Improving odor classification through self-organized lateral inhibition in a spiking olfaction-inspired network

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Abstract—In this study, we propose unsupervised learning of the lateral inhibition structure through inhibitory spike-timing dependent plasticity (iSTDP) in a computational model for multivariate data processing inspired by the honeybee antennal lobe. After exposing the network to a sufficient number of input samples, the inhibitory connectivity self-organizes to reflect the correlation between input channels. We show that this biologically realistic, local learning rule produces an inhibitory connectivity that effectively reduces channel correlation and yields superior network performance in a multivariate scent recognition scenario. The proposed network is suited as a preprocessing stage for spiking data processing systems, like for example neuromorphic hardware or neuronal interfaces.

I. INTRODUCTION

The insect olfactory system is capable of classifying odors by encoding and processing the neural representations of chemical stimuli. The insect olfactory system is well described at a structural level [1]. In the antennae of insects, odors are transformed into a neuronal representation by a number of receptor classes, each of which encodes a certain combination of chemical features. Axons from each receptor class converge into separate compartments (so-called glomeruli) in the antennal lobe (AL). The activity pattern of those glomeruli resembles a multivariate representation of the stimulus space [2]. Olfactory receptors are broadly tuned and hence the response spectra of glomeruli overlap, that is, they exhibit channel correlation. It has been proposed that the AL reduces this channel correlation through lateral inhibition, expanding coding space and using it more efficiently for distributed odor representations [3], [4], [5].

The insect olfactory system thus provides an efficient basis for bio-inspired computational methods to process and classify multivariate data with channel correlation. The AL operates as a decorrelation filter on neural representations of odors before they are delivered to higher brain areas. In previous work, we demonstrated how lateral inhibition in an olfaction inspired network reduces correlation between channels and facilitates separation of multivariate patterns [6], [7]. In this network, the strength of lateral inhibition between any two glomeruli was set according to the correlation in their odor response spectra, as previously suggested by modeling studies [8].

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Spike-timing dependent plasticity (STDP) is a well-established mechanism for synaptic regulation. STDP adapts synaptic strength according to the temporal relation of pre- and postsynaptic spikes [9]. STDP is a local, unsupervised learning mechanism that depends only on information available at the synapse and doesn’t rely on a teacher signal. STDP is ubiquitously observed in various sensory systems in vitro and in vivo [10]. Furthermore, STDP is experimentally observed in inhibitory synapses as well [11], [12]. Recently, it has been shown that STDP in inhibitory synapses facilitates establishing a state of irregular, asynchronous activity in a balanced spiking network [13].

Here, we propose an unsupervised learning of the lateral inhibition structure in an olfaction-inspired neuronal network via inhibitory spike-timing dependent plasticity (iSTDP). To this end, we implemented an olfaction-inspired spiking network model with lateral inhibitory connections that support iSTDP. We show how the inhibitory connectivity self-organizes to effectively reduce channel correlation. Furthermore, channel decorrelation ensures odor pattern decorrelation which enhances the performance of a Naïve Bayes Classifier in a scent recognition scenario.

II. METHODS & RESULTS

A. Input data & Response patterns

The input data for the AL network model contained 836 odorants from Sigma-Aldrich Flavors and Fragrances Catalog [14]. Odorants in this data set are labeled according to their scent (‘fruity’, ‘balsamic’, ‘green’, ‘nutty’ etc.) and one odorant may bear more than one label. Odorants in the data set were represented by 184 physico-chemical molecular descriptors. These 184-dimensional vectors were transformed into a ten-dimensional multivariate firing-rate representation using ten virtual receptors (VRs [6]). In brief, a VR is defined as a point in $n$-dimensional data space and is used to encode $n$-dimensional real-valued multivariate data into a $k$-dimensional firing rate representation using $k$ virtual receptors. The activity $r_k$ of the $k$-th VR depends on the distance $d(s,p_k)$ between a data point $s$ and a VR $p_k$ according to

$$ r_k = \frac{d(s,p_k) - d_{\text{min}}}{d_{\text{max}} - d_{\text{min}}} \quad (1) $$

with $d_{\text{max}}$ and $d_{\text{min}}$, the largest and the smallest distance encountered in the data set. In other words, a VR responds strongly if the stimulus data point is close, and weakly if the distance is large. Thus, VRs encode the real-valued input data set into a bounded, positive representation that can be converted into population firing rates.
Virtual receptors are placed in data space using a self-organizing map (SOM) [15]. Consequently, VRs cover all relevant parts of chemical space and preserves the local topology in their low-dimensional projections. Fig. 1 depicts a two-dimensional projection of the original 184-dimensional data set and the locations of the VR placed by the SOM.

We used the SOMMER application [16] to train SOMs with a $2 \times 5$ toroidal architecture, yielding a ten-dimensional VR representation. In the scope of our model, the evoked response patterns correspond to activation of receptors in the AL.

The VR encoding mimicks two important properties of the olfactory code: Each odorant activates multiple receptors (redundant coding) and each receptor is activated by several odorants (broad tuning curves). Furthermore, odors that are chemically similar according to their location in the 184-dimensional chemical property space evoke similar VR response patterns.

B. Network Layout

Our network model comprises two stages and is directly inspired by the insect olfactory system (Fig. 2). In the first stage, the response of the VRs is translated into spiking activity of $k$ populations of olfactory receptor neurons (ORNs) using a stochastic point process model. To this end, we used Poisson neurons as ORNs to generate independent spiking events based on the population firing rate. The VR activity pattern was mapped into the firing rate interval $[0, 120]$ spikes/s, such that the lowest VR response was transformed into a poisson spike train with 0 spikes/s, and the highest response elicited 120 spikes/s in the ORNs.

The second stage implements a decorrelation network in analogy to the AL network in insects. Each ORN projects to PNs in one glomerulus, which project on LNs in the same glomerulus, which project to PNs in all other glomeruli. Weights from LNs to PNs support STDP.

C. Self-organizing lateral inhibition with spike-timing dependent plasticity

We exposed the network to stimulus patterns. Data points were presented consecutively in random order. We presented each of the 836 odor patterns for one second of biological time. During training, synapses from inhibitory LNs to PNs were subject to iSTDP as described in [13]. According to this learning rule, pairs of pre- and post-synaptic spikes caused potentiation of the inhibitory synapse by an amount proportional to $L$ (eq. 2).

$$L = \frac{e^{-|\Delta t|}}{2\pi \tau_{\text{STDP}}},$$  \hspace{1cm} (2)

with $\Delta t$ the time difference between pre- and postsynaptic spikes, and $\tau_{\text{STDP}}$ defining the width of the iSTDP window.
rates $\eta$ resulting classification scores depending on different learning connectivity matched the VR correlation structure, but only for the input correlation. For high learning rates, subsequent odor patterns overwhelm produced in the inhibitory connectivity for low learning rates. This structure is well repro-

In order to determine the benefit of self-organized lateral inhibition for stimulus separation, we trained a Naïve Bayes classifier to predict the scent labeling of odors evoked in PNs. We measured classifier performance according to the recognition of “Fruity” and “Non-Fruity” odors (5-fold stratified cross-validation, 1000 repetitions with random train and test data splits). Deco-

D. Decorrelation and benchmarking network performance

In order to compare these results to a non-spiking approach to decorrelation, we performed principle component analysis (PCA) on the data and trained the Naïve Bayes classifier on the 10 components explaining the most variance in the data set (total 80% explained). This approach achieved slightly better results than the spiking iSTDP approach presented above (avg. 72.0% correct, $P_{25}/P_{75} = 69.9/74.4$ for 1000 repetitions of fivefold cross-validation). Similarly, the performance on the original untreated 184-dimensional dataset yielded slightly better performance values (avg. 73.8% correct, $P_{25}/P_{75} = 72.0/76.2$). However, a direct comparison of absolute classification scores between spiking and non-

III. CONCLUSIONS

We presented the unsupervised learning of input data correlation structure in a scent recognition scenario. We tested how channel correlation affects the weights of STDP-enabled inhibitory synapses in a network inspired by the insect antennal lobe. We showed that upon exposure to artificial stimulus patterns, the inhibitory connectivity of this network resulted in stronger inhibition that reduced the postsynaptic firing rate to a level close to $\rho_0$. However, the spike count observed from a poisson process in a fixed time interval (1 s in our case) exhibits higher variance when the average firing rate is low. Thus, the spike count variance at low rates acts like adding noise to the stimulus representation and consequently has negative impact on the classification performance.

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were used. Hence, correlation-based lateral inhibition is better suited for brain-like, massively parallel computing where data dimensionality potentially has less impact on computational efficiency, but rather the distributedness of the code can be exploited without penalty on computational efficiency. This circumstance argues for a neuromorphic implementation of the present network as a preprocessing step in neuromorphic data processing schemes.

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REFERENCES