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Terrain-Relative Navigation with Neuro-Inspired Elevation Encoding

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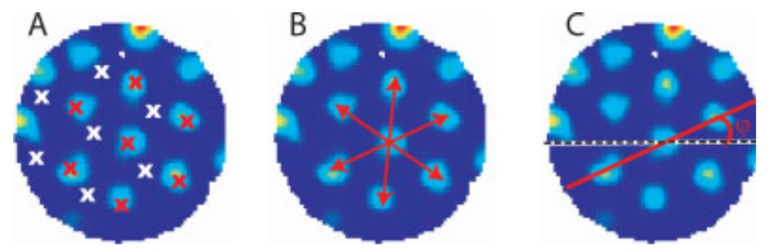
Introduction / Motivation

This work presents an inertial navigation filter with a neuro-inspired terrain-relative position measurement. During aided inertial navigation, information from onboard inertial measurement units is fused with periodic observations of the environment. We use the **NeuroGrid** algorithm (Wang et al., *ICONS*, 2021) to produce two-dimensional position measurements from LIDAR scans. These position measurements are used to update the state estimate in an Extended Kalman Filter (EKF). NeuroGrid is inspired by neural activity observed during experiments with rats. Remarkably, even though the animal roams freely, the **grid cell** activity is characterized by distinct spatial clusters. These clusters form a hexagonal grid pattern.

Grid cell activity during three experiments with rats. Adapted from (Barry et al., *Nature Neuroscience*, 2007).

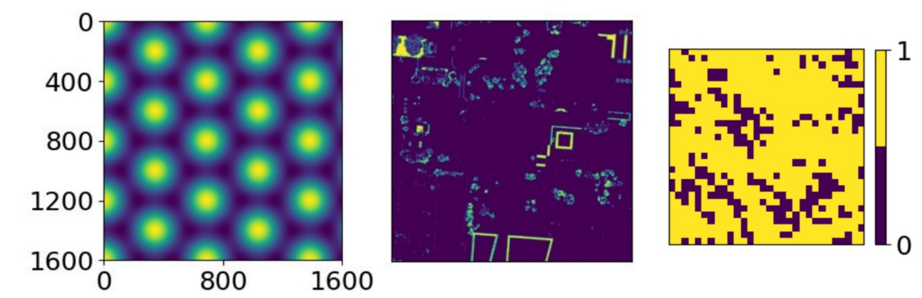
Approach

Each grid cell fires with distinct *x- and y-spatial offset* $(\phi_{x,i}, \phi_{y,i})$, *spatial scale* $\boldsymbol{\lambda_i}$, *orientation* $\boldsymbol{\theta_i}$.



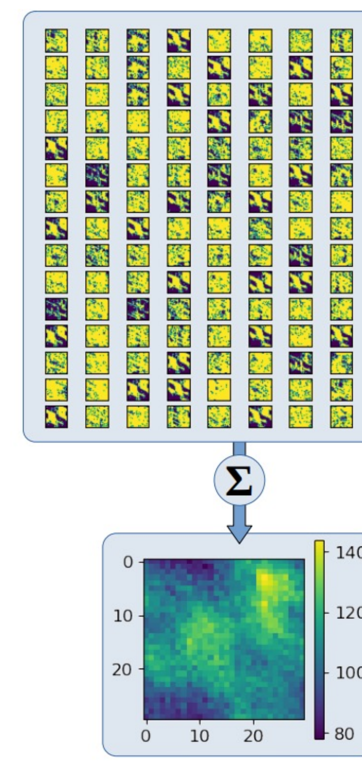
Grid parameters (Moser and Moser, *Hippocampus*, 2008)

The relationship between elevations and grid cell activity is encoded in a **phase candidate dictionary.**

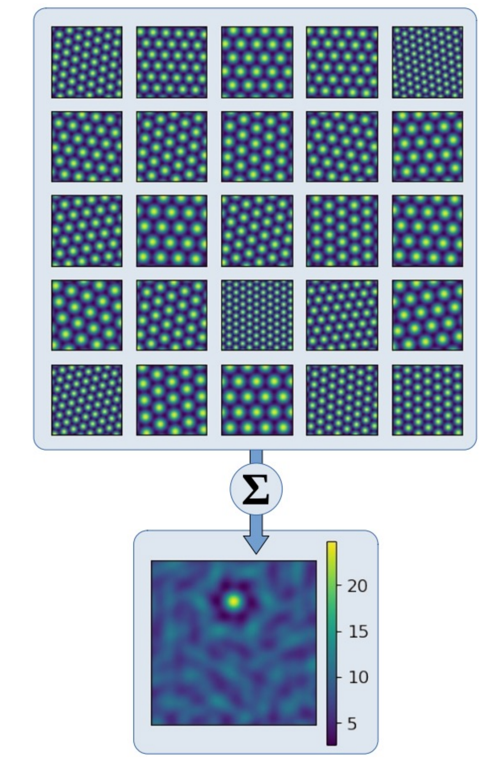


Building the phase candidate dictionary. "If I was on grid (λ_i, θ_i), what would be my spatial phase offset $(\phi_{x,i}, \phi_{y,i})$?"

The NeuroGrid Algorithm



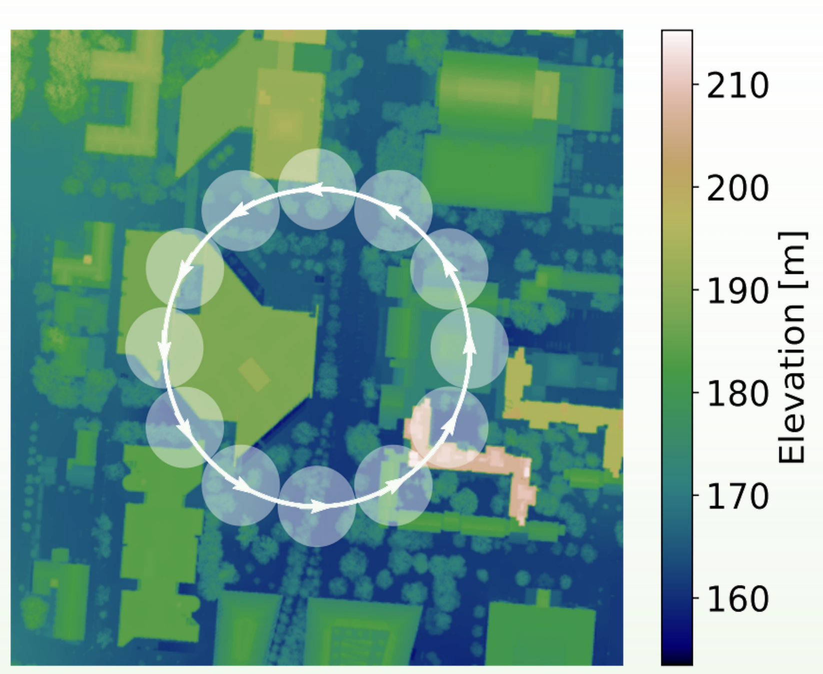
Sum of 30 × 30 binary phase candidate matrices for P = 150 elevation measurements for grid module (λ_i= 357 px, θ_i = 206°)



Grid sum of N = 25 1600 × 1600 grid images. The vehicle is located at the center of the yellow circle in the bottom image.

Current Status / Results

We test the filter on data from a simulated flight over a section of the University of Texas at Austin campus. The vehicle flies in a circular trajectory at a constant altitude of 350 m. The radius of the circle is 100 m. The vehicle completes one revolution around the circle in 60 s.



Elevation map with trajectory and measurements

Major contributions of this work:

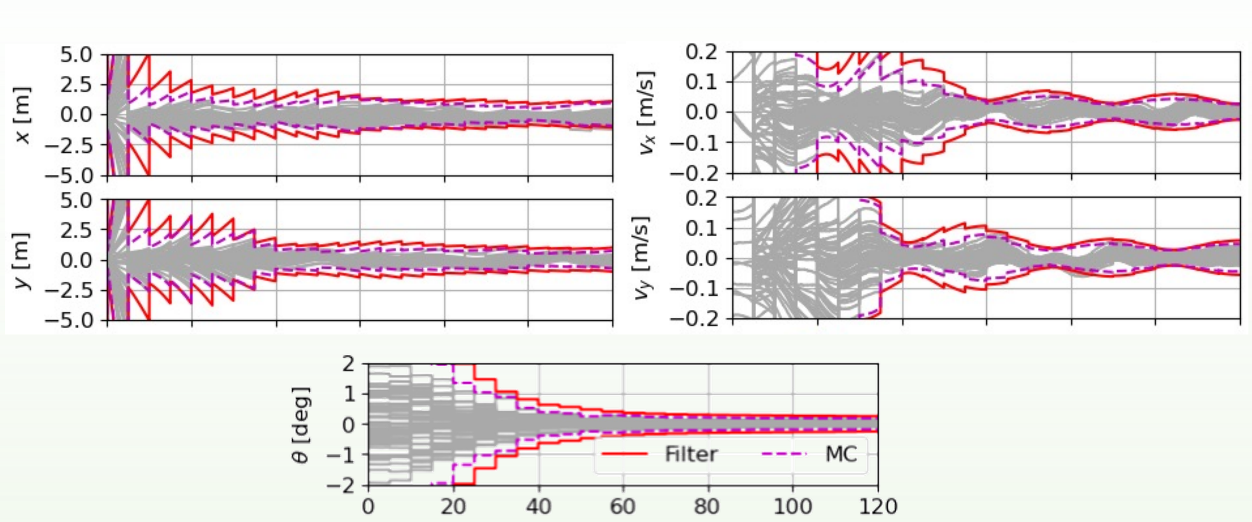
- Phase candidate rejection

$$\max(S_{pc}) - mean(S_{pc}) > P/10$$

- Online covariance computation

Require: (1) A grid sum image G; (2) A pixel-to-m conversion factor α, which is the resolution of G

1) Find the index $(i,j) = \texttt{arg max}\{G\}$.
2) Step down the rows n times until $G(i+n,j) < c * \texttt{arg max}\{G\}$, where $0 < c < 1$.
3) Set $\sigma = \alpha n$.
4) Set $R = \begin{bmatrix} \sigma^2 & 0 \\ 0 & \sigma^2 \end{bmatrix}$.



Estimation error results with 3σ covariance bounds

Challenges

- Choosing the value c for online covariance computation

Meas. Reject.	c	Mean posn. RMSE [m]
OFF	0.9950	1.438
ON	0.9950	0.7881
ON	0.9990	0.6812
ON	0.9995	0.6795
ON	0.9999	0.7176

- Incorporating a noisy heading measurement

$$\theta_m = \theta + \xi$$
$$\xi \sim N(0, R_{mag})$$

- Integrating the NeuroGrid software into an inertial navigator
  - Reducing computation time of NeuroGrid algorithm
  - Converting states in [m] to location estimates in [px] and vice versa

Next Steps / Future Work

In the future, we will introduce new techniques that further reduce the computational cost of generating NeuroGrid position measurements. In principle, the phase candidate dictionary can require less memory than the DEM. However, NeuroGrid still computes a floating-point matrix the size of the DEM for each measurement.

We will reduce the size of the phase candidate dictionary by incorporating state estimation into the phase candidates themselves. This way, we will be able to carry fewer grids in the phase candidate dictionary. Finally, we will improve the heading estimate used in the NeuroGrid algorithm using an autofocusing scheme.