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A model of path integration that connects neural and symbolic representation

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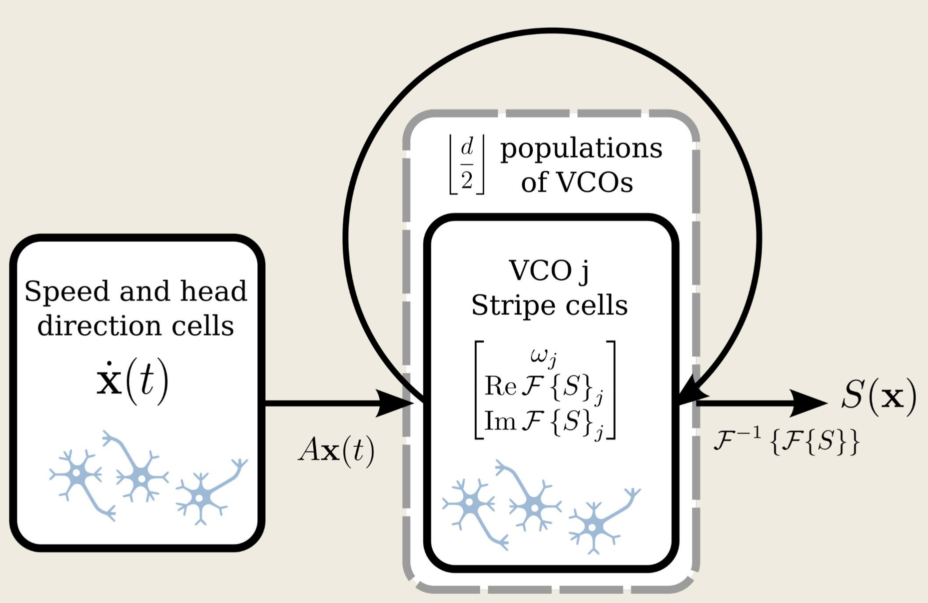
SUMMARY

- *Path integration:* integrating self-motion cues to maintain an estimate of one's position
- How is path integration connected to downstream tasks, such as cognitive mapping of objects and landmarks?
- We use a framework for symbol-like representation in the brain, the Semantic Pointer Architecture, and an extension for continuous variable representation, Spatial Semantic Pointers (SSPs)
- We constructed a recurrently-connected spiking neural network using SSPs that performs path integration in any number of dimensions
- We incorporated a simple model of working memory to show how symbol-like object representations can be bound to continuous SSP representations

MODELS

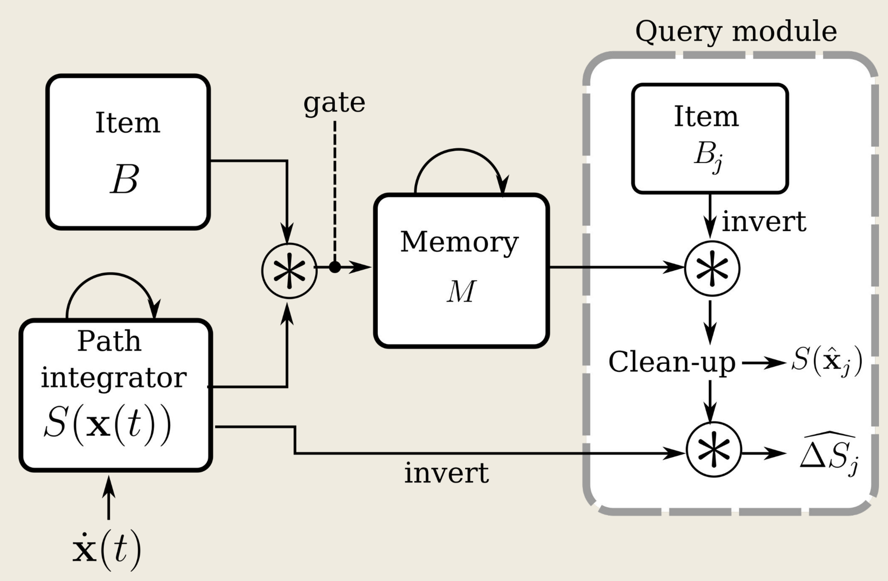
Path Integrator

- Maintains an estimate of position as space is explored, using only velocity input
- An SSP represents the model's position estimate
- For each SSP component: a neural population represents its real and imaginary parts, in addition to the frequency at which the component is oscillating



Cognitive mapping

- Maintains a working memory of items bound with locations – i.e., a simple cognitive map
- A neural integrator serves as a working memory
- As input it receives symbol-like representations of objects/ items bound with the path integrator's estimate of the location at which they were observed
- The memory is queried for item locations
- The vector between current position and recalled item locations is computed



CONCLUSION

- We've presented a novel model of path integration that both captures neural cell types observed in the brain (such as grid cell) and allows for symbol-like representations to be incorporated into cognitive maps
- Coupling low-level neural models with cognitive architectures in this manner is critical for building sophisticated models of biological cognition
- By implementing a path integrator out of spiking neurons, we have linked the activity of spatial sensitive neurons to a symbolic description of path integration using SSPs
- Furthermore, by incorporating this path integration model into a model that uses working memory, we have constructed a system that can learn a simple map of objects in a continuous space

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METHODS

Vector Symbolic Architecture

- Symbols are represented as high dimensional vectors
- *Similarity:* Cosine similarity of vectors indicates semantic similarity
- *Bundling:* Add vectors to group together
- *Binding:* Combine vectors into a new vector with circular convolution (e.g., slot-filler representation)
- *Inverse:* Undo the effect of binding

Neural Engineering Framework

- *Representation:* Vectors represented by a population's spiking activity

$$a_i(t) = \mathcal{G}_i\left[\alpha_i \mathbf{e}_i \cdot S(t) + \beta_i\right]$$

(Neural activity (spike train); Leaky integrate-and-fire; Encoders; Gain; Bias)

- *Transformation:* Connections between neural populations approximate functions $f(S)$ as

$$\hat{f}(S) = D^f \mathbf{a}(t) * h(t)$$

(Decoding matrix (synaptic weights); Activities; Synaptic filter (first-order low-pass filter))

Decoder weights set to minimize $|f(S) - \hat{f}(S)|$

- *Dynamics:* Recurrent connections set to approximate dynamical systems

$$\dot{S}(t) = f(S)$$

Spatial Semantic Pointers (SSPs)

- SSPs represent low-dimensional continuous variables **x** using high-dimensional unit-length vectors S(**x**):

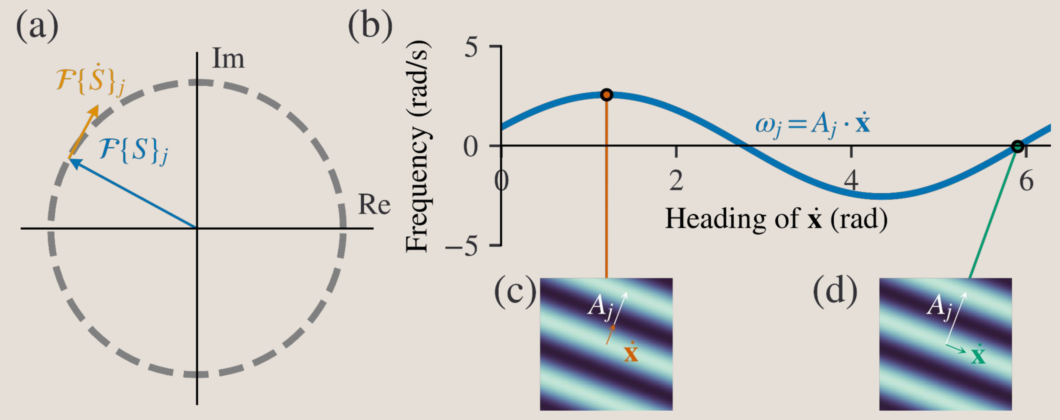
$$S(\mathbf{x}) = \mathcal{F}^{-1}\{e^{iA\mathbf{x}}\}$$

- The dynamics of a component of an SSPs in the Fourier domain is that of a simple harmonic oscillator whose frequency is modulated by velocity

$$\frac{d}{dt}\begin{bmatrix}\mathrm{Re}\mathcal{F}\{S\}_j \\ \mathrm{Im}\mathcal{F}\{S\}_j\end{bmatrix} = \begin{bmatrix}0 & -\omega_j \\ \omega_j & 0\end{bmatrix}\begin{bmatrix}\mathrm{Re}\mathcal{F}\{S\}_j \\ \mathrm{Im}\mathcal{F}\{S\}_j\end{bmatrix},$$

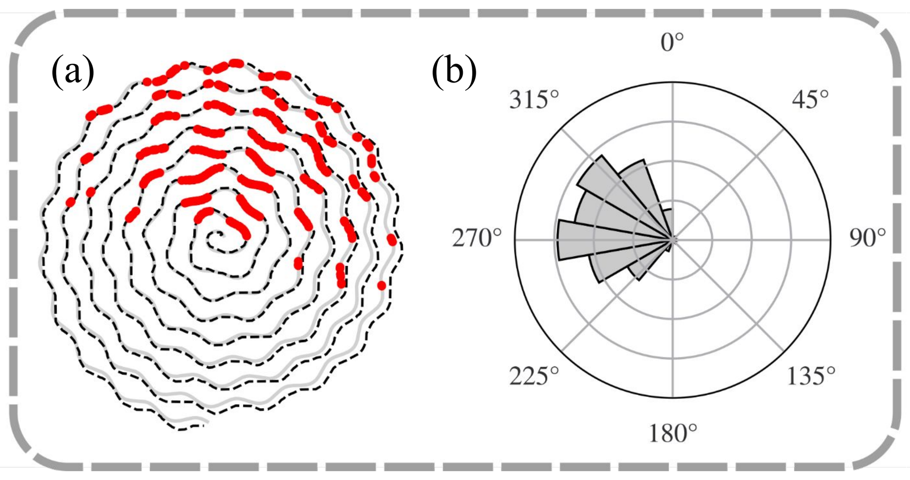
$$\text{where } \omega_j \equiv A_{j;} \cdot \dot{\mathbf{x}}(t)$$

i.e., a velocity controlled oscillator (VCO)



- (a) A component of an SSP in the Fourier domain. (c) & (d) Colouring represents the phase of the VCO as the animal moves throughout space.

RESULTS

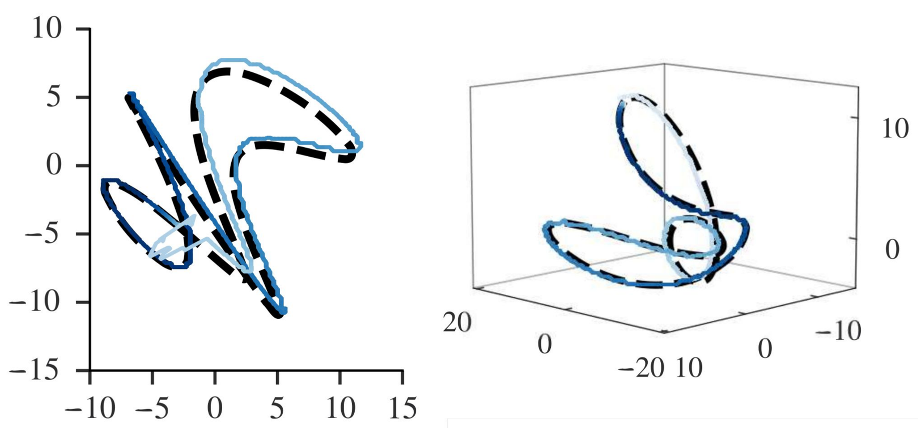


Spatial sensitive neurons

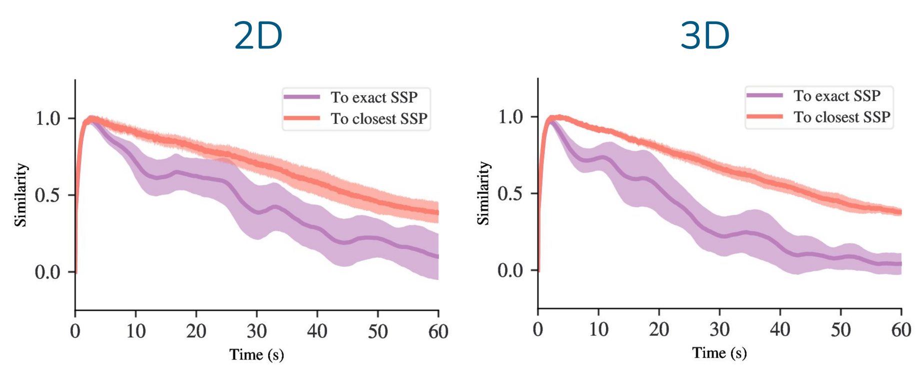
- The solid grey line depicts the true path and the dashed black line depicts the model's estimate. The red dots are locations where a particular neuron fired.
- (a) VCO populations contain neurons whose activity patterns are spatial striped and sensitive to head direction
  - (b) Firing of the neuron in (a) binned by heading direction
- (c) Output of all VCO populations is combined into a grid cell population representing self-position

Path integration in 2D and 3D

- The PI model was tested on 60 second 2D & 3D paths randomly generated from frequency-bounded white noise signals
- 151-dimensional SSPs, 75,000 spiking neurons in total for the VCO populations, and 1,000 neurons for the population representing the velocity input
- The path is accurately followed for almost the entire duration



Path integration trials



- (-) The similarity of the path integrator output to the SSP representing the correct location along the path
- (-) The similarity to closest SSP
- Results are averaged over ten different paths

Cognitive mapping with working memory

- Results from memory queries over time
- (b) Similarity between recalled item locations and true locations
- (c) Similarity between computed vector to items and true vectors
- Once items were observed, the memory estimate of their location and the vector to them was accurate
- Future work will explore long term memory with synaptic weight changes for cognitive mapping