The inertial-DNF Model: Spatiotemporal Patterns with Two Time-Scales.

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Abstract

We introduce the inertial-DNF (iDNF) model, an expansion of the Dynamic Neural Filter (DNF) model, as a model that generates spatiotemporal patterns similar to those observed in the Locust Antennal-Lobes (ALs). The DNF model, which was described in previous works, includes one temporal scale defining the discrete dynamics inherent to the model. It lacks a second, slow, temporal scale that exists in the biological spatiotemporal data, where one finds slow temporal patterns in the behavior of individual neurons in response to odor. Using the iDNF, we examine mechanisms that lead to temporal ordered spatiotemporal patterns, similar to those observed in the experimental data. We conclude that the second temporal scale is crucial for the creation of temporal order within the evolving spatiotemporal pattern.

Key words: Olfaction; Temporal Coding; Dynamic Neural Filter; Recurrent Networks

1 Introduction

The Dynamic Neural Filter (DNF) (4) was used in previous work (1)(2) as a model that generates spatiotemporal patterns which bear similarity to those observed in the experimental data obtained from the locust ALs (6). We have specified, within the model, inputs corresponding to different odors and different concentrations of the same odor, and have analyzed the resulting spatiotemporal patterns of the neurons of our model. Using SVD we investigated

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three sets of data corresponding to three different information classes: global spatiotemporal data, which are the spatiotemporal patterns over the period of odor presentation, spatial data, which are the total spike counts during this period, and local spatiotemporal data, which are spike counts in single temporal bins. We have shown that the DNF model can produce long spatiotemporal patterns that are different for different inputs, and that for an appropriate definition of inputs, representing different odors and different odor-concentrations (OCs), the different patterns can be fairly clustered according to the correct odor, and the correct OC. The quality of the clustering varies depending on the type of information source that was analyzed. However, in the spatiotemporal data of the DNF we could not show structures that reveal the evolvement of the spatiotemporal patterns with time as demonstrated in the experimental analysis of (6), who have demonstrated a representation of odors as manifolds with concentrations as trajectories delineated by the temporal order of the local spatiotemporal data. The original DNF, with its one time-step dynamics, lacked a second, longer time-scale dynamics of the kind observed in the firing patterns of PNs of the Locust (3)(6). This second time-scale may be responsible for some short-term memory that carries the odor information after it is being removed, leading also to the temporal-ordered trajectories mentioned above. In the current work we show that adding suitable inertial characteristics to the DNF, allows our model to reproduce concentration-trajectories in the local spatiotemporal analysis.

2 The inertial-DNF Model

The DNF (4) is a recurrent binary network with one-step dynamics that represent a fast (50msec) synchronized clock. In the inertial-DNF (iDNF) model we add inertia through two mechanisms operating on the level of individual neurons: self-excitation and dynamic threshold variation. Self-excitation is induced by adding positive diagonal elements to the synaptic weight matrix. This increases the probability of a neuron, once excited, to fire another action potential at the next time step. This mechanism adds consistent, prolonged behavior of neurons over time, but causes the system to move to fixed points. To avoid undesired fixed points we add dynamic thresholds, designed to decrease the neuron's sensitivity to its input with firing. When the neuron is quiet its threshold decays to its original value. The dynamic threshold obeys

$$\theta_i(t) = \theta_i(t-1) + \delta\theta_i(t) \qquad \delta\theta_i(t) = a_i n_i(t-1) - (\theta_i(t-1) - \theta_i(0))/\tau_i$$

where, $\theta_i(t)$ is the threshold of neuron i, at time t. $\delta\theta_i(t)$ is the change in the threshold of neuron i, between time t-1 and time t. $n_i(t-1)$ is 0/1 indicating the behavior of neuron i, at the previous time step. a_i determines the increase in the threshold of neuron i, upon firing, and τ_i is the decay parameter, into the threshold's original value $\theta_i(0)$. This mechanism, combined with self-excitation, leads to inertial behavior (persistence over hundreds of msec), yet avoids the pitfall of fixed points. It should be regarded as a simple representation of a possibly complex mechanism involving the single neuron as well as the whole network. Inertia is being activated with odor onset in order to mimic the slow temporal patterns exhibits by the PNs in the ALs (3).

3 Simulations

We performed 5-second simulations in a 100-neurons iDNF. Inspired by the findings of Rospars et al. (5), the inputs were expressed in terms of the logarithms of the concentrations as described in previous work (2). The inputs applied to the iDNF are similar to the inputs applied to the original DNF, i.e. 15 OCs - 3 different odors, 5 concentrations each. Each OC was tested in 15 trials, differing from one another by noise. Thus we have altogether 225 spatiotemporal patterns. In all simulations odor was applied after one second of baseline activity, kept for one second, and then allowed to decay for 3 seconds.

Examples of spatiotemporal patterns, produced by the iDNF model, are presented in figure 1.

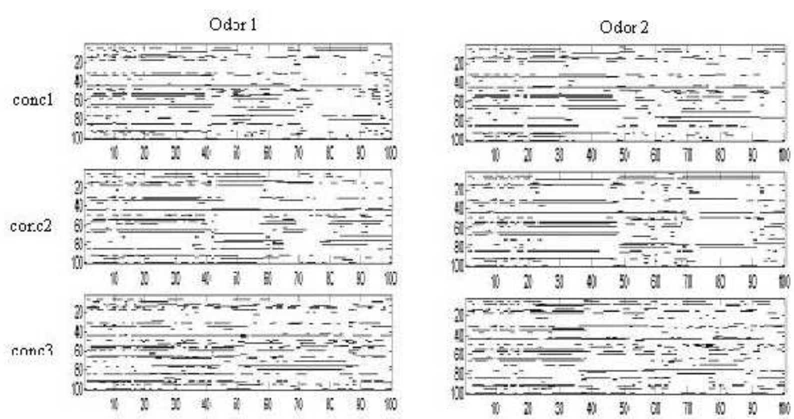

Fig. 1: Spatiotemporal patterns produced for 2 different odors, 3 concentrations each, in a 100-neurons iDNF, in 5-seconds simulations. Odor was applied after one second of baseline activity kept for one second and then allowed to decay. The self-excitation and dynamic threshold mechanisms caused an inertial behavior of the neurons. Black color represents firing, white color represents quiescense.

Similar to the original DNF model, the iDNF's spatiotemporal patterns change considerably across odors and also across concentrations of the same odor. The novel feature is the inertial behavior of the iDNF neurons. The behavior of 4 selected iDNF neurons in 15 different trials of each OC is plotted in figure 2.

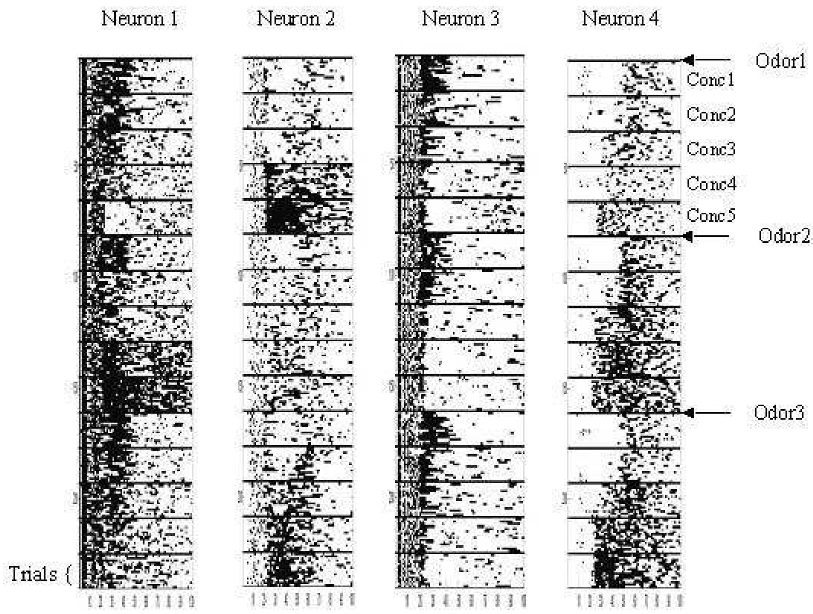

Fig. 2: Examples of the behavior of 4 different neurons in 15 trials of each of the 15 OCs (3 odors, 5 concentrations each) in 100-neurons iDNF, in 5-seconds simulations. Within each small frame is the behavior of the neuron in the 15 trials of a specific OC.

The variation in the behavior of a neuron, in different trials of the same OC, is larger than in the original DNF model, but the consistency across trials is still clear (see the small frames in Figure 2). The important feature seen in the behavior of the iDNF neurons is the periods of excitation and inhibition in a slow time scale of hundreds msec. This feature, which characterizes the behavior of the PNs in response to odor, was absent in the original DNF model.

4 Analysis of the spatiotemporal data

We analyze the 225 spatiotemporal patterns that were produced by a 100-neurons iDNF in response to the 15 OCs. We follow the analysis of the original DNF data presented in previous work (2) and examine three data sets. As far as the spatial data (neuronal spike counts) and the global spatiotemporal data are concerned, we find in the analysis of the iDNF model results similar to those of the DNF model. Of particular interest is the analysis of local spatiotemporal data, where the iDNF makes an important difference. As we will show below, the iDNF achieves temporal order within the local spatiotemporal patterns, similar to what is observed in the biological data. SVD is again used as our main processing tool.

The data points for the analysis of local spatiotemporal information were all individual time bins from the 5-seconds simulations. Prior to the analysis, all trials of the same OC were summed together giving one spatiotemporal pattern for each OC. To further simplify the calculations we consider time bins of 100 msec (i.e. sum of 2 time steps). Each local spatiotemporal data point is an N-dimensional vector. Each such vector is an average over trials and over 100 msec of simulation. Figure 3a shows 3 dimensions of the SVD operated on 750×100 data matrix that includes 15×50, 100-dimensional neural spatial patterns. Figure 3b shows the results when SVD was operated on the 250×100 data matrix of 5 concentrations of only one odor.

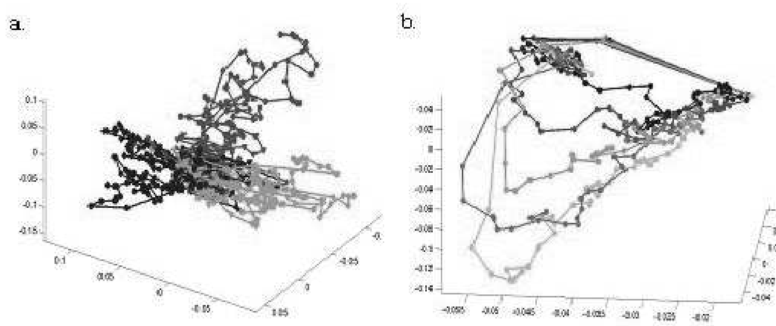

Fig. 3: Plots of 3 dimensions of SVD operated on the local spatiotemporal data from 5-seconds simulations in a 100-neurons iDNF. 15 trials of each OC were summed before applying SVD on 100 msec time bins. a. A plot of dimensions 3, 4, and 5 of the SVD, which was operated on the time bins of 3 odors, 5 concentrations each. b. A plot of dimensions 1, 2, and 3 of the SVD, which was operated on the time bins of 5 concentrations of only one odor.

The self-excitation and dynamic threshold mechanisms add temporal order within the spatiotemporal patterns. As seen in figure 3, the 50 data points of each specific OC form a trajectory in the reduced space (3b) on the odors' manifold representations (3a). This is similar to the representation of the biological data (6). We note that in order to reveal reasonable odor separation, the elements used in the plot were dimensions 3, 4, 5 of the SVD space. However, for revealing concentration trajectories the first three SVD dimensions were enough.

5 Discussion

The original DNF model lacks a second time scale in which the slow temporal patterns of individual PNs can be well represented. In this work we introduce one possible way to incorporate this slow time scale in the DNF model, by adding mechanisms that lead to inertial behavior. We have shown that this allows individual neurons to exhibit inerital behavior on top of the fast inherent 50 msec clock. Similar to the slow temporal patterns at the ALs, the inertia was turned on with odor onset. When analyzing the spatiotemporal patterns of the iDNF we have obtained odor and concentration clusters similar to those obtained for the original DNF spatiotemporal patterns. However, adding inertia, we have obtained an important new result: the temporal bins of the local spatiotemporal data analysis exhibit temporal order similar to the one observed in the analysis of the biological spatiotemporal patterns.

The generalization from DNF to iDNF proved to be a successful and simple way of adding short-term memory to single-step dynamics. It may therefore be recommended as a general recipe for modeling purposes whenever there is a need to incorporate slow time scales into simple discrete dynamics.

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