Sequential Sparsening by Successive Adaptation in Neural Populations

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1 Introduction

Sparse coding of sensory input in neural systems is desirable because it allows for an efficient representation of the environmental scene at any point in time with only a small number of vocabulary elements. Moreover, a sparse code of sensory input may support the efficient formation and subsequent retrieval of associative memories at later processing stages in the brain \cite{6,2}. A series of experimental studies in a number of different model systems have provided evidence for a sparse stimulus representation in neural spike responses at different processing stages (for a comprehensive review see \cite{10} and references therein).

However, despite extensive theoretical studies of the possible role and efficiency of a sparse code in neural information processing and associative memory, the underlying mechanisms that translate a sensory data into a sparse representation are yet unknown. Among many possibilities, the mutual roles of network architecture and interaction of inhibition and excitation are possible candidate mechanisms that can affect the sparseness of a representation \cite{1,3,7}.

Here, we explore the role of the neuron-intrinsic mechanism of spike frequency adaptation (SFA) in producing temporally sparse responses to sensory stimulation at higher processing stages. Our results suggest that SFA leads to an increased sparseness of the neural response across successive processing stages in the sense of a temporal sparseness where the response becomes increasingly shortened and sharpened. This is commonly known as \textit{lifetime sparseness} \cite{13}.

2 Results

2.1 Iterative sparsening in a SFA neuron model

In order to investigate the effect of adaptation on the single neuron response dynamics, we numerically simulate a five-dimensional master equation for a conductance-based integrate-and-fire neuron with spike-frequency adaptation, using the parameters given in \cite{9}. We then take an iterative approach to mimic a feed-forward network connection scheme. At the first processing stage, we provide the model with a step-like Poissonian input (Fig. 1). A spontaneous rate:
2 Results

Fig. 1: The effect of iterative spike-frequency adaptation in a single cell. A: Spiking activity of a single adaptive conductance based neuron [9] averaged across 100 independent trials, estimated in bins of 50ms size. The neuron is driven by Poisson input as described in the text. B and C: Trial-averaged activity of the same neuron model when it is stimulated with the output population activity of the previous iteration. Simulations performed with pyNEST [4].

1 kHz, response rate: 300 Hz, response duration: 1 s) and repeat the simulation 100 times. The trial-averaged response is illustrated in the Peri-Stimulus-Time-Histogram (PSTH) of Fig. 1A. It shows a clear phasic-tonic response with a strong onset transient and offset inhibition. We now use the combined output spike trains from all 100 trials and use this as the single trial input to the same neuron model at the next processing stage. Again we repeat this complete scenario for 100 times and estimate the PSTH in Fig. 1B. We reiterate once more with 100 repetitions to estimate the response at the third processing stage (Fig. 1C).

From Fig. 1 we can infer two major results. First, the response to the initial step-like input turns into a phasic response that becomes increasingly ‘sharp’ across repeated iteration. Second, the response maximum as estimated by the binned firing rate increases from stage to stage. This response strength naturally scales with the number of pooled repetitions used for input into the next stage (simulations not shown). A third but less prominent effect is expressed in a suppression of spiking during a short period following the stimulus epoch.

2.2 Response sparsening in a feed-forward network model

It has been shown that the primary neurons in the insect mushroom body - the Kenyon cells (KCs) - use a sparse representation of olfactory stimuli [1, 12] where at each moment in time only a small fraction of neurons represent the sensory input (spatial sparseness) and each neuron responds with only a short response even to long-lasting sensory stimuli (lifetime sparseness). In a simplified view we may consider the insect olfactory pathway as a feed-forward network where the olfactory receptor neurons (ORNs) provide input to the first processing layer of projection neurons (PNs; approx. 950 uniglomerular PNs in the honeybee) in the antennal lobe. The PNs project to the layer of KCs (approx. 160,000 in the honeybee), which in turn provide convergent input to the mushroom body extrinsic neuron layer (ENs; approx. 400 in the honeybee).

Here, we designed a reduced feed-forward network with three layers, ar-
3 Discussion

We report here that the simple neuron-intrinsic mechanism of spike-frequency adaptation can account for the sparse spike response scheme known as lifetime sparseness \[13\] in downstream neurons. SFA reflects high-pass filter properties with respect to the temporal profile of the neuron’s input activity. This suggests that a feed-forward network with SFA neurons focuses on the temporal differences of the sensory input. In other words, it suggests that for higher brain centers it is most relevant to process dynamic changes in the sensory environment and to neglect the static part of receptor sensation.

We designed our network model in coarse analogy to the insect olfactory system. The network ranged in a $10 \times 100 \times 10$ lattice with full connectivity. This structure represents the processing layers in the olfactory pathway: PN→KC→EN. All neurons are modeled identically using the 5D model and identical parameters as described in the previous section. As a means of control we repeated the same network simulation but with zero adaptation. To match the spontaneous output rates of both models we increased synaptic weights by a factor of 1.3 in the latter.

As ORN input to the PN layer we again used a step-like Poisson input, independent for all neurons. We then repeated the simulation for 10 independent runs and estimated the population activity for each layers by constructing the PSTH across all neurons within this layer as shown in Fig. 2. Our result clearly shows that the population response becomes increasingly phasic as it propagates through the network of SFA neurons (Fig. 2, upper row). However, in the control case where we switched off SFA in all neurons, the step-like input is conserved across all layers and the changes in response strength reflect the neuron number in each layer.

Fig. 2: Simplified network of feed-forward processing in the insect olfactory system. Average activity of simulated network for 10 independent trials in 50ms bins without adaption for control (first row) and with SFA (second row), where synapses are assumed to produce an $\alpha$ shaped excitatory conductance profile. The network simulation was conducted in pyNEST \[4\].
system. Our model observation match with experimental observations. At the first processing level of projection neurons the stimulus response still shows a strong and outlasting tonic part, as was e.g. observed in intracellular recordings from PNs in the honeybee [8]. The effect fully develops in the second layer of KCs with a sharp transient response. This matches the repeated experimental observations in extracellular recordings from the locust (e.g. [3]) and imaging results in the honeybee [12]. Finally, the phasic responses in ENs match with experimental recordings in the honeybee [11].

Note
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