Continuous Attractor Model for Place Cells Representing a Large Region

Kathryn Hedrick and Kechen Zhang
Dept. of Biomedical Engineering, Johns Hopkins University, Baltimore, MD 21205
Contact: khedrick@jhu.edu, kechen@bme.jhu.edu

Several continuous attractor models have been proposed for the CA3 subregion of the hippocampus due to the prevalence of recurrent collaterals among its place cells. In their standard form, the models assume that each place cell has a single place field in a given environment. However, recent experiments conducted in large regions indicate that multiple fields is a fundamental characteristic of place cells, where the number of fields increases with the size of the enclosure. This characteristic may be crucial, as models with one field per cell are limited by the size of the enclosure, and there is no natural way to extend the attractor when the rat moves beyond the artificial boundaries of the map. Furthermore, continuous attractor models appear to be inconsistent with the partial remapping observed among place cells. Resolving these issues is an important step forward as attractor networks create a stable spatial framework on which non-spatial information can be encoded.

We propose that place cells form a *megamap*, or a single continuous attractor in which each cell has multiple, irregularly spaced place fields within a large environment. When the simulated rat is stationary at any location, relatively weak external input drives the system to an attractor state in which a localized activity bump is centered at the rat's location. As the rat moves, this weak input moves the bump along the rat's trajectory. Unlike previous models, the attractor has no artificial boundaries and can be extended naturally to include contiguous regions using a supervised learning rule. We compare the emergent properties of the megamap to those of a standard continuous attractor model, including the propensity for partial remapping.

Model Description

Given a network of place cells with recurrent excitation and feedback inhibition, the state is governed by

$$\tau u'(t) = -u(t) + Wf(u(t)) - g(u(t))\mathbb{1} + \mathcal{I}(t), \quad f(u) = \overline{f}\max\{u, 0\}, \quad g(u) = \overline{g}\max\{\mathbb{1}^T f(u) - \theta, 0\}.$$

The activity profile of any place cell should be the sum of Gaussians centered at each of its place field centers, assumed to follow a Poisson distribution. Accordingly, we set the desired states to be the sum of shifted Gaussians such that $f(u)$ approximates this activity profile. The optimal megamap is obtained by setting the weights to minimize the least squares error between the fixed points and the desired states, which is equivalent to a supervised learning rule. On average, the resulting weights decay with distance between each place field pair, and adding ℓ_1 regularization leads to a sparse weight matrix.

Fig. 1 illustrates an attractor state in a megamap representing a 3m$\times$1m rectangle in which each place cell has between zero and six place fields. A Gaussian input with a peak of 0.1 and a standard deviation of 2.5 cm leads to an attractor state in which the activity approximates a Gaussian with peak $\overline{f} = 15$ Hz and a standard deviation of 5 cm. As shown in (A), the ensemble of place cells encodes the rat's position through the coherent activity bump, and the isolated firing is the repeated representations of cells within the bump. As shown in (B), place cell activity decays with distance from the nearest place field. Partial remapping can occur when conflicting inputs lead to multiple, coherent activity bumps.

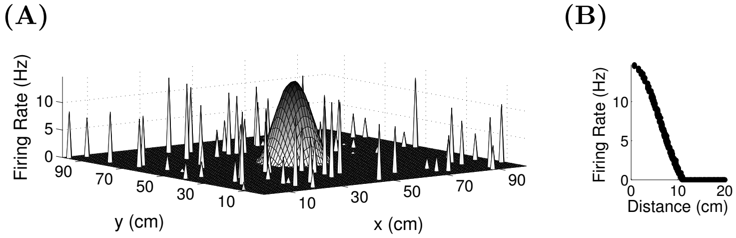

Fig. 1: Attractor state in the megamap. **(A)** The firing rate of each cell is plotted at each of its place field centers, where only the first 1 m^2 is shown. The remaining 2 m^2 consists of isolated firing. **(B)** Firing rate of each cell as a function of distance between the rat's location and the cell's nearest place field.