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#### 2 Review

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# Neuronal circuits and computations: Pattern decorrelation in the olfactory bulb

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#### ABSTRACT

Neuronal circuits in the olfactory bulb transform odor-evoked activity patterns across the input channels, the olfactory glomeruli, into distributed activity patterns across the output neurons, the mitral cells. One computation associated with this transformation is a decorrelation of activity patterns representing similar odors. Such a decorrelation has various benefits for the classification and storage of information by associative networks in higher brain areas. Experimental results from adult zebrafish show that pattern decorrelation involves a redistribution of activity across the population of mitral cells. These observations imply that pattern decorrelation cannot be explained by a global scaling mechanism but that it depends on interactions between distinct subsets of neurons in the network. This article reviews insights into the network mechanism underlying pattern decorrelation and discusses recent results that link pattern decorrelation in the olfactory bulb to odor discrimination behavior.

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### 47 1. Computational functions of neuronal circuits and the48 olfactory system

49 Higher brain functions are not directly determined by the biophysical properties of individual neurons but emerge from interac-50 tions between many neurons in synaptically connected networks. 51 Deciphering such networks is central to understanding the princi-52 ples of biological computation, the relationship between brains 53 and computers, brain dysfunction in mental disorders, and the very 54 55 nature of humans and other animals. Neurons are organized in structured networks, or circuits, that are typically defined as cir-56 cumscribed populations of interconnected neurons. Small circuits 57 such as repetitive columnar elements of the optic lobes in Droso-58 phila may be comprised of <100 neurons [1] while large circuits 59 such as mammalian piriform cortex or cerebellar lobules can con-60 tain 10<sup>6</sup> neurons or more [2]. Most neuronal circuits consist of 61 62 functionally diverse types of neurons and contain prominent feedback loops. The computational potential of such systems is enor-63 mous [3] but we are only beginning to understand how this 64

Q2 \* Corresponding author at: Friedrich Miescher Institute for Biomedical Research, Maulbeerstrasse 66, 4058 Basel, Switzerland. *E-mail address:* Rainer.Friedrich@fmi.ch (R.W. Friedrich). potential is realized in biological circuits. A systematic and somewhat reductionist approach to understand brain functions may thus ask *what* different circuits compute, and *how* these computations are achieved mechanistically as neurons exchange and integrate biophysical signals.

The challenge to understand a neuronal computation obviously 70 depends on the complexity of the computation and the underlying 71 circuit. Some computations can be described based on first-order 72 statistical properties of neuronal connectivity (average connection 73 strength) and based on univariate properties of neuronal activity or 74 simply mean firing rate. These quantities can often be measured 75 using well-established methods and the computations can often 76 be described by tractable mathematical models. One example of 77 such a computation is "normalization", an important elementary 78 operation that scales responses of individual neurons as a function 79 of the mean population activity [4,5]. Other computations, how-80 ever, depend on higher-order properties of connectivity and on 81 multivariate properties of activity patterns. These diverse and 82 potentially complex computations have not yet been explored 83 exhaustively. Some of these computations are likely to depend 84 on the activity of specific subsets of neurons and on specific con-85 nectivity. For example, receptive field properties of neurons in pri-86 mary visual cortex are thought to be shaped by specific 87

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88 connectivity among neurons with similar feature selectivity [6], 89 and storage of arbitrary information in memory networks such as 90 the hippocampus is thought to depend on experience-dependent 91 modifications of synaptic connections between specific subsets of 92 neurons [7]. Analyzing the mechanisms underlying such computa-93 tions, and even defining the computations themselves, is often 94 hampered by experimental constraints. It is, for example, possible 95 to record activity only from subsets of neurons within a large 96 population. The sample size of population activity measurements 97 may thus be sufficient to determine simple statistical properties 98 of neuronal activity patterns but fail to resolve higher-order fea-99 tures. Detailed descriptions of the connectivity among individual neurons are lacking for most circuits, with few exceptions [1,8-100 10]. Furthermore, mathematical analyses of networks with 101 102 higher-order structure can become extremely complex. Under-103 standing neuronal computations depending on higher-order circuit 104 features is therefore a major challenge in neuroscience.

105 This review focuses on the decorrelation of odor-evoked activity 106 patterns in the OB, a computation that reduces the overlap (Pearson product-moment correlation coefficient) between activity pat-107 108 terns representing different, yet structurally similar, odors. A 109 neuronal activity pattern at time t may be represented by a vector where each element represents the firing rate of one neuron, mea-110 sured during a small time window around t. Highly overlapping 111 112 activity patterns are thus represented by vectors that have a high 113 Pearson correlation coefficient, i.e., they project in similar direc-114 tions within the high-dimensional coding space. Pattern decorrela-115 tion reorganizes activity patterns so that the Pearson correlation coefficient of the corresponding activity vectors decreases and 116 117 their angular separation increases. As a consequence, it becomes 118 easier to find a procedure – a classifier – to distinguish between the activity vectors. Pattern decorrelation is thus useful for pattern 119 120 classification, a key operation in many higher brain functions such 121 as object recognition, decision making and associative memory. 122 Models of pattern classification in the brain assume that activity 123 patterns are at least partially decorrelated. This assumption is 124 often necessary to achieve good performance, to avoid destructive 125 phenomena such as catastrophic interference, and to enable var-126 ious other operations [11–17]. However, few studies have directly 127 analyzed pattern decorrelation in the brain, possibly because it has been difficult to measure neuronal activity patterns across large 128 129 numbers of neurons.

One brain area where pattern decorrelation was observed is the 130 131 dentate gyrus of the hippocampus [18,19], which is assumed to pre-process activity patterns representing complex, multisensory 132 133 information for storage and classification in other hippocampal 134 subfields such as CA3 [20,21]. However, the underlying mechan-135 isms are not understood in detail. Another brain area where pat-136 tern decorrelation has been studied is the OB, particularly in 137 zebrafish [22–26]. Among the multiple targets of the OB is the piri-138 form cortex, a large paleocortical area with an architecture similar to that of hippocampal area CA3. Like CA3, piriform cortex has 139 been proposed to function as an associative memory system for 140 the storage of information encoded by distributed activity patterns 141 [27-29]. Pattern decorrelation may therefore subserve similar gen-142 eral functions in the OB and in the dentate gyrus although differ-143 144 ences in the neuronal architecture of these circuits suggest that the underlying mechanisms are not identical. 145

The OB is the only olfactory processing center between sensory 146 147 neurons in the nose and multiple higher telencephalic areas. Olfac-148 tory input reaches the OB through an array of discrete input chan-149 nels, the olfactory glomeruli (Fig. 1), each of which receives 150 convergent input from sensory neurons expressing the same odor-151 ant receptor [30]. Individual odorant receptors and glomeruli 152 respond to multiple odorants, and each odorant activates a specific 153 combination of glomeruli [30,31] (Fig. 2A). Odors are therefore

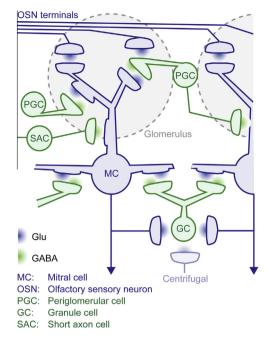


Fig. 1. Schematic illustration of selected cell types and synaptic connections in the OB. Modified from [91].

encoded in a combinatorial fashion and presented to the OB as discrete, usually distributed, glomerular activation patterns. Odorants with similar molecular features activate overlapping combinations of glomeruli, probably as a direct consequence of the molecular mechanisms governing receptor-ligand interactions. Glomerular representations of chemically similar odorants are therefore highly correlated. In order to facilitate stimulus classification, autoassociative memory and other tasks it appears useful to reduce these correlations at an early stage of sensory processing.

Sensory input from the array of glomeruli is processed in the OB by a network of principal neurons, the mitral/tufted cells (MCs), and multiple classes of interneurons including periglomerular cells, short-axon cells and granule cells [32] (Fig. 1). MCs are glutamatergic, receive glutamatergic input from sensory neurons and inhibitory input from interneurons, and convey the output of the OB to multiple higher brain areas including piriform cortex. Individual MCs receive sensory input only from one or a few glomeruli and are not directly coupled to MCs associated with other glomeruli. Periglomerular cells are located in the input (glomerular) layer of the OB and comprise multiple subtypes [33]. They are small neurons that receive input from various sources and provide GABAergic output to MCs. Short-axon cells are also located mainly in superficial layers but often have long processes [34]. They can have inhibitory or depolarizing effects on MCs that are mediated by GABAergic synapses and gap junctions, respectively [35]. Granule cells are located in deep layers and are by far the most numerous cell type in the OB. They are axonless, receive glutamatergic input from dendrites and axon collaterals of MCs, and make GABAergic synapses back onto MCs. Many of the dendro-dendritic connections between MCs and granule cells are reciprocal. The synaptic connectivity among neurons in the OB therefore provides multiple paths for interactions between MCs, even though MCs are not directly connected across glomeruli. These synaptic pathways extend over multiple spatial scales and often have inhibitory effects on MCs. In addition, multiple types of interneurons, but not MCs, receive input from higher brain areas.

MCs respond to odor stimulation with slow modulations of their firing rates (Fig. 2B) and with oscillatory synchronizations

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