

The inertial-DNF Model: Spatiotemporal Coding on Two Time-Scales

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Abstract

We introduce the inertial-DNF (iDNF) model, an expansion of the Dynamic Neural Filter (DNF) model, a model generating 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 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 a 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 Network; Inertia.

1 Introduction

The Dynamic Neural Filter (DNF) (4) is a recurrent binary network with one time-step dynamics representing, e.g. a (50msec) synchronized clock: $n_i(t+1) = H(h_i(t+1)) = H(\sum_j w_{ij}n_j(t) + R_i - \theta_i)$ where n_i are the neural activity values, w_{ij} are the synaptic weights, R_i is an external input and θ_i is the threshold. H is the Heaviside step function taking the values 0 for negative arguments and 1 for positive ones. The DNF was used in previous works (1)(2) as a model that generates spatiotemporal patterns which bear similarity to

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those observed in the experimental data obtained from the locust ALs (6), a system known to exhibit a local field potential (LFP) with temporal width of 50ms (3). 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. We compared our results to the experimental work of (6), who have analyzed the behavior of neurons in the ALs. Using SVD we investigated 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. Similarly to the experimental data (6) the DNF model produced long spatiotemporal patterns that are different for different odors and different odor-concentrations (OCs). The different patterns can be clustered to classify the correct odor, and the correct OC. The quality of the clustering varied 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 evolution of the spatiotemporal patterns with time as demonstrated in the experimental analysis of (6). They have demonstrated a representation of odors as manifolds with concentration as trajectories delineated by the temporal order of the local spatiotemporal data. The original DNF, with its one time-step dynamics, lacks 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 inertial-DNF (iDNF) is an extension of the original DNF (4), introducing a longer time scale on top of the fast synchronized clock. The iDNF uses the same dynamics as the original DNF model with two mechanisms added to produce inertial behavior on the level of individual neurons: self-excitation and dynamic threshold variations. 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 neurons sensitivity to its input upon firing. When the neuron is quiet its threshold decays to its original value. The dynamic threshold obeys $\theta_i(t) = \theta_i(t-1) + \delta\theta_i(t)$ with

$\delta\theta_i(t) = a_i n_i(t-1)(\theta_i(t-1) - \theta_i(0))/\tau_i$, 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 thresholds original value $\theta_i(0)$. This mechanism, combined with self-excitation, leads to inertial behavior (persistent 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

Similarly to the work of (6) we performed 5-seconds simulations on our 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. Similarly to the orig-

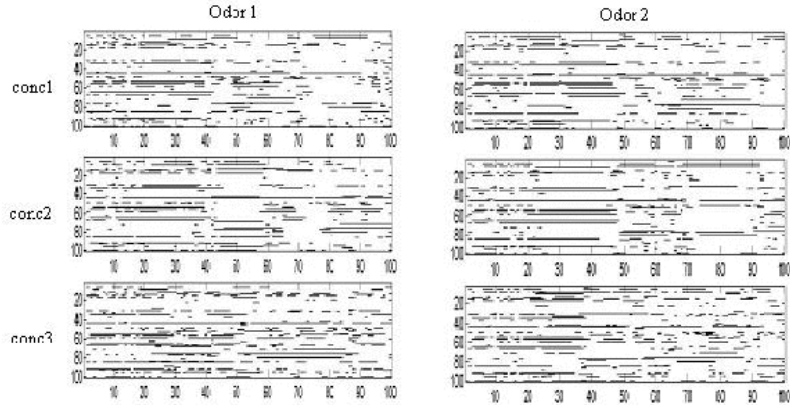


Fig. 1: Spatiotemporal patterns produced for 2 different odors, 3 concentrations each, in a 100-neurons iDNF, in a 5-seconds simulations. The self-excitation and dynamic threshold caused an inertial behavior of the neurons. Black color indicates firing, white color indicates no firing.

inal DNF model (2), the iDNFs spatiotemporal patterns change considerably across odors and also across concentrations of the same odor. The novel feature is the inertial behavior of the iDNFs neurons. The behavior of 4 selected

iDNF neurons in 15 different trials of each OC is plotted in figure 2. The vari-

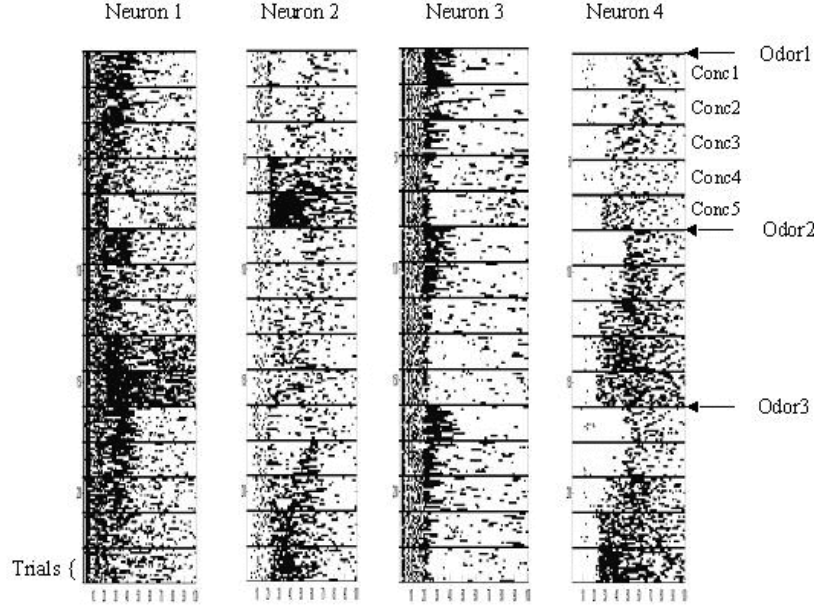


Fig. 2: Examples of the behavior of 4 different neurons in 15 trials of each of the 15 OCs (3 odors, 5 concentrations each) in 100-neurons iDNF, in 5-seconds simulations. Within each small frame is the behavior of the neuron in 15 different trials of a specific OC.

ation in the behavior of a neuron, in different trials of the same OC, is larger than in the original DNF model, probably since the dynamic threshold variations accumulate the effects of noise over time. The important new features in the behavior of the iDNF neurons are the periods of high and low activities over durations of hundreds msec. This feature, which also characterizes the behavior of the PNs in response to odor, was lacking 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 the three data sets. As far as the spatial data (neuronal spike counts) and the global spatiotemporal data are concerned, we find the results of the iDNF model to be 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, like the biological data. SVD is used as our main processing tool. The data points for the analysis of local spatiotemporal information are 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 thus an N-dimensional vector. Each such vector is an average over trials and over 100 msec of a simulation. Figure 3a shows 3 dimensions of the SVD applied to the 750×100 data matrix that includes 15×50 , 100-dimensional neural spatial patterns. Figure 3b shows the results when SVD was applied to the 250×100 data matrix of 5 concentrations of only one odor. The self-excitation and

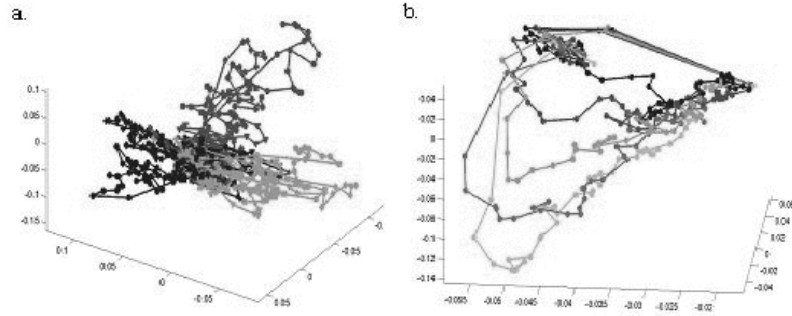


Fig. 3: Plots of 3 dimensions of SVD applied to the local spatiotemporal data from 5-seconds simulations in a 100-neurons iDNF. a. A plot of dimensions 3, 4, and 5 of an SVD analysis of time bins of 3 odors, 5 concentrations each. b. A plot of dimensions 1, 2, and 3 of an SVD analysis of 5 concentrations of only one odor.

dynamic thresholds 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 reminiscent of the biological results (6). We note that in order to reveal reasonable odor separation, one has to use dimensions 3, 4, 5 of the SVD space. However, for discerning concentration trajectories the leading three SVD dimensions suffice.

5 Discussion

A detailed computational model of the AL and its connections is presented in (7). A more abstract theoretical framework (winnerless competition) for odor encoding in the antennal lobe is presented in (8). Recently, another model was suggested by (9). The dynamics of this model is somewhat similar to the DNF, though the parameters are different. In all these studies, the evolution of the spatiotemporal patterns in time, as demonstrated experimentally for different concentrations of the same odor, were not addressed.

The DNF model has been proposed as a simplified AL model that exhibits

spatiotemporal odor coding. Here we have extend it to the iDNF model, that has the additional advantage of exhibiting temporal structures similar to those observed in the ALs. By incorporating new mechanisms we have allowed individual neurons to exhibit inertial behavior on top of a fast inherent 50 msec clock. 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. With the added inertia, we have obtained an important new result: the temporal bins of the local spatiotemporal data analysis exhibit temporal order observed in the biological spatiotemporal patterns. The generalization from DNF to iDNF proved to be a successful 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 variations into simple discrete dynamics.

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