Contrast enhancement of sensor-array patterns through hebbian/anti-hebbian learning

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Abstract

The olfactory bulb is able to enhance the contrast between odor representations through a combination of excitatory and inhibitory circuits. Inspired by this mechanism, we propose a new Hebbian/anti-Hebbian learning rule to increase the contrast of sensor-array patterns in a neurodynamics model of the olfactory system: the KIII. In the proposed learning rule, a Hebbian term is used to build associations within odors and an anti-Hebbian term is used to reduce correlated activity across odors. The system is characterized on synthetic data showing its ability to increase the separation between patterns and its robustness against noise. Experimental data from an array of temperature-modulated metal-oxide sensors is used to validate the contrast enhancement ability of the system.

1. Introduction

The olfactory system has been optimized over evolutionary time to allow animals detect and interpret the information from volatile molecules in the environment. The striking similarity between the olfactory system across phyla suggest that its architecture has been shaped to reflect basic properties of olfactory stimuli. This suggests that the underlying mechanisms of the olfactory system could be of great use in the processing of gas sensor array data. Motivated by this idea, the long term goal of this work is to develop biologically-inspired computational models to process data from chemical sensor arrays, commonly referred to as the electronic nose.

Particularly, in this paper we focus on the ability of the olfactory bulb to improve the separability of odor representations. The olfactory bulb receives direct inputs from olfactory receptor neurons in the epithelium, and reshapes this information through excitatory-inhibitory circuits, increasing the contrast across odor representations [1]. Borrowing inspiration from this computational function, this article proposes a learning rule to improve the discrimination of patterns from gas sensor array systems.

The proposed learning rule is validated on the KIII, a neurodynamics model of the olfactory system developed by Freeman and colleagues over the last thirty years [2, 3]. The KIII model has gone largely unnoticed in the machine olfaction literature, with a few exceptions [4-6]

2. Contrast enhancement through Hebbian/anti-Hebbian learning

Contrast enhancement in the olfactory bulb is performed through the inhibition of mitral cells, which receive projections from olfactory receptor neurons, by nearby granule interneurons [7]. This inhibition has the effect of reducing the molecular tuning range (i.e., the number volatile molecules detected) of a mitral cell relative to that of olfactory receptor neurons, effectively orthogonalizing patterns across odors. This computational function can be achieved by means of anti-Hebbian learning [8], which leads to a decorrelation of input channels to the system. The anti-Hebbian learning rule is the opposite of the Hebbian rule, and states that the strength of the connection between two neurons should decrease when both activate simultaneously:

$$\Delta w_{kl} = -x_k x_l \tag{1}$$

where x_k and x_l are the *k-th* and *l-th* inputs to the system. We propose a new learning rule that combines Hebbian and anti-Hebbian terms to provide both robustness to sensor failures and enhanced pattern separability, respectively. Assuming a pattern recognition problem with N odor patterns $p^i = \left[x_1^i\, x_2^i \ldots x_M^i\right]^T; 1 \le i \le N$, and a recurrent network with M fully-laterally-connected neurons, the strengths of the lateral connections can be computed with the following off-line expression:

$$w = \overbrace{\sum_{i=1}^{N} p^i \cdot (p^i)^T}^{hebbian} - \overbrace{\sum_{i=1}^{N} \sum_{\substack{j=1 \\ j \neq i}}^{N} p^i \cdot (p^j)^T}^{anti-hebbian} \tag{2}$$

The first term in equation (2) is the Hebbian rule, which strengthens the connection between neurons that are active *within* a pattern. The second term is the anti-Hebbian component, which reduces the connection weights between neurons that are active for multiple patterns, on the average reducing the overlap *across* patterns. Negative mitral-to-mitral connections are avoided by forcing to zero all elements in equation (2) that become negative.

3. Contrast enhancement in the KIII

The proposed learning mechanism is implemented on the KIII, a neurodynamics model of the olfactory system.

3.1. The KIII model

The output of the KIII reproduces electroencephalographic (EEG) recordings in the olfactory system by modeling the oscillatory behavior of neuron populations [3]. The topology of the model, shown in Figure 1, is based on the physiological structure of the mammalian olfactory system [2]. Each node in the KIII represents a population of neurons, modeled by a second order differential equation, and each edge models the interaction between two populations. The strength of this interaction is controlled by a weight, which is positive when the connection is excitatory and negative if the connection is inhibitory.

Odor stimuli are presented to the system as a pattern through an input layer of receptors. Each receptor is connected to a periglomerular cell and a set of one mitral and one glomerular ensemble, forming a channel. Each of these channels can then be associated with one dimension of the input stimulus and the corresponding output pattern. The KIII is usually able to store previously seen patterns by means of Hebbian lateral connections at the M mitral layer. This allows the model to work as an associative memory for recovering incomplete or corrupted stimuli.

In the absence of an external stimulus, the KIII channels follow an aperiodic oscillatory behavior known as a basal state. When an input is presented, the system moves into a global attractor in state space, which can also be observed as pseudo-periodic oscillations in the output channels. The amplitude of the oscillations at each channel depends on the activation level of its receptor input, but is also influenced by other receptors as a result of the lateral connections. The output pattern of the KIII is commonly assumed to be encoded in the amplitude or RMS of the oscillations of each channel [2].

3.2. Hebbian/anti-Hebbian learning in the KIII model

Application of anti-hebbian learning to the KIII model is not trivial because of the oscillatory nature of the KII sets: the interaction between laterally-connected oscillators is a vector operation. Depending on the relative phase of the two oscillators, it is therefore possible for an inhibitory connection to have an excitatory effect. The proposed learning rule is applied to the mitral-to-mitral connections, and addresses this problem by combining hebbian and anti-hebbian terms. The role of the hebbian term is two-fold. First, it preserves the associative-memory function of the KIII, allowing the model to learn odor-specific attractors. Second, it provides positive mitral-to-mitral connections, which are subsequently reduced by an anti-hebbian term.

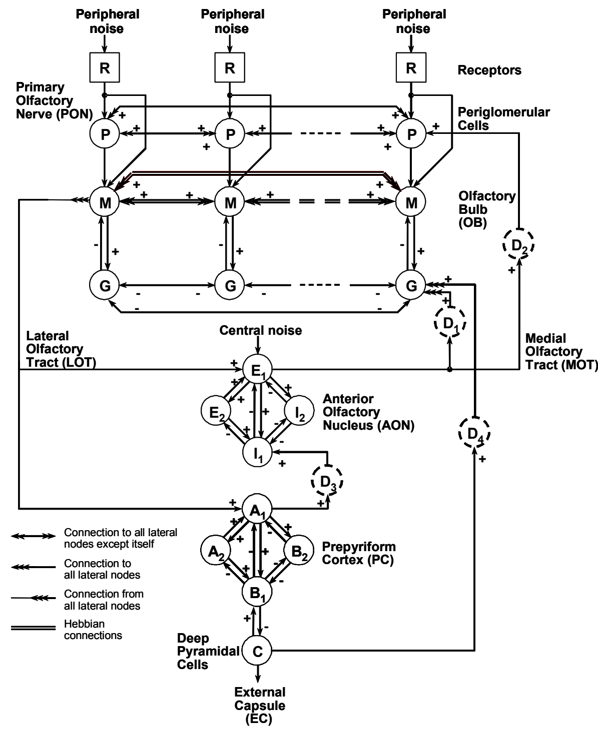

Figure 1. The KIII model architecture

4. Enhanced pattern separability

The KIII trained with the propose Hebbian/anti-Hebbian learning is able to increase the separability of the output patterns through two mechanisms: reduction of overlap and reduction of crosstalk. The reduction in overlap naturally leads to an increase of the output pattern separability. The crosstalk in an associative memory occurs when the stored patterns overlap and therefore interfere with the pattern that we want to retrieve. Since the contrast enhancement mechanism reduces the overlap between the stored patterns, the crosstalk is also reduced. Thus, the crosstalk reduction is a direct consequence of the overlap reduction

To evaluate the ability of the Hebbian/anti-Hebbian learning to increase the separability of different patterns, the KIII is trained with overlapping binary patterns and excited with noisy versions of those. The separability of patterns obtained by the KIII model is compared to that achieved through three other procedures: Hopfield network, KIII with Hebbian learning, and Linear Discriminant Analisys (LDA). The separability of the input patterns is computed also and used as a baseline of the improvement in separability achieved by the procedures.

4.1. Measure of separability: Fisher discriminant function

To measure the separability between patterns we use the Fisher Discriminant Function [9]. Assuming a c-class problem with same number of elements per class, the Fisher Discriminant Function is computed following the expression [10]:

$$J = \frac{tr(S_B)}{tr(S_W)} \tag{3}$$

S_B is the between-class scatter,

$$S_B = \sum_{i=1}^{c} (\mu_i - \mu)(\mu_i - \mu)^t \tag{4}$$

and S_W is the within-class scatter,

$$S_W = \sum_{i=1}^{c} \overbrace{\sum_{y \in C_i} (y - \mu_i)(y - \mu_i)^t}^{S_W^i} \tag{5}$$

where μ_i is the mean value of class i, μ is the mean value of all classes, and C_i is the set of elements belonging to class i. The between-class scatter is a measure of the distance between the mean value of each one of the classes, and the within-class scatter is a measure of the spread of the classes. The classes will be more separable as S_B increases and S_W decreases, leading to increasing values of J.

4.2. Characterization on synthetic inputs

To test the ability of the proposed learning rule to increase the separability of patterns the system is presented with a three class problem with 16-dimensional binary inputs. The three overlapping patterns A, B, and C, shown in Figure 3, which represent the three classes, are used to train the KIII. The testing examples are generated by flipping bits randomly across the 16 dimensions of the patterns. Six levels of noise are considered by flipping from 1 to 6 bits, which corresponds from a 6% to a 37% of the original pattern. 1000 examples are generated for each noise level. This number of examples makes the variation of J less than 5% of its value when the random generation of the examples is repeated 10 times.

The separability of patterns obtained with the KIII-Hebbian/anti-Hebbian is compared to that obtained using the raw inputs and to that obtained by processing the same inputs with three other procedures: Hopfield Network, KIII with Hebbian learning, and LDA. The two first procedures are associative memories and are used to determine the performance of the KIII with Hebbian/anti-Hebbian learning as compared to systems that use only Hebbian learning. LDA represents a good upper bound for separablility performance since it finds an optimum linear projection maximizing the Fisher discriminant function. The separability of raw inputs and the separability of the LDA output are taken as lower and upper bounds respectively for the performance of the other procedures.

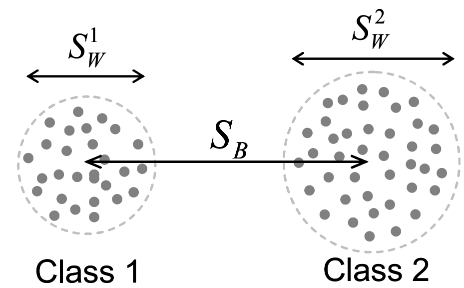

Figure 2. Illustration of between class-scatter S_B, and within class-scatter S_W^1, S_W^2.

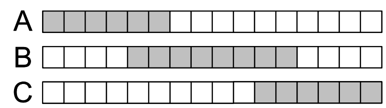

Figure 3. Overlapping binary patterns used to test the pattern separability of the system.

Figure 4 shows the pattern-separability obtained by the four procedures and that of the input. The separability, computed as J, is plotted against the amount of noise introduced to the input patterns. The KIII-Hebbian/anti-Hebbian clearly outperforms the ability of the KIII-Hebbian and the Hopfield network to increase the separability of the patterns and it performs close to the upper bound set by LDA. This result can be explained in terms of the mechanisms that increase the pattern separability at each network. The Hopfield network and the KIII-Hebbian model are able to increase the separability existent at the input through pattern completion. They are able to partially restore the stored patterns from the noisy version presented at the input, reducing the within-class scatter, S_W. The KIII-Hebbian/anti-Hebbian uses not only pattern completion to increase output pattern separability, but also overlap and crosstalk reduction. Both mechanisms increase the between class-scatter S_B.

5. Sensor array-patterns validation

The contrast enhancement ability of the KIII-Hebbian/anti-Hebbian was validated on experimental data from a gas sensor array with four MOS sensors (TGS2600, TGS2620, TGS2611, and TGS2610) [11]. The sensors were modulated in temperature [12] with a sinusoidal profile to increase the information content of the response. The sensors were exposed to the headspace of acetone (A), isopropyl alcohol (B), and ammonia (C). The temperature-modulated response of one of the sensors was used to train the KIII model, previous L1 normalization of each response pattern. This preprocessing is necessary to balance the total input to the KIII, which ensures that the model operates in a well-behaved dynamic region.

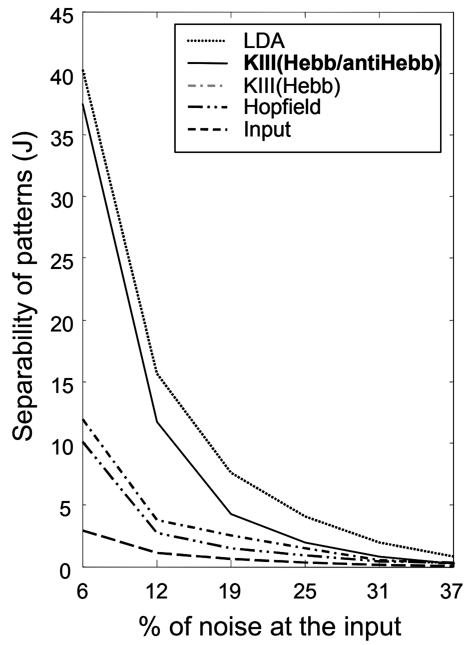

Figure 4. Separability of the output patterns against the level of noise introduced in the input patterns. Separability of the output patterns of LDA, KIII-Hebbian/anti-Hebbian, KIII-Hebbian, Hopfield output, along with the separability of the raw input.

The normalized sensor response patterns to the three pure analytes (A, B, and C), shown in Figure 5 (left column), were used to train the KIII model using the new learning rule. Even though the sensor provides a unique response pattern to each analyte, there is also a significant degree of overlap that shadows the most relevant discriminatory information. Figure 5 (right column) shows the output of the KIII to the three analytes; the KIII is able to noticeably reduce the overlap across patterns and enhance the channels (i.e., operating temperatures) with highest selectivity. The response pattern for analyte A is sharpened around the two peaks (channels 16 and 45). Although theses peaks are present for the three analytes, their activity relative to other channels is highest for pattern A. A more interesting response is obtained with analyte B, for which the most discriminatory information is provided by the secondary peaks around channels 7 and 54. As a result, the trained KIII increases contrast in these channels. Note that the secondary peak around channel 53 is minimally noticeable in the original sensor response (Figure 5(b)), but is clearly resolved in the output of the model (Figure 5(e)). Finally, the sensor response pattern for analyte C is transformed by enhancing activity in the central channels, which is where discriminatory information for this analyte is highest.

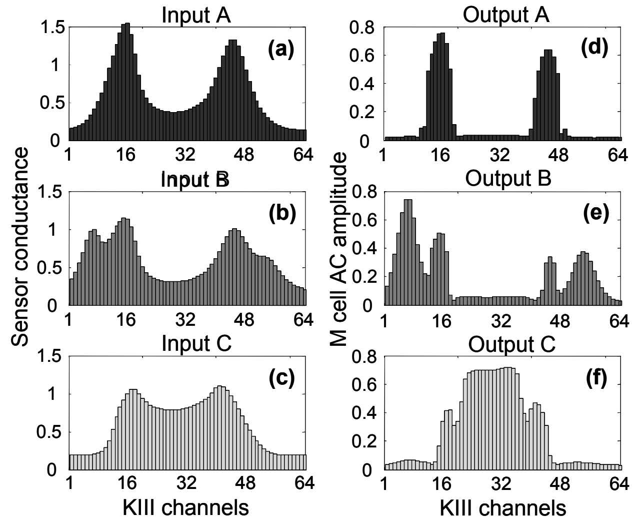

Figure 5. Contrast enhancement in the KIII with experimental data from a gas sensor. The left column shows the sensor response to the three analytes, which serves as the input to the KIII. The right column shows the corresponding output of the KIII (i.e. AC amplitude in mitral cells).

6. Discussion

The proposed Hebbian/anti-Hebbian learning rule for the KIII model has been shown to increase the separability between output patterns as a consequence of its ability to increase the within class-scatter S_W and to reduce the between class-scatter of the output distribution with respect to the input distribution. This function is similar to the contrast enhancement performed by the olfactory bulb.

In section 4.2., to ensure a fair comparison between LDA, which considers second order statistics on the input distribution, and the rest of the procedures, which only consider first order statistics, a distribution of testing examples that have all the class-information in the mean is used. The input distribution generated has no class-information in the variance since the noise used to generate the examples is equally distributed across all dimensions of the input space. Despite the lack of class-information in the variance, the close performance of the KIII-Hebbian/anti-Hebbian to that obtained by LDA is a remarkable result, since LDA finds the optimal linear performance based on J.

In addition to the characterization of the proposed learning rule with synthetic patterns, the ability of the proposed system to enhance the contrast of sensor array-patterns has been shown for the sensor response to three analytes. This shows the potential use of the KIII-Hebbian/anti-Hebbian for increasing the separation of sensor array-patterns.

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