Discrimination and Association in Insect Olfaction

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Abstract

The task of odor classification has several different aspects. On the one hand some similar odor receptions need to be classified as the same odor whereas on the other hand distinct odors have to be discriminated from each other. In addition some quite different odors might have the same *meaning* and therefore need to be *associated* with each other. The main question is how the olfactory system accomplishs these quite different tasks with the available natural *technology*. There are three known stages of neural processing of odor information before classification: *Data collection* from the sensors in the antenna, *information compression* and *temporal decorrelation* by the Antennal Lobe (AL), and *nonlinear projection/expansion* to the Kenyon cells (KC) of the Mushroom Body (MB). These three stages have been extensively studied and a good understanding of many aspects has been achieved. Nevertheless there are also still many remaining open questions. The inspiration for the present work emerged from the main working hypothesis of Gilles Laurents lab that the first relay stations in olfactory information processing create a large coding space in which the representations of different classes of odors are spread out to allow easy discrimination. We propose a theory of odor classification that relies on this large coding space and requires sparse coding, random connectivity, Hebbian learning and mutual inhibition. We show that these are necessary and *sufficient* elements to accomplish the classification tasks described above. Sophisticated global learning algorithms or a sophisticated network topology are not required.

Our main hypothesis is that the classification decision occurs in the $\alpha, \beta, \gamma-$ lobes that receive inputs from the KCs. This hypothesis is inspired by the theory of support vector machines (SVM) and Cover's theorem which states that a nonlinear projection into a high dimensional space enhances the ability to classify using hyperplanes (linear classification). We distinguish three processing layers of the classification circuit: The AL as the input layer, the MB as the nonlinear projection/expansion, and the $\alpha, \beta, \gamma-$ lobes as the decision layer. For simplicity we do not treat the processing stages from the antenna to the AL and within the AL explicitly. It has been found consistently that the first relay station of the olfactory system, the AL, encodes the information available by the sensors in an at least partly temporal code. This temporal coding mechanism has

been addressed before and we consider only static snapshots of this activity here. This is justified because the olfactory system of the *locust* has an internal formatting clock of 20 Hz due to mutual inhibition in the AL and feed-forward inhibition onto the MB through lateral horn inter-neurons (LHI). One therefore can consider the activity within a time window of 50 milliseconds as a static snapshot that is read by the coincidence detector KCs.

The first stage we consider is the projection of the snapshots of activity in the AL into the large screen of the ensemble of KCs. The main coding characteristic observed experimentally at this level is a low neural activity in the KCs pointing to the existence of a sparse code. Our hypothesis is that the projection from the AL to the MB should be injective or one-to-one, *i.e.* that no information is lost at this level, since we think that the classification decision is carried out at a later stage. The main goal of this phase is to create a large coding space. In a previous paper, we studied the possible ranges for the connectivity degree from the PNs in the AL to the KC layer and for the activation threshold of the KCs that allow an injective representation using random connectivity. The parameter values obtained match those observed experimentally in locust.

Once the representations in the AL have been widely separated in the KC layer they can be classified in the next processing stage. Here a biologically feasible learning mechanisms is needed to allow memory formation and self-organization in the network. In classical Hebbian learning the synaptic strength between two neurons is enhanced whenever they are concurrently active. We show that the resulting local synaptic modifications at the linear classification stage between the KC layer and the α, β, γ-lobes are a sufficient dynamical element to efficiently solve the classification problem.

One may argue that learning takes place at an earlier stage. However, we were able to show in a separate work [1] that Hebbian learning of the synapses from the AL to the MB does not improve the representation of information in the MB.

In summary, we demonstrate in this work that non-specific connectivity from the AL to the MB, a large KC layer, Hebbian learning in the connections from the KC layer to the α, β, γ lobes, and mutual inhibition between α, β, γ lobe neurons are sufficient elements to achieve efficient classification and that, in addition, sparse coding in the screen layer (the KC layer) is crucial for its functionality.

References

[1] Marta García-Sanchez and Ramón Huerta, *Neural networks with Hebbian learning do not outperform Random Networks in fan-out systems*, CNS 2003