

Mixture segmentation and background suppression in chemosensor arrays with a model of olfactory bulb-cortex interaction

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Abstract

We present a model of olfactory bulb-cortex interaction for the purpose of mixture processing with gas sensor arrays. The olfactory bulb is modeled with a neurodynamic model whose lateral inhibitory connections are learned through a modified Hebbian-anti-hebbian rule. Bulbar outputs are then projected in a non-topographic fashion onto the olfactory cortex. Associational connections within cortex using Hebbian learning form a content addressable memory. Finally, inhibitory feedback from cortex is used to modulate bulbar activity. Depending on the form of feedback, Hebbian or anti-Hebbian, the model is able to perform background suppression or mixture segmentation. The model is validated on experimental data from a gas sensor array.

I. INTRODUCTION

Recognizing odors against complex backgrounds and identifying the components of a mixture are common olfactory discrimination tasks encountered in daily life situations. Several computational models have put forth the hypothesis that cortical feedback to the bulb may play a role in achieving these computational functions. Ambrose-Ingerson et al. [1] have modeled these feedback connections to account for hierarchical recognition of odors by humans. In this model, cues common to a subset of odors are recognized before those that are odorant-specific. Li and Hertz [2] have shown that centrifugal connections may cause odor-specific adaptation, leading to segmentation of odor mixtures. Grossberg [3] has proposed that cortical connections to the bulb may selectively filter the bulb input and cause resonance between the two regions. Yao and Freeman [4] have implicated these feedback connections with chaotic dynamics in the bulb.

In this paper, we will present a model of olfactory bulb-cortex interaction, and show that two different computational functions can be achieved (mixture segmentation, weaker odor/background suppression) depending upon the learning rule that is used to establish the cortical feedback connections to the bulb: anti-Hebbian or Hebbian, respectively. We validate the use of these computational models to handle odor mixture signals from an array of gas sensors.

II. NEURODYNAMICS MODEL

The olfactory bulb is the first relay station in the olfactory pathway, and the site where the bulk of the signal processing

takes place. We model the OB using the classical additive model from neurodynamics [5, p. 676], as follows:

$$\frac{dv_j^O(t)}{dt} = -\frac{v_j^O(t)}{\tau_j} + \sum_{k=1}^M L_{kj} \varphi(v_k^O(t)) + I_j^O + \sum_{i=1}^P FB_{ij} \varphi(y_i^O(t)) \quad (1)$$

where v_j is the activity of bulb neuron j , τ_j is the time constant that captures the dynamics of the neuron, L_{kj} is the synaptic weight between neurons k and j , M is the number of neurons, I_j is the external input from the olfactory epithelium, FB is the feedback connectivity matrix, y_i is the activity of cortical neuron i , and $\varphi(\cdot)$ is a non-linear activation function (logistic function) given by:

$$\varphi(v_j) = \frac{1}{1 + \exp(-a_1 \cdot (v_j - a_2))} \quad (2)$$

where the constants a_1 and a_2 are set to 5.8889 and 0.5 respectively to match the dynamic range of input signals from the chemosensor array ($[0, 1]$).

The lateral connections L in the bulb are established through a Hebbian update rule proposed in [6] as follows:

$$L = \alpha \cdot \sum_{O_1=1}^N I^{O_1} \cdot (I^{O_1})^T - \beta \cdot \sum_{O_1=1}^N \sum_{\substack{O_2=1 \\ O_2 \neq O_1}}^N I^{O_1} \cdot (I^{O_2})^T \quad (3)$$

where I^{O_1} is the input olfactory bulb pattern for odor O_1 , α and β are scaling parameters, which provide a necessary tradeoff between the first correlation term and the second decorrelation term. This form of update has been shown to enhance the contrast between input patterns [6].

The olfactory bulb sends non-topographic and many-to-many projections to the olfactory cortex. These convergent and divergent (many-to-many) projections suggest that cortical neurons detect combinations of co-occurring molecular features of the odorant, and therefore function as ‘‘coincidence detectors’’ [7]. Apart from these forward connections, the cortex is characterized by excitatory and inhibitory lateral connections that are known to play an important role in the storage odors with minimum interference and pattern completion of degraded stimuli [8]. Together, these two architectural features of the PC (many-to-many connection from OB, and lateral

association connections between cortical cells) form the basis for the synthetic processing of odors [7].

We model these olfactory circuits using an additive model, similar to the olfactory bulb in equation (1), as follows:

$$\frac{dy_i^o(t)}{dt} = -\frac{y_i^o(t)}{\lambda_i} + \sum_{k=1}^P AC_{ki} \phi(y_k^o(t)) + \sum_{j=1}^M FF_{ji} \phi(v_j^o(t)) \quad (4)$$

where y_j is the activity of cortical pyramidal neuron i , λ_i is the time constant of the neuron, AC_{ki} is the synaptic weight between neurons k and i obtained through Hebbian learning, P is the number of neurons, FF is the feedforward connectivity matrix established through Hebbian learning, and v_j is the activity of bulb neuron j .

The associational connections AC within cortex are established through Hebbian learning, such that neurons that code for *at least* one common odor have purely excitatory connections between them, and neurons that encode for different odors (no common odor) have purely inhibitory connections between them. The excitatory lateral connections perform pattern-completion of degraded inputs from the bulb [8], whereas the inhibitory connections introduce winner-take-all competition among cortical neurons [9].

The last component of the model involves feedback connections from the cortex to the bulb. To model these feedback connections (FB) in equation (1), we use either anti-Hebbian or Hebbian rule as follows:

$$FB = \gamma(-YV^T) \quad (\text{anti-Hebbian}) \quad (5)$$

$$FB = \gamma(YV^T) \quad (\text{Hebbian})$$

where Y is the matrix of cortical neuron outputs to different pure odors (organized as row vectors), V is the matrix of bulb

neuron outputs to pure odors (row vectors), and γ is a scaling parameter.

In the case of anti-Hebbian learning, all connections are initialized to 0. The anti-Hebbian update forms feedback connections between the cortical and the bulb neurons that respond to *at least* one common odor. The resulting feedback from cortex inhibits bulb neurons responsible for the cortical response, in a manner akin to the model proposed in [1], resulting in the temporal segmentation of binary mixtures.

In the case of Hebbian learning, all connections are initialized to -1 . The Hebbian update retains only those connections between cortical neurons and bulb neurons that respond to different odors (no common odor). The resulting feedback from cortex inhibits bulb neurons other than those responsible for the cortical response, causing cortical activity to resonate with OB activity as suggested in [3]. This type of resonance allows the model to lock onto a particular odor and suppress the background/weaker odor.

Proof of concept for this model is best illustrated with an example. Let the encoding of two simulated odors at the bulb be $OB_A=[1,0,0,1,1,0]^T$ and $OB_B=[0,1,1,1,0,0]^T$, and the encoding at the cortex be $OC_A=[1,1,0,0,0,0]^T$ and $OC_B=[0,0,1,1,0,0]^T$, respectively. Using these patterns, lateral connections in the OB (not shown in Fig 1) and associational connections within cortex (shown in Fig 1 (a)) were established through Hebbian learning as described above. Time constants were set to 10ms and 5ms for bulb and cortical neurons, respectively. Model parameters were set as follows: $\alpha=0.1$, $\beta=0.075$, and $\gamma=1$.

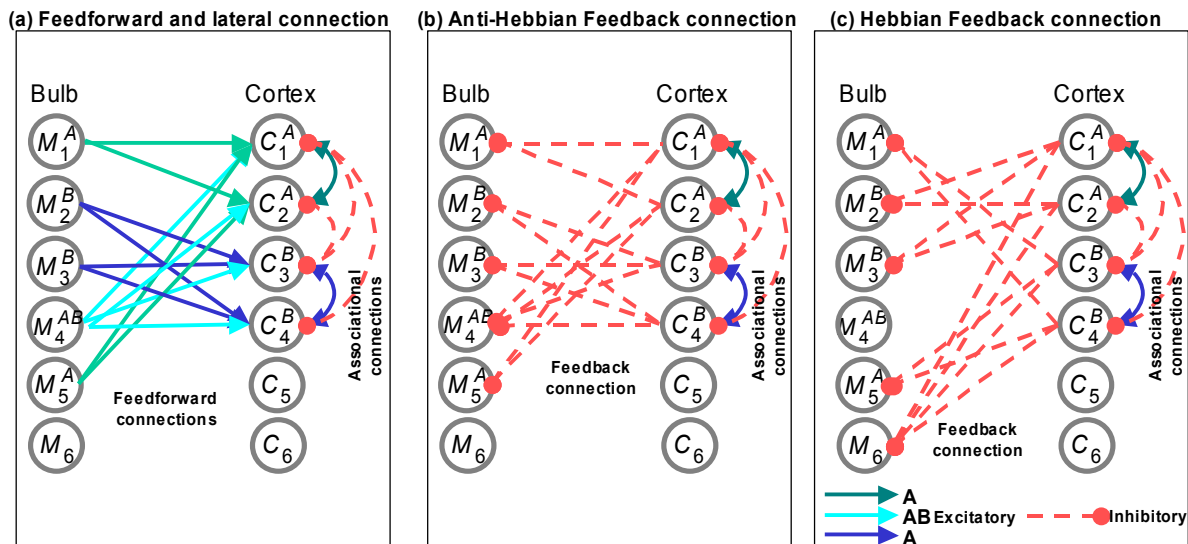


Fig 1. Bulb-cortex interaction. (a) Lateral connections in OC are learned through Hebbian updates (single analytes used for training). (b) Feedback connections established through anti-Hebbian updates. (c) Feedback connections established through Hebbian updates.

A. Case 1: Anti-Hebbian learning for temporal segmentation

Anti-Hebbian feedback connections are shown in Fig 1(b). Note that these connections are the reverse of the forward connections in Fig 1(a). Following learning with pure odors, the model is exposed to a mixture of odor A and B $[0.8,0.5,0.5,0.6,0.8,0.0]^T$. As a result of lateral inhibition, OB activity for the stronger odor A suppresses the weaker activity of odor B. Hence odor A is first recognized by the cortex. Subsequently, feedback from cortex suppresses odor A activity in the bulb, allowing odor B to win the competition. To illustrate this effect, Fig 2 shows the activity in the OB and the OC over the course of several periods. The activity of B1 and B5, which code for odor A, become out of phase with B2 and B3, which code for odor B. The common mode B4 is removed. Further, the activity of C1 and C2, which code for odor A, becomes out of phase with C3 and C4, which code for odor B. Hence anti-Hebbian learning of centrifugal projections realizes temporal segmentation of odor mixtures in both bulb and cortex.

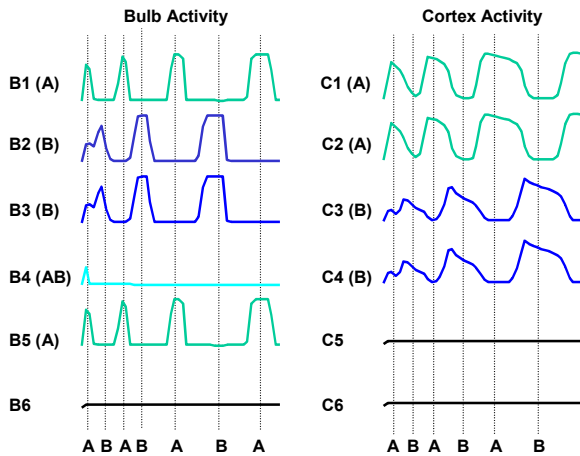


Fig 2. (a) Temporal segmentation of binary mixtures through anti-Hebbian feedback connections.

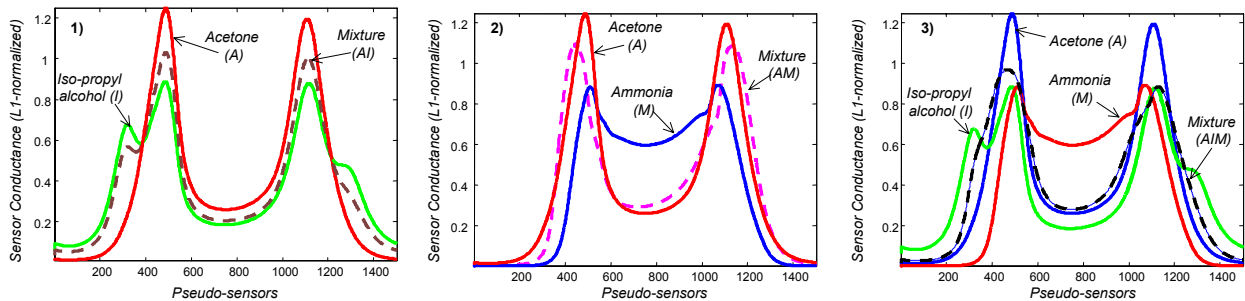


Fig 4. Temperature-modulated response of a MOS sensor to three pure analytes and their binary mixtures: (1) acetone (A), isopropyl alcohol (I) and their binary mixture (AI); (2) acetone (A), ammonia (M) and their binary mixture (AM); (3) isopropyl alcohol (I), ammonia (M) and their binary mixture (IM). Only the pure analytes were used to train the model.

B. Case 2: Hebbian learning for background suppression and resonance

Hebbian feedback connections are shown in Fig 1(c). Following learning with pure odors, the model is exposed to a mixture of odors A and B $[0.8,0.5,0.5,0.6,0.8,0.0]^T$. In this case, cortical feedback suppresses the weaker background odor (B) immediately and resonates with odor A, as shown in Fig 2.

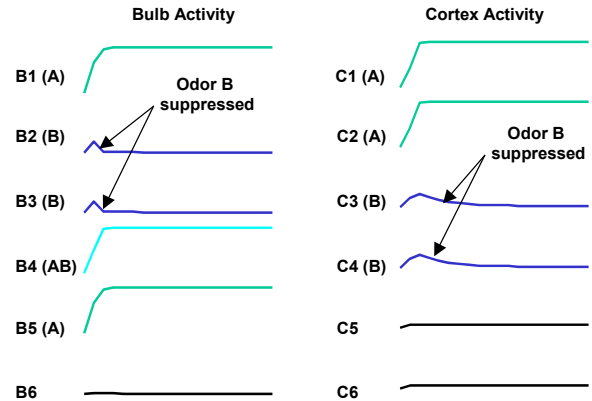


Fig 3. Suppression of background/weaker odor through Hebbian feedback connections.

III. EXPERIMENTAL RESULTS

To validate the model, we have used experimental data from an array of gas sensors exposed to acetone (A), isopropyl alcohol (I), ammonia (M), as well as their binary mixtures. Two Figaro MOS sensors (TGS 2600, TGS 2620) [10] were temperature modulated using a sinusoidal heater voltage (0-7 V; 2.5min period; 10Hz sampling frequency). The L1-normalized response of a single MOS sensor (TGS 2620) to each of these analytes is shown in Fig 4. Since the selectivity of MOS materials is dependent on the operating temperature [11], the response of the sensors at each point in the temperature cycle can be considered as a separate pseudo-sensor, and used to generate a high-dimensional odor signal.

A. Forming olfactory bulb patterns

In the biological olfactory system, the projection of olfactory receptor neurons (ORNs) in the epithelium onto the OB is organized such that ORNs expressing the same receptor gene converge onto one or a few OB neurons [12]. To mimic this convergence, we cluster the pseudo-sensors based on their selectivity, which we defined as the vector of responses across the three pure odors. Fig 5 shows the clustering of the pseudo-sensors based on their response to each of three pure odors. All the pseudo-sensors belonging to a particular cluster then project to a single olfactory bulb neuron. The input to each bulb neuron is given by:

$$I_j^O = \frac{\sum_{i=1}^N W_{ij} R_i^O}{\sum_{i=1}^N W_{ij}} \quad (6)$$

where R_i^O is the response of pseudo-sensor i to odorant O , N is the number of pseudo-sensors, and $W_{ij}=1$ if pseudo-sensor i converges to bulb neuron B_j and zero otherwise.

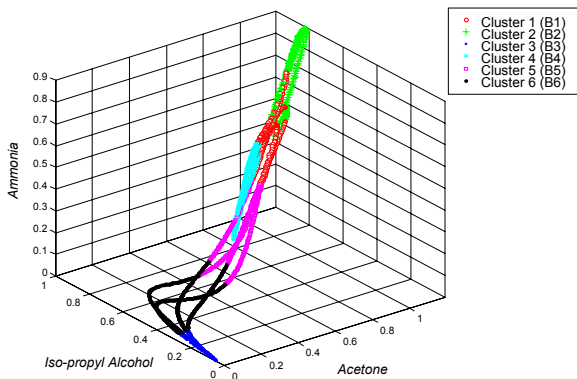


Fig 5. k-means clustering of pseudo-sensors based on their selectivity.

B. Mixture Segmentation

In order to perform binary mixture segmentation on the experimental datasets, we used a model with six bulbar neurons in the olfactory bulb, and six cortical neurons. The OB-OC network was initially trained using the three pure odors. The activity of the trained network with anti-Hebbian feedback connections when exposed to the each of two binary mixtures and the ternary mixture is shown in Fig 6 (a-c). As mentioned in section II, anti-Hebbian feedback results in the removal of bulb activity that is responsible for activity in the cortex. In case a), isopropyl alcohol is first recognized in the cortex since is the stronger odor in the mixture. Subsequently, feedback from cortex inhibits bulb neurons (B1, B6) responsible for this cortical activity, allowing acetone to be detected. Fig 7(a) shows the relationship between the activity of cortical neuron C3 and bulb neuron B6, both of which encode for isopropyl alcohol. Input from the bulb neuron B6 increases

the activity in cortical neuron C3. The cortical feedback from C3 then suppresses the activity of B6 and thereby itself, allowing the next odor to be recognized. The removal of feedback again increases activity in B6 and this cycle is repeated. Fig 7 (b) shows the negative correlation between cells C2 and C3, which represent acetone and isopropyl alcohol, respectively.

Similar behavior can be observed in case b), where acetone (the stronger odor) is detected prior to ammonia, and the activity of cortical and bulb neurons for these two odors become out of phase. In the case of iso-propyl alcohol and ammonia (results not shown), the mixture response resembles that of iso-propyl alcohol alone. As a result, the model is unable to segment the mixture into its constituents. Hence, the proposed anti-Hebbian feedback mechanism appears to be limited to the segmentation of binary odor mixtures that are relatively additive. Finally, the response of the model to the ternary mixture of acetone, isopropyl alcohol, and ammonia is shown in Fig 6 (c). The two strong components in the ternary mixture (isopropyl alcohol and acetone) are clearly detected and segmented. However, cortical neurons encoding ammonia show feeble activity, and only during the period of transition of cortical response from acetone to isopropyl alcohol.

C. Background suppression

In order to perform background suppression, the same model with six bulbar neurons and six cortical neurons was used. The OB-OC network was initially trained using the three pure odors. The activity of the trained network with Hebbian feedback connections when exposed to the each of three binary mixtures is shown in Fig 8 (a-c). In case a) and c), cortical feedback from the stronger odor (isopropyl alcohol) suppresses the weaker odor (acetone and ammonia, respectively). In case b), cortical activity for acetone suppresses the weaker odor, in this case ammonia. Hence, Hebbian feedback leads to suppression of the weaker odor in a binary mixture.

IV. CONCLUSIONS

We have presented a neurodynamic model of the bulb-cortex interaction. Depending on the type of update rule used to learn these feedback connections, Hebbian or anti-Hebbian, the model realizes background suppression or mixture segmentation functions, respectively. Anti-Hebbian feedback connections result in the identification of binary mixture components as a time series. Hebbian feedback connections allow the olfactory cortex to selectively filter the background or weaker odor input from the bulb, in analogy with the selective attention mechanism proposed by Grossberg [3]. The next stage in this research is to extend the model to the segmentation of higher mixtures, and suppression of strong background odor.

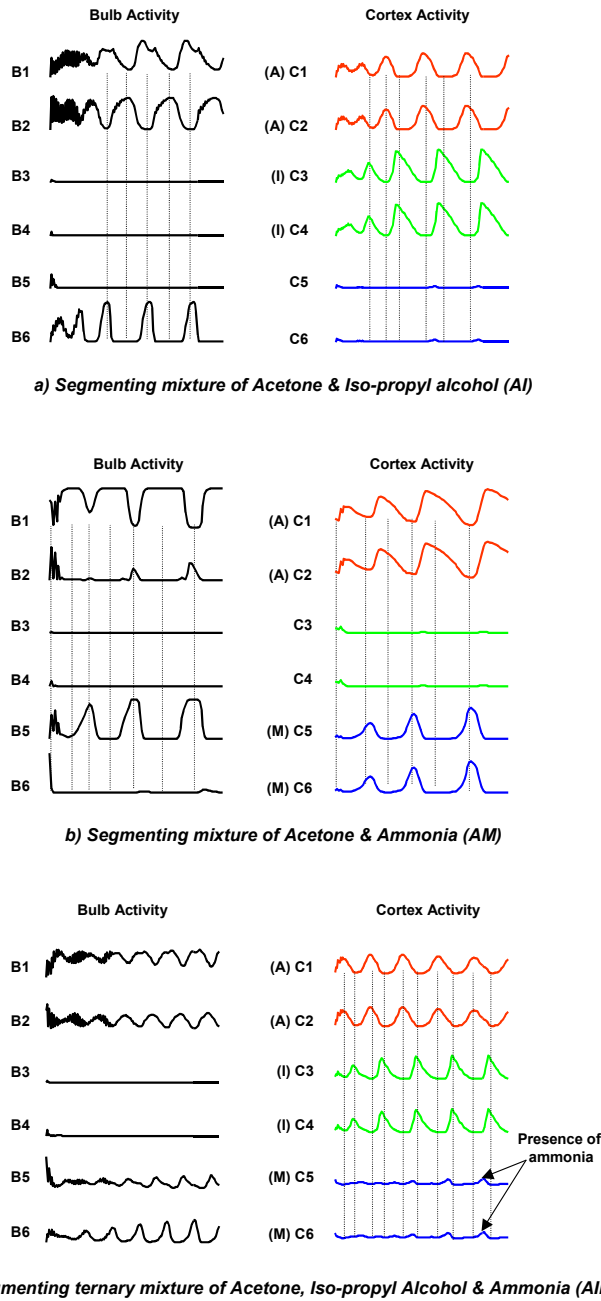


Fig 6. Segmentation of binary mixtures by anti-Hebbian cortical feedback. The parameter were set as follows: $\tau=10\text{ms}$, $\lambda=5\text{ms}$, $\alpha=0.8$, $\beta=0.6$, and $\gamma=0.4$.

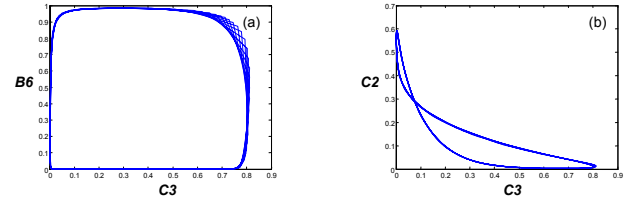


Fig 7. Evolution of activity a) C3 (coding Iso-propyl alcohol) vs. B6 (coding Iso-propyl alcohol) b) C3 (coding Iso-propyl alcohol) vs. C2 (coding Acetone).

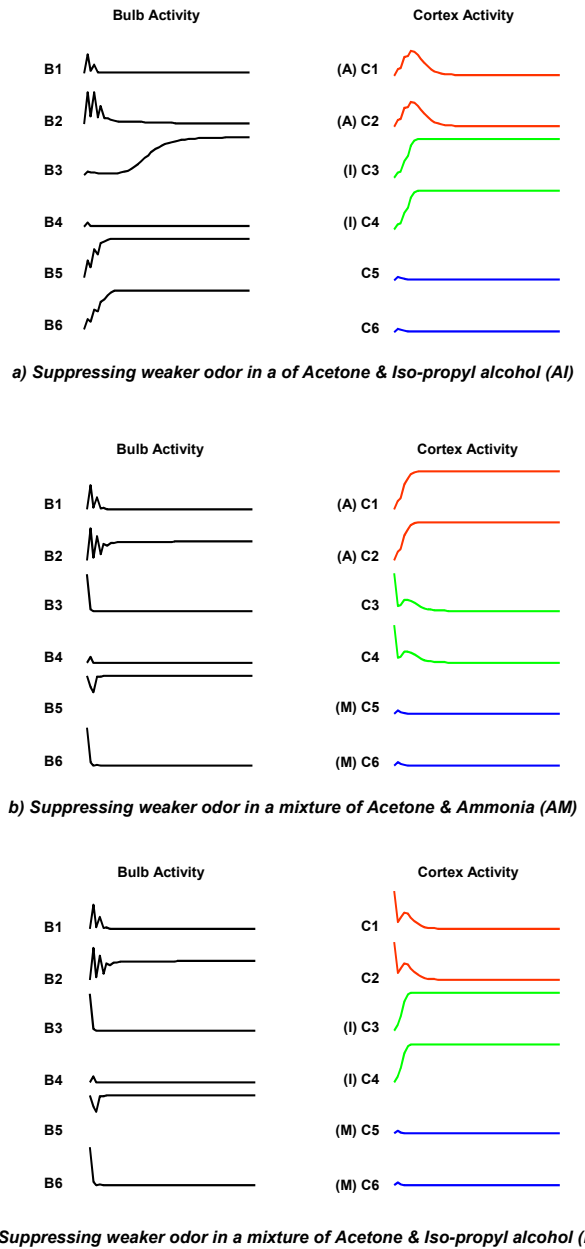


Fig 8. Suppression of weaker/background odor by Hebbian cortical feedback. The parameter were set as follows: $\tau=10\text{ms}$, $\lambda=5\text{ms}$, $\alpha=0.8$, $\beta=0.6$, and $\gamma=0.1$.

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