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https://github.com/theresejoseph/Trajectory_Tracking_via_MCAN.git

QUT Centre for Robotics

Trajectory Tracking via Multiscale Continuous Attractor Networks

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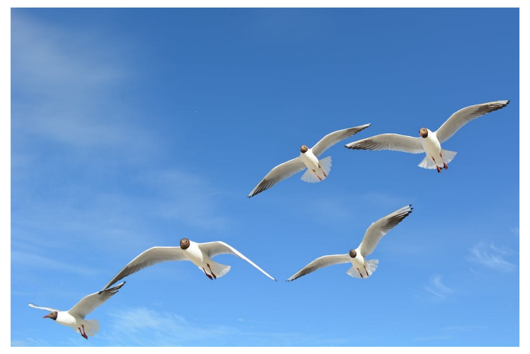
Motivation

We strive to improve robotics by leveraging neuroscience insights to develop advanced navigation systems. These systems aim to enhance existing bio-inspired models, like RatSLAM [1] and NeuroSLAM [2], which are handcrafted, single-scale attractor networks.

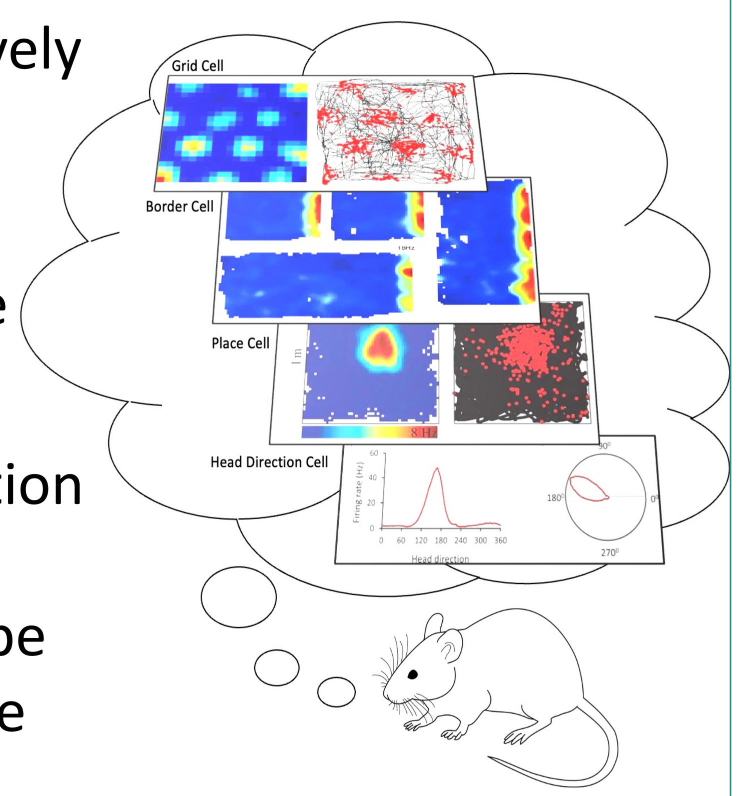


Mechanisms in the brain for Spatial Navigation

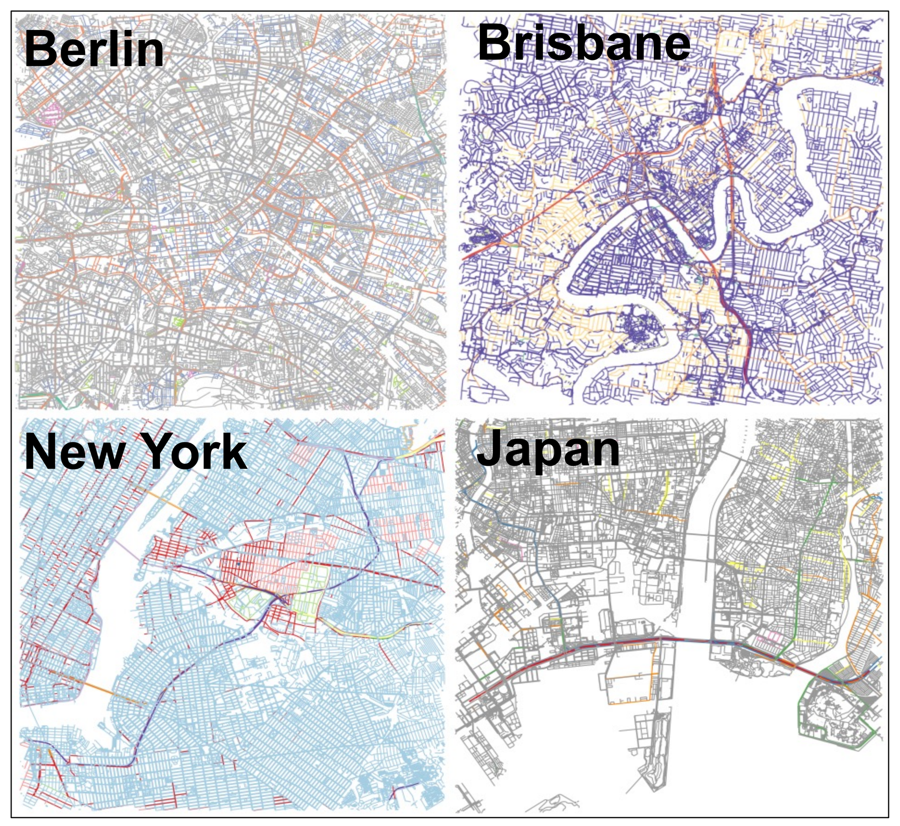
Place Cells: encodes place by selectively responding to unique spatial regions

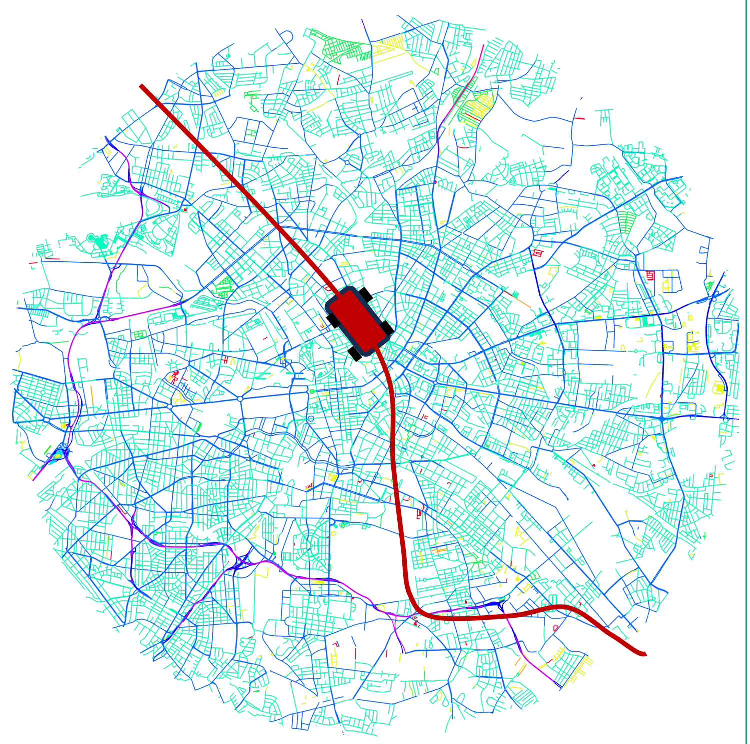
Head Direction Cells: encodes orientation by firing maximally in the preferred direction

Grid cells: integrates spatial information at different scales, by producing tessellating firing patterns, that can be combined to uniquely identify a place



City Scale Navigation Simulator





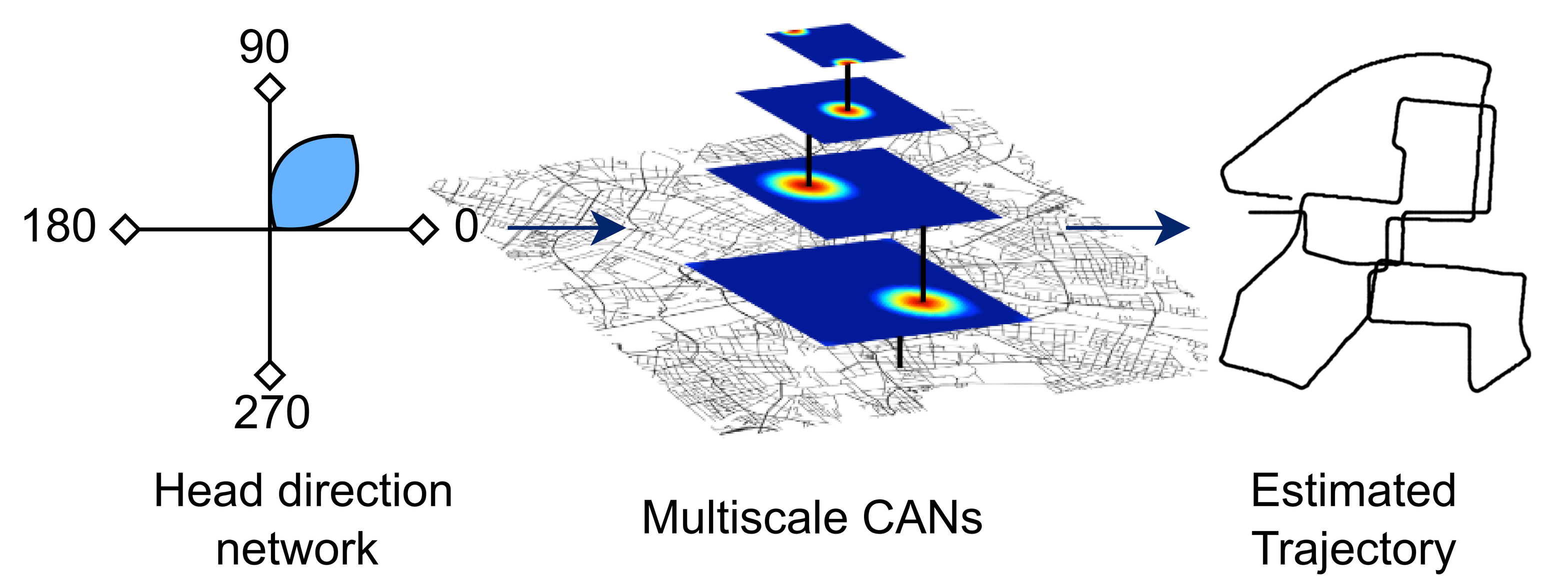
To provide challenging navigational scale ranges, we contribute a flexible city-scale navigation simulator that adapts to any street network.

References

[1] M. Milford and G. Wyeth, "Persistent navigation and mapping using a biologically inspired slam system," The International Journal of Robotics Research, vol. 29, no. 9, pp. 1131–1153, 2010.
[2] F. Yu, J. Shang, Y. Hu, and M. Milford, "NeuroSLAM: A brain-inspired slam system for 3d environments," Biological cybernetics, vol. 113, pp. 515–545, 2019.
[3] Y. Burak and I. R. Fiete, "Accurate path integration in continuous attractor network models of grid cells," PLoS computational biology, vol. 5,no. 2, e1000291, 2009.

Methodology

Our proposed Multiscale Continuous Attractor Networks (MCAN) is a bio-inspired neural network architecture with parallel networks at various spatial scales. This allows the network to operate at a wide range of velocities, without incurring excessive memory usage. As shown below, MCAN integrates linear velocity and head direction inputs at various scales to generate trajectory estimates.



Continuous Attractor Network Dynamics

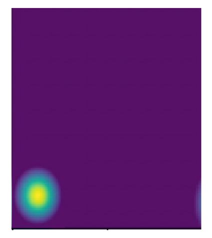
An attractor network consists of recurrently connected neurons that can integrate input information through the excitation and inhibition of neighboring neurons [3]. The following steps illustrates one network update at a single scale.

Initialise the network as a 2D gaussian with an activation width of A x A

$$\mathbf{G}(i,j) = \exp\left(-\frac{(i-x_0)^2}{2\sigma_x^2} - \frac{(j-y_0)^2}{2\sigma_y^2}\right)$$

$$\mathbf{X}(0,i,j) = \begin{cases} \mathbf{G}(i,j), & \text{if } i \in [x_0-A, x_0+A], \\ & \quad j \in [y_0-A, y_0+A] \\ 0, & \text{otherwise} \end{cases}$$

Initialisation

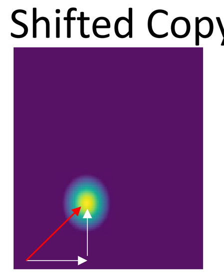


Shift the active neurons based on input velocity and store it as a copy

$$\mathbf{C}_{(i',j')} = \begin{cases} \mathbf{X}_{(t,i,j)}, & \text{if } \mathbf{C}_{(i',j')} > 0, \\ 0 & \text{otherwise,} \end{cases}$$

$$(i',j') = \Big((i+\alpha_x) \bmod N_x, (j+\alpha_y) \bmod N_y\Big)$$

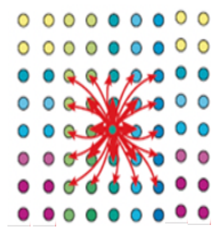
Shifted Copy



Excite neurons weighted by the strength of its neighbours within an E x E region

$$\boldsymbol{\epsilon}(i,j) = \sum_{n=1}^{N_x \times N_y} W_n \cdot \exp\left(-\frac{(i-x_n)^2}{2\sigma_x^2} - \frac{(j-y_n)^2}{2\sigma_y^2}\right)$$

Excitations



Inhibit neurons by the sum of network activity weighted by an inhibition factor

$$\mu = \sum_{i=1}^{N_x} \sum_{j=1}^{N_y} \mathbf{X}_{i,j} \times \phi$$

Network Update:

$$\mathbf{X}(t+\delta t,i,j) = \frac{\mathbf{X}(t,i,j) + \mathbf{C_f}(i,j) + \boldsymbol{\epsilon}(i,j) - \mu}{\|\mathbf{X}(t,i,j) + \mathbf{C_f}(i,j) + \boldsymbol{\epsilon}(i,j) - \mu\|}$$

Final Update

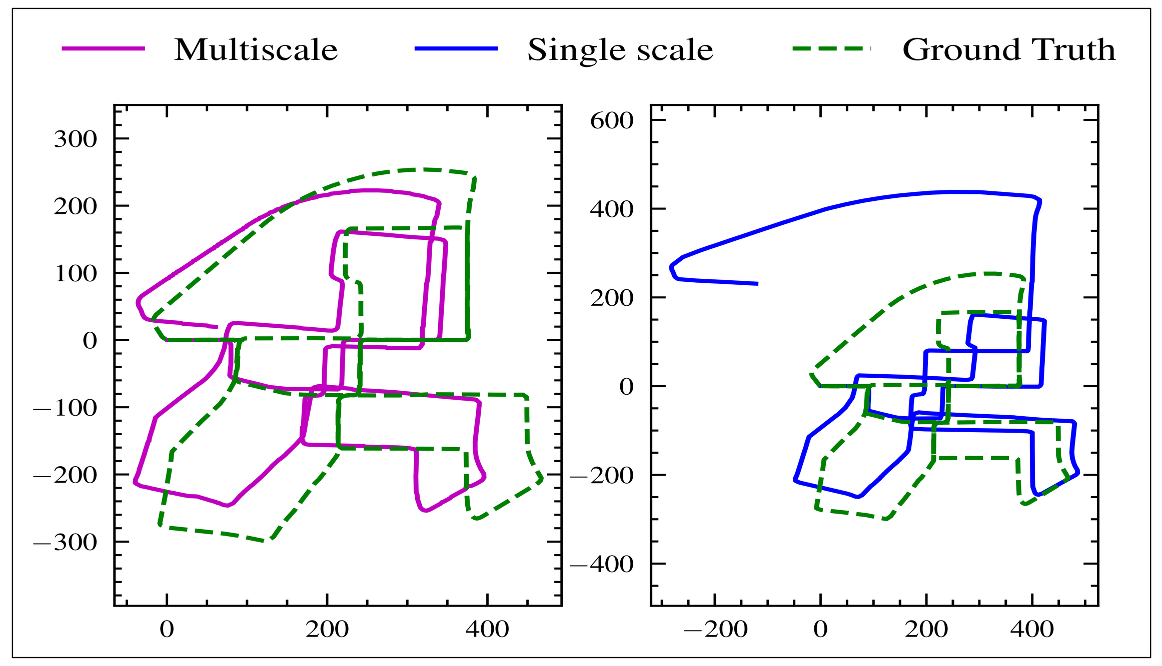
Results

The absolute trajectory error for our multiscale system was orders of magnitude lower than the single-scale baseline.

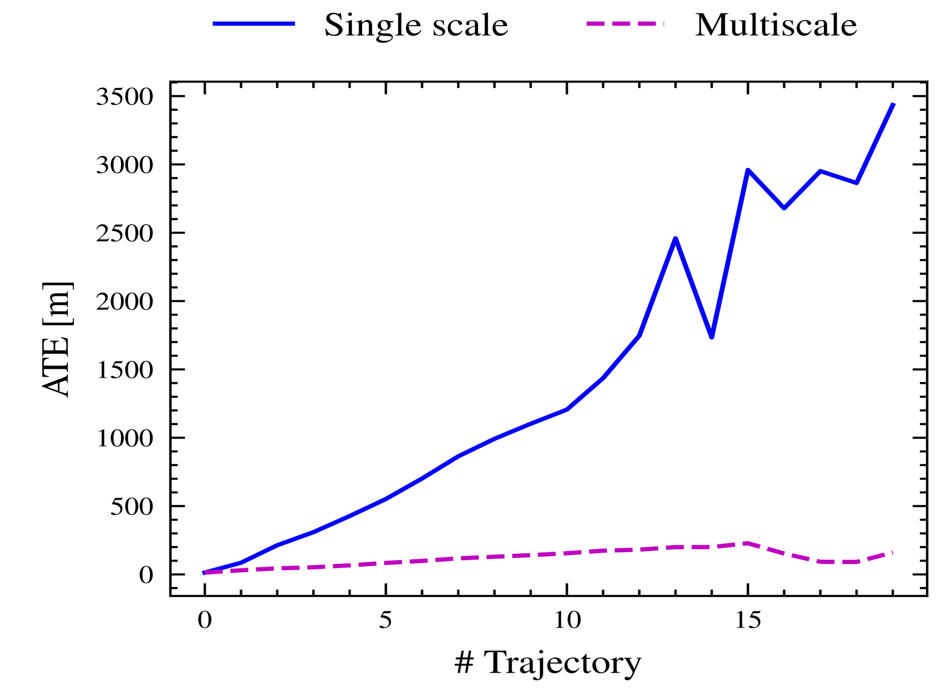
Dataset	*Single-scale*	*Multiscale (ours)*
Tokyo (CSN simulation)	1.093 ± 0.110	**0.068 ± 0.010**
Brisbane (CSN simulation)	0.934 ± 0.102	**0.070 ± 0.019**
Berlin (CSN simulation)	0.896 ± 0.166	**0.046 ± 0.021**
New York (CSN simulation)	0.893 ± 0.137	**0.070 ± 0.028**
Kitti (odometry)	0.136 ± 0.138	**0.041 ± 0.02**

Performance

The MCAN accurately tracks the path across Kitti and simulated trajectories, with improved performance at regions of high velocity in comparison to the single scale network.



The multiscale and single scale networks were tested on 20 trajectories with increasing velocity ranges, revealing the robustness to velocity change within the multiscale network.



Future Direction

Develop a complete bio-inspired SLAM system with a dead reckoning back end and localization front end, using the CAN framework.

Acknowledgements

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