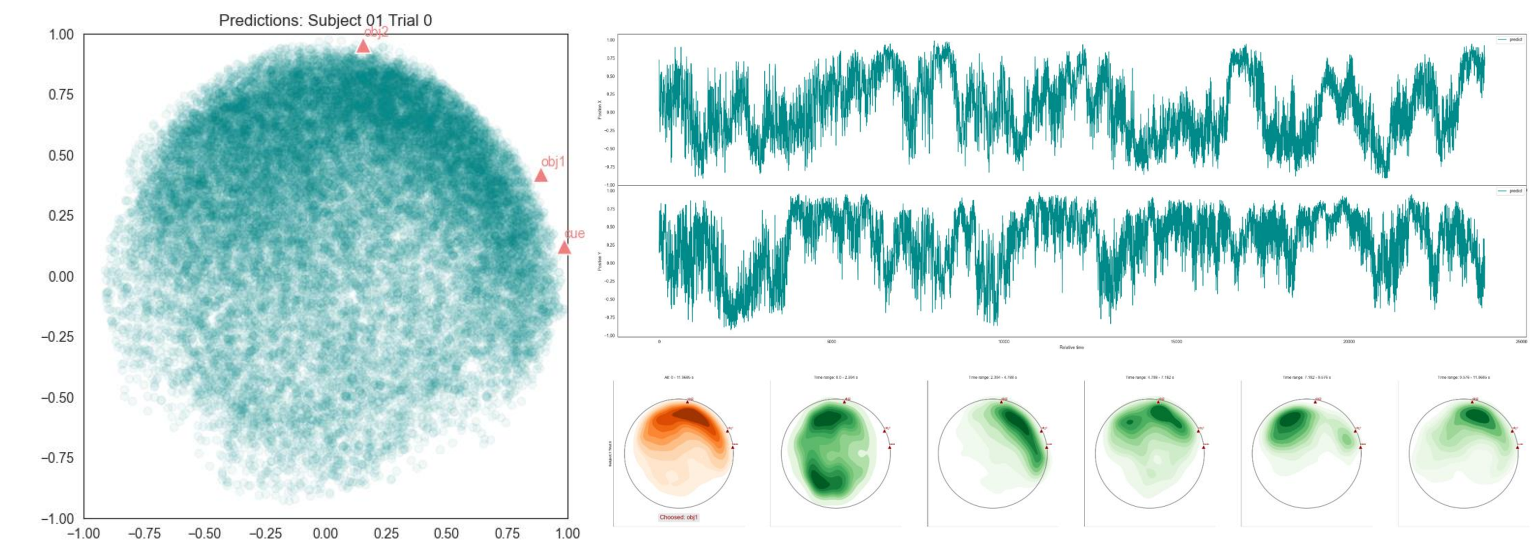


Figure 5. Left: Top view of decoded locations of each sample during question onset to response. **Right top:** Decoded coordinates of x and y. **Right bottom:** Kernel density estimation of decoded location (all time- orange / 20% time – green)

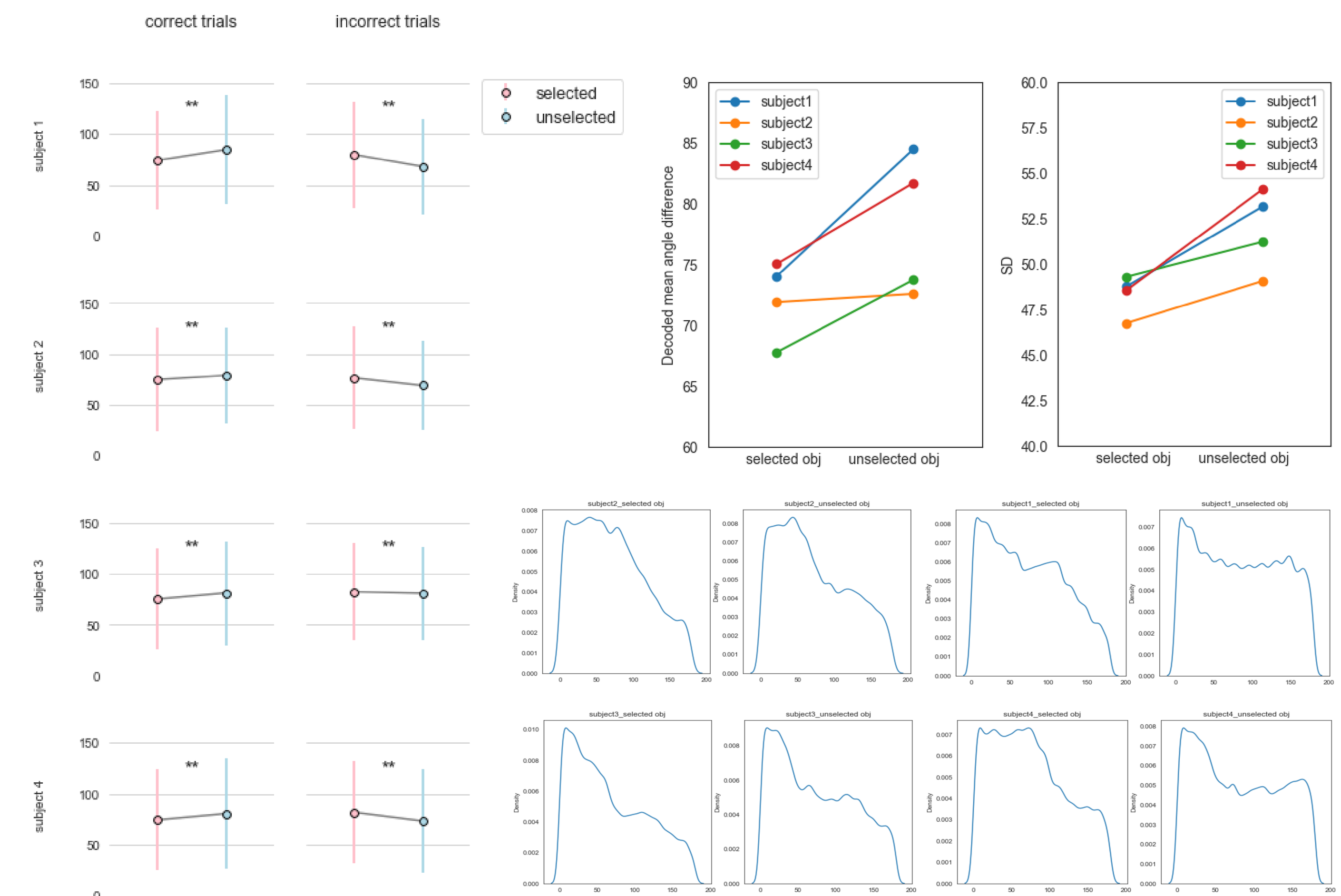


Figure 6. Left: 4 subjects' mean angle difference in correct & in correct trials. **Right top:** Angle difference & SD in correct trials. Right Bottom: desity plots of 4 subjects. (***Mean Angle difference*** of each subject = *∑(Angle*$_{(each\ sample's\ decoded\ location)}$ - *Angle*$_{(selected\ or\ unselected\ object's)}$*)* / *n*$_{samples}$)

Leveraging on the high temporal resolution (0.5 ms / step), we revealed that the memory search trajectory follows a truncated power law, suggesting Lévy flight foraging search in the episodic memory space. (Fig 7)

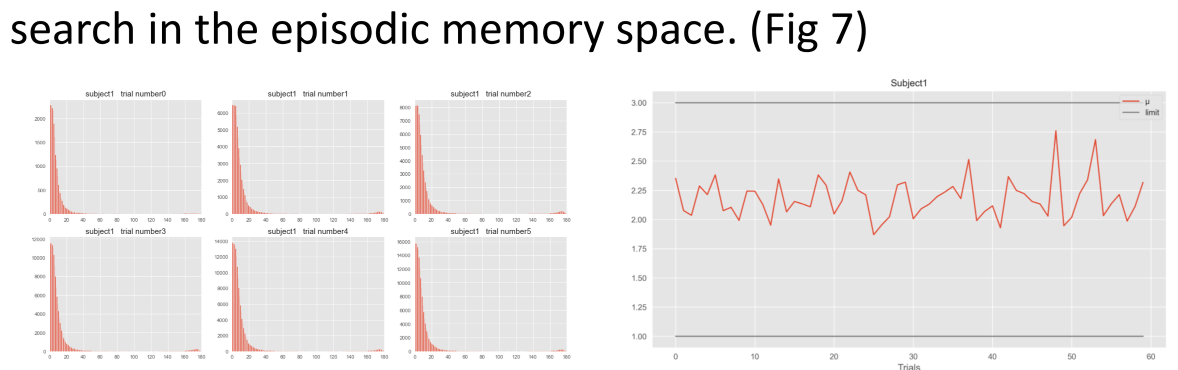


Figure 7. Left: Desity plot of subject 1 first 6 trials. **Right:** Subject 1 all trials' μ. (*powerlaw* package, Alstott et al, 2014）

Conclusions

Our LFP results delineate a navigational cognitive map in the human hippocampus and made a link between episodic retrieval trajectories in memory space with Lévy foraging phenomenon in physical space.

Affiliation

1 Shanghai Key Laboratory of Brain Functional Genomics, Key Laboratory of Brain Functional Genomics Ministry of Education, Shanghai Key Laboratory of Magnetic Resonance, Affiliated Mental Health Center (ECNU), School of Psychology and Cognitive Science, East China Normal University, Shanghai 200062,China.
2 Division of Natural and Applied Sciences, Duke Kunshan University, Duke Institute for Brain Sciences, Kunshan, Jiangsu, China
3 Shanghai Changning Mental Health Center, Affiliated Mental Health Center, Shanghai, China
4 Department of Neurosurgery, The Second Affiliated Hospital, School of Medicine, Zhejiang University, Zhejiang, 310003, China
5 Qiushi Academy for Advanced Studies, Zhejiang University, Zhejiang, 310014, China
*Corresponding author
E-mail: sze-chai.kwok@st-hughs.oxon.org

References

1. Tulving, E. (2002). EPISODIC MEMORY : From Mind to Brain.
2. Frey, M., Tanni, S., Perrodin, C., O'leary, A., Nau, M., Kelly, J., Banino, A., Bendor, D., Lefort, J., Doeller, C. F., & Barry, C. (2021). Interpreting wide-band neural activity using convolutional neural networks. ELife, 10, 1–22. https://doi.org/10.7554/ELIFE.66551
3. Frey, M., Tanni, S., Perrodin, C., O'leary, A., Nau, M., Kelly, J., Banino, A., Bendor, D., Lefort, J., Doeller, C. F., & Barry, C. (2021). Interpreting wide-band neural activity using convolutional neural networks. ELife, 10, 1–22. https://doi.org/10.7554/ELIFE.66551
4. Ekstrom, A. D., Kahana, M. J., Caplan, J. B., Fields, T. A., Isham, E. A., Newman, E. L., & Fried, I. (2003). Cellular networks underlying human spatial navigation. Nature, 425(6954), 184–187. https://doi.org/10.1038/nature01964
5. Ekstrom, A. D., Caplan, J. B., Ho, E., Shattuck, K., Fried, I., & Kahana, M. J. (2005). Human hippocampal theta activity during virtual navigation. Hippocampus, 15(7), 881–889. https://doi.org/10.1002/hipo.20109
6. An, X., Kuang, D., Guo, X., Zhao, Y., & He, L. (2014). A deep learning method for classification of EEG data based on motor imagery. Lecture Notes Comput. Sci., 8590 LNBI, 203–210. https://doi.org/10.1007/978-3-319-09330-7_25
7. Bostock, E., Muller, R. U., & Kubie, J. L. (1991). Experience - dependent modifications of hippocampal place cell firing. Hippocampus, 1(2), 193–205.
8. Haynes, J. D., & Rees, G. (2005). Predicting the orientation of invisible stimuli from activity in human primary visual cortex. Nature Neurosci., 8(5), 686–691. https://doi.org/10.1038/nn1445
9. Haynes, J. D., & Rees, G. (2006). Decoding mental states from brain activity in humans. Nature Reviews Neuroscience, 7(7), 523–534. https://doi.org/10.1038/nrn1931