Odor recognition and segmentation by coupling the olfactory bulb and cortex

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Outline

- Odor recognition and segmentation problem.
- Olfactory system structure, and assumptions of functions.
- A model of the neural circuit and dynamics of the olfactory cortex.
- Odor storage, recognition, and segmentation by the model.

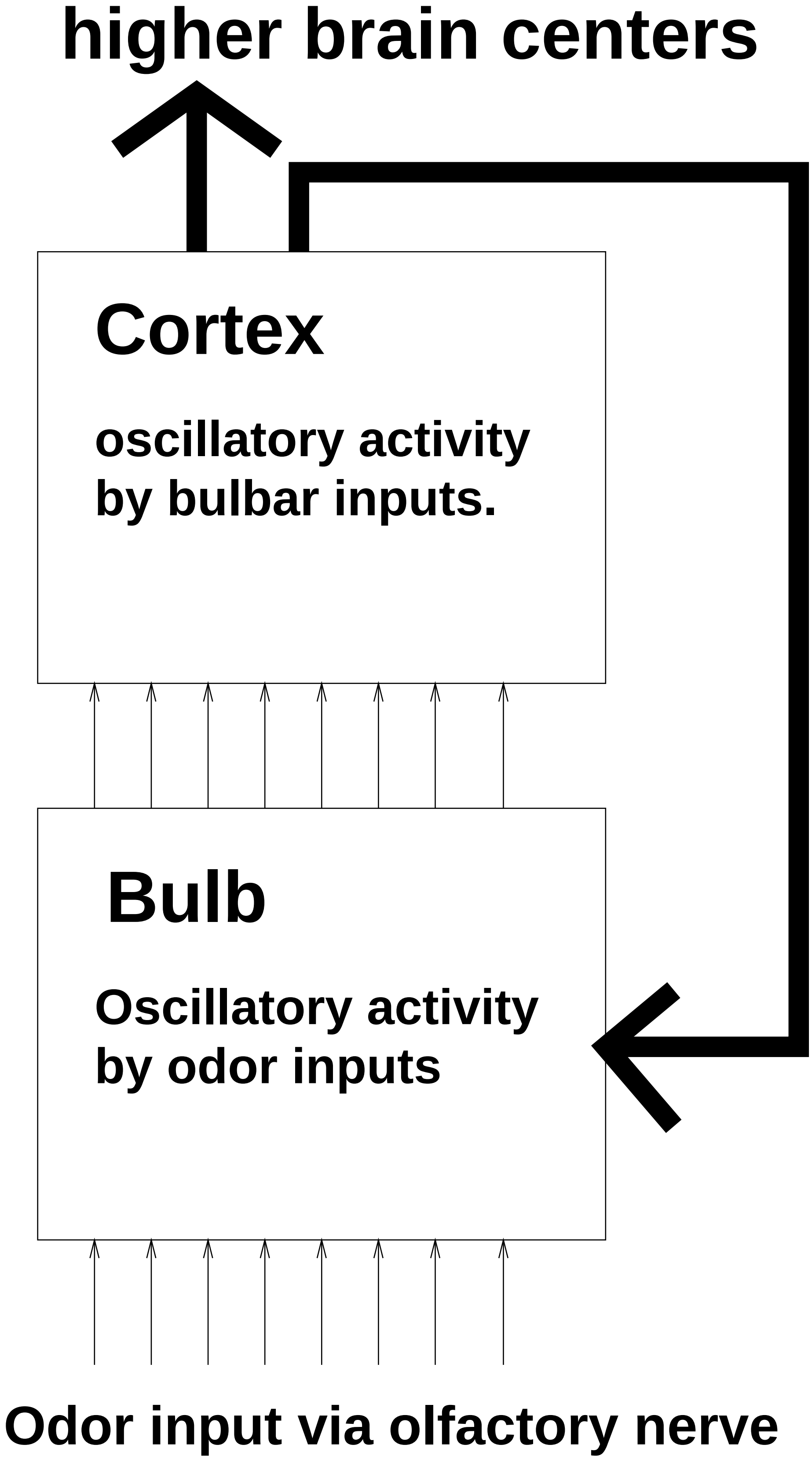
Olfactory tasks

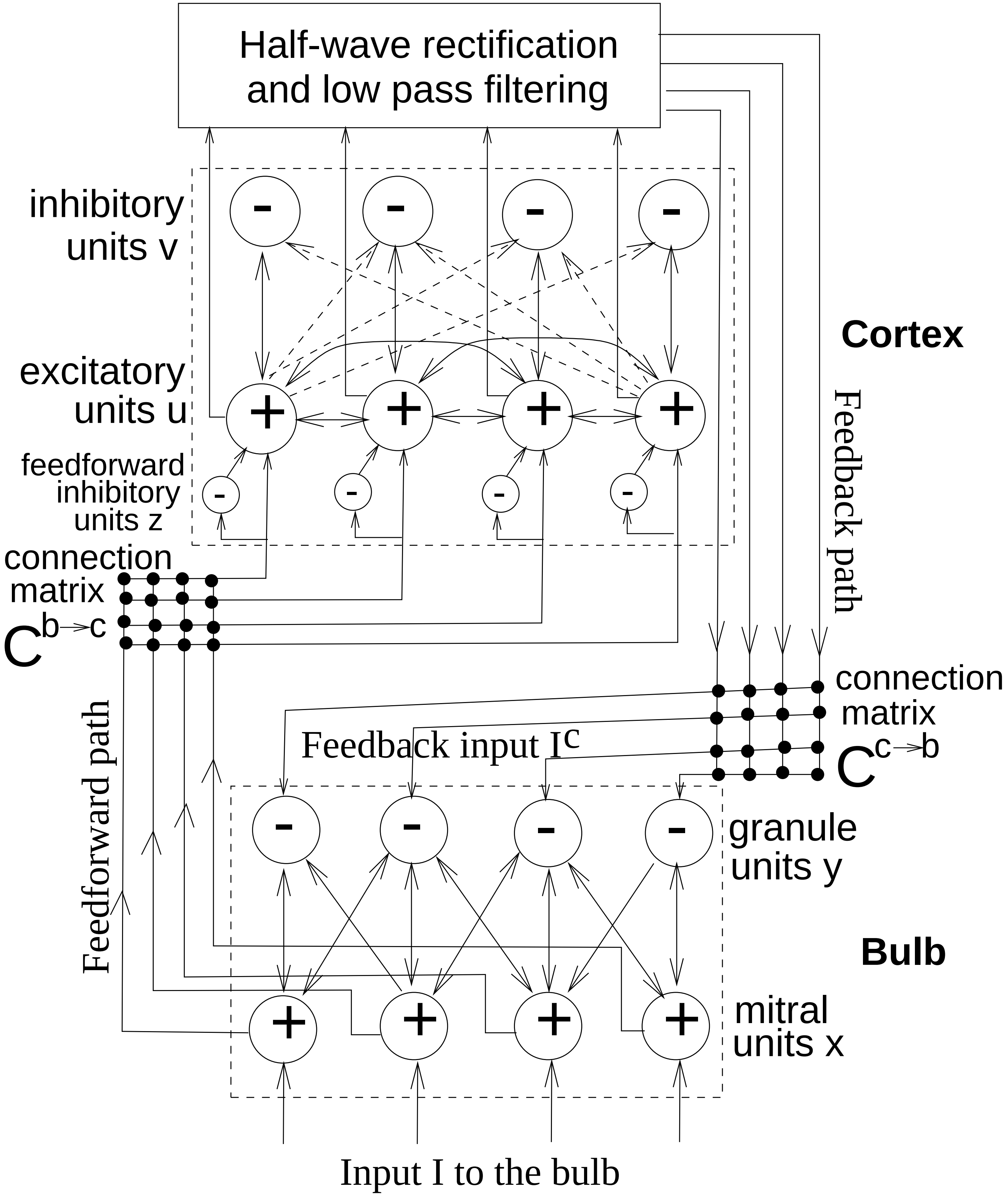
Odor (detection and) recognition

Odor segmentation — the odor environment often has odor mixtures.

Human olfactory behavior

Humans are poor at recognizing the components in an odor mixture.


higher brain centers
Cortex
oscillatory activity by bulbar inputs.
Bulb
Oscillatory activity by odor inputs
Odor input via olfactory nerve


Half-wave rectification
and low pass filtering
inhibitory
units v
excitatory
units u
feedforward
inhibitory
units z
connection
matrix
$C^{b \to c}$
Cortex
Feedback path
connection
matrix
$C^{c \to b}$
Feedback input I^c
Feedforward path
granule
units y
Bulb
mitral
units x
Input I to the bulb
-
+

Anatomy and Physiology of the olfactory system

- Odor receptors increase firing with odor intensity. Each receptor neuron has a specific sensitivity spectrum to different odor molecules.

- The glomeruli activity (input to bulb) pattern is odor specific.

- Olfactory bulb activities oscillate with inhale, terminates with exhale or pinched nose. The oscillation frequency is the same across the whole bulb in each sniff. The oscillation pattern is odor specific.

- The oscillation frequency is around 40 Hz, but breathing frequency is around 1-5 Hz.

- Odor receptors have limited adaptation to odor exposure, but response adaptation occurs in the olfactory bulb.

- the excitatory cells in the cortex send long (non-local) axons to other neurons.

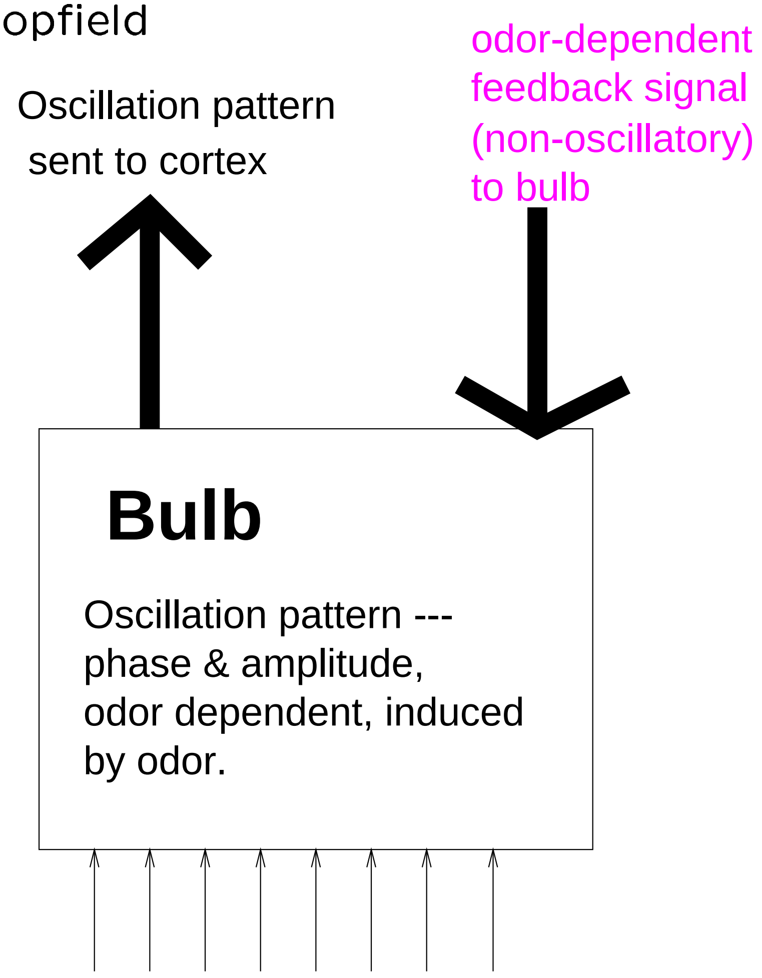
- The cortex oscillates only with inputs from the bulb.

- The cortex feeds back to the bulb, targeting mainly inhibitory interneurons. Cooling the olfactory cortex enhances the activities in the bulb.

In the model, we assume the following functions for the bulb and the cortex:

- Bulb — code odor in the global oscillatory neural activities, by the amplitude and phase patterns of the oscillation (not talked in detail today).
- Cortex — odor recognition, by resonating to the oscillatory signals from the bulb, when the oscillation matches one of the stored memories in the cortex.
- Bulb and cortex — odor segmentation through feedback from the cortex to bulb, by olfactory adaptation.

Briefly on the bulb model Previous work with John J. Hopfield



odor-dependent feedback signal (non-oscillatory) to bulb

Oscillation pattern sent to cortex

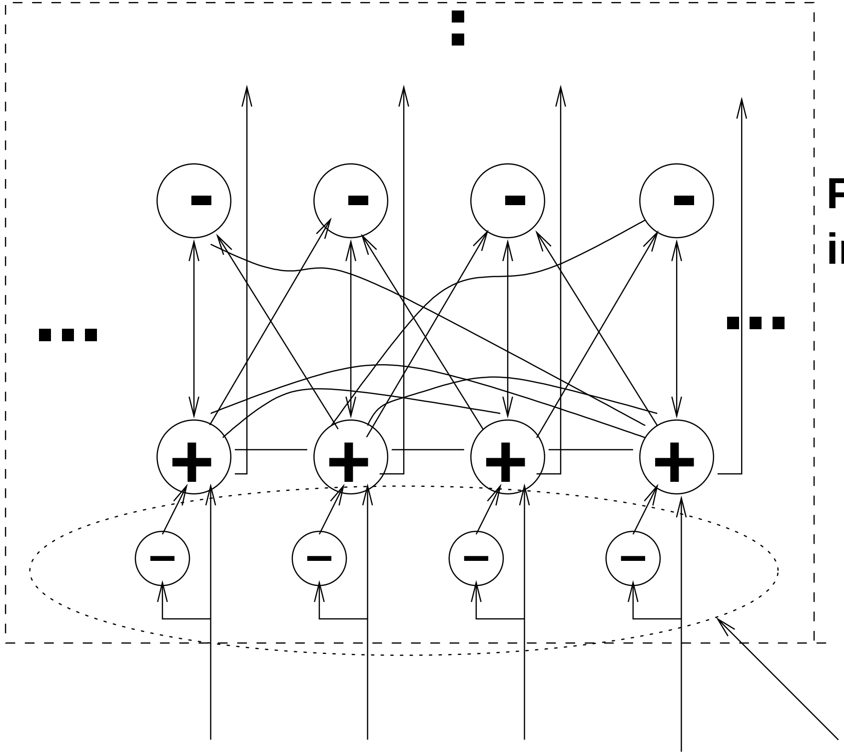
Bulb

Oscillation pattern --- phase & amplitude, odor dependent, induced by odor.

Odor input via olfactory nerve

Odor dependent, non-oscillatory Feedback to bulb inhibits bulbar activity (Gray and Skinner 1988), modeled for olfactory adaptation and segmentation.

AC signal processing — from bulb to cortex.



Cortical outputs.

Cortical circuit.

Feedback interneurons

Principal (excitatory) cells

Feedforward interneurons

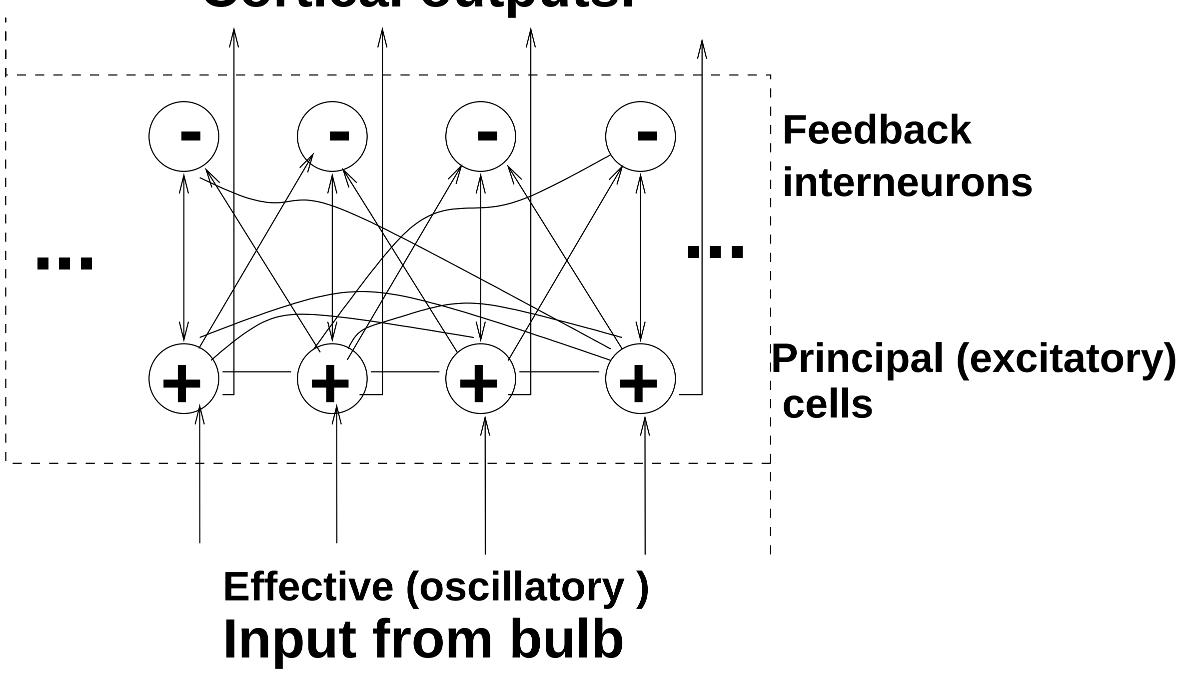
High pass

Input from bulb

The feedforward inhibitory interneuron serves to high pass the bulbar input, thus extracting the oscillatory component.

A model of the olfactory cortex

- Modeling the olfactory cortex as an associative memory.
- The memory is in the form of the oscillating patterns.
- The cortex recognizes the bulbar activities by resonance.
- The cortex constructs the feedback signal from its activities to send to the olfactory bulb for odor adaptation and segmentation.



Model the cortex as individual oscillators connected only via axons from the excitatory cells.

$$\dot{u}_i = -\alpha u_i - \beta^0 g_v(v_i) + \sum_j J^0_{ij} g_u(u_j) + I^b_i$$

$$\dot{v}_i = -\alpha v_i + \gamma^0 g_u(u_i) + \sum_j \tilde{W}^0_{ij} g_u(u_j) + I^c_i$$

individual oscillators Coupling External input

The I^b_i is mostly the AC component of the bulbar outputs.

Cortex as a coupled oscillator system driven by an input oscillatory pattern.

- Assume I_i^c fixed in time. Approximate for simplicity that each oscillator has the same fixed points under the DC signals.

- Linearize around the fixed points.

$$\begin{aligned} \dot{u}_i &= -\alpha u_i - \beta v_i + \sum_j J_{ij} u_j + I_i^b \\ \dot{v}_i &= -\alpha v_i + \gamma u_i + \sum_j W_{ij} u_j \end{aligned}$$

  Now I_i^b is strictly AC.

- Eliminating v

Oscillators $\ddot{U} + 2\alpha\dot{U} + (\alpha^2 + \beta\gamma)U$

Coupling and drive $= J\dot{U} + (\alpha J - \beta W)U + \dot{I}^b + \alpha I^b$

Storing the odor patterns in the cortex

Take $I^b, U \propto \xi^\mu e^{-i\omega t}$, then $\dot{U} \sim -i\omega U$,
$\ddot{U} = -i\omega \dot{U}$.

$$\begin{aligned} \dot{U} &+ [2\alpha + \frac{i}{\omega}(\beta\gamma + \alpha^2)]U \\ &= [J - \frac{i}{\omega}(\beta W - \alpha J)]U + \frac{i}{\omega}(-i\omega + \alpha)I^b \end{aligned}$$

The cortex resonates to I^b or ξ^μ if

$$\beta\gamma + \alpha^2 \sim \omega^2$$ Frequency match

$$J - \tfrac{i}{\omega}(\beta W - \alpha J) \sim 2\alpha|\xi^\mu >< \xi^\mu|$$ Pattern match stored

Local **Outer-product rule** (cf. Hopfield model)

Thus, if $\xi_i^\mu = |\xi_i^\mu| \exp(-i\phi_i^\mu)$

$$\begin{aligned} J_{ij} &\propto \sum_\mu |\xi_i^\mu||\xi_j^\mu| \cos(\phi_i^\mu - \phi_j^\mu) \\ W_{ij} &\propto \sum_\mu |\xi_i^\mu||\xi_j^\mu|[\omega \sin(\phi_i^\mu - \phi_j^\mu) + \alpha \cos(\phi_i^\mu - \phi_j^\mu)] \end{aligned}$$

Hebbian online learning of oscillation patterns

The outer-product oscillator coupling can be easily learned via Hebbian

$$\dot{J}_{ij} \propto u_i(t)u_j(t) \qquad \dot{W}_{ij} \propto v_i(t)u_j(t)$$

when the network state is clamped by input, i.e., J and W (long-range) connections inactive (by neuromodulatory effects) during learning — as has been suggested (Hammelmo).

With inactive J and W, $I^b \propto \xi_i^\mu e^{-\mathrm{i}\omega t} + \xi_i^{\mu *} e^{\mathrm{i}\omega t}$

$$\begin{aligned} \dot{u}_i + \alpha u_i &= -\beta v_i + \xi_i^\mu e^{-\mathrm{i}\omega t} + \xi_i^{\mu *} e^{\mathrm{i}\omega t} \\ \dot{v}_i + \alpha v_i &= \gamma u_i, \end{aligned}$$

One can easily calculate that:

$$\begin{aligned} \delta J_{ij} &\propto \int_0^{2\pi/\omega} u_i(t)u_j(t)dt \propto |\xi_i^\mu||\xi_j^\mu| \cos(\phi_i^\mu - \phi_j^\mu) \\ \delta W_{ij} &\propto \int_0^{2\pi/\omega} v_i(t)u_j(t)dt \\ &\propto |\xi_i^\mu||\xi_j^\mu|[\omega \sin(\phi_i^\mu - \phi_j^\mu) + \alpha \cos(\phi_i^\mu - \phi_j^\mu)] \end{aligned}$$

Silvia Scarpetta (Salerno University, Italy) recently joined us to study

Spike-Timing-Dependent Learning for Oscillatory Networks

Silvia Scarpetta, Zhaoping Li, John Hertz.

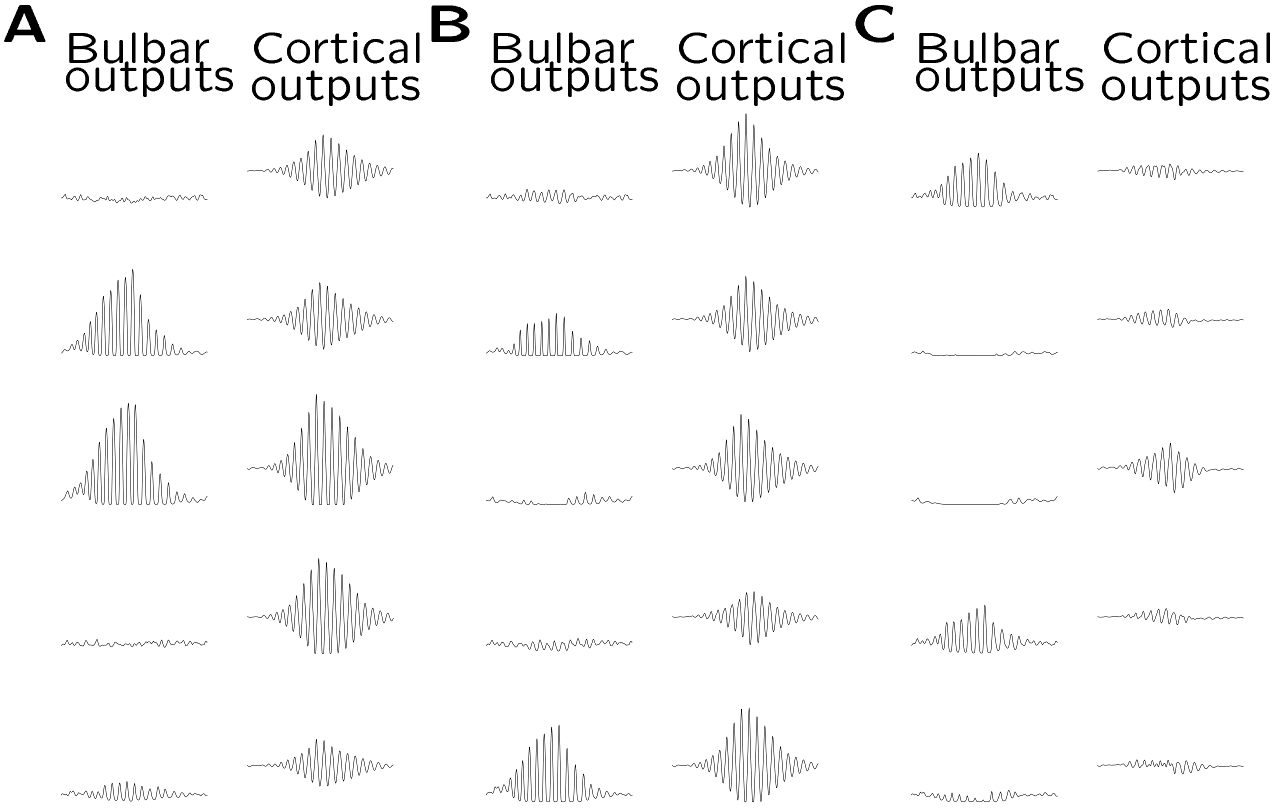
where we explore such learning in the light of experimental observations of LTP and LTD (and their dependence on the pre-synaptic and postsynaptic spike timing) in hippocampus and other cortical structures.

The properties of the associative memory

- If the number of stored patterns $P \ll N$, the cortex does not respond significantly to a random unstored pattern. This defines the storage capacity.

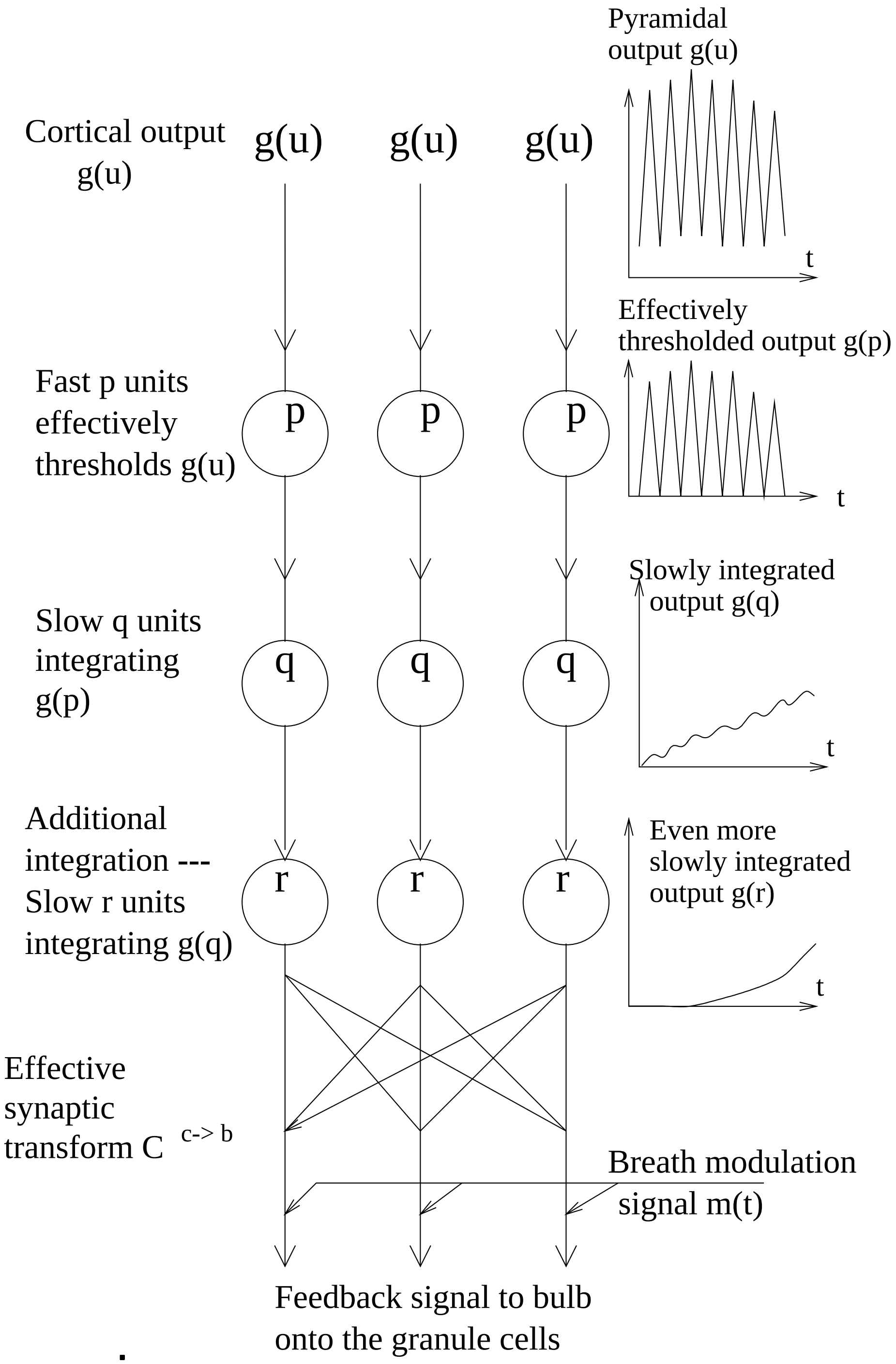
- Since the bulb is non-linear, the mixture of odor μ and odor ν gives an input pattern not the same as $\xi^{\mu} + \xi^{\nu}$. The cortex's response to the mixture looks neither like ξ^{μ} nor ξ^{ν} or the sum of them.
  — odor segmentation necessary.

Simulation Results Odor coding and recognition — the cortex resonating to the bulbar activities.



Odor A and B are stored in the memory of the cortex, but odor C is not. The bulb responds to odor A, B, C, but the cortex responds substantially only to odor A and B.

Constructing the feedback signal to bulb


Cortical output g(u)

Fast p units effectively thresholds g(u)

Slow q units integrating g(p)

Additional integration --- Slow r units integrating g(q)

Effective synaptic transform $C^{c \to b}$

Breath modulation signal m(t)

Feedback signal to bulb onto the granule cells

Pyramidal output g(u)

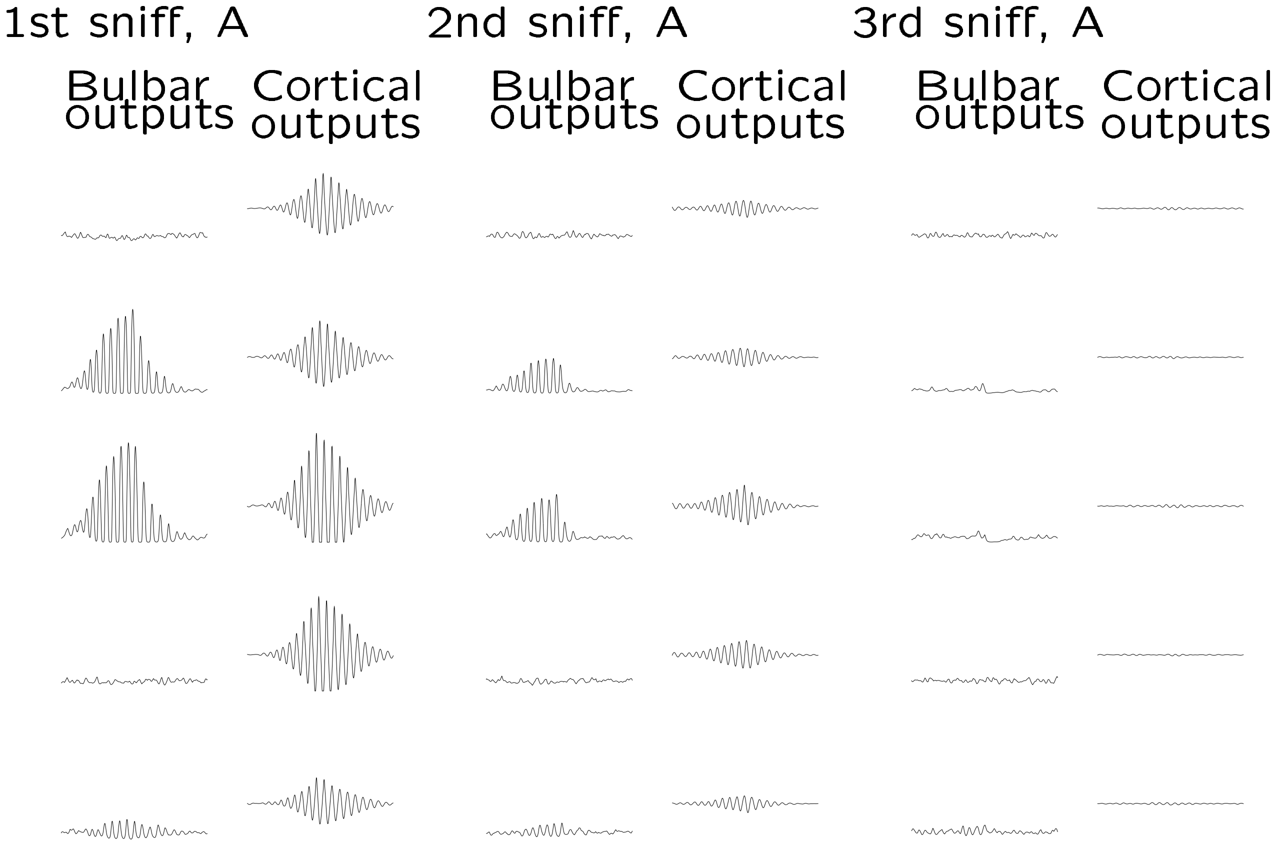
Effectively thresholded output g(p)

Slowly integrated output g(q)

Even more slowly integrated output g(r)

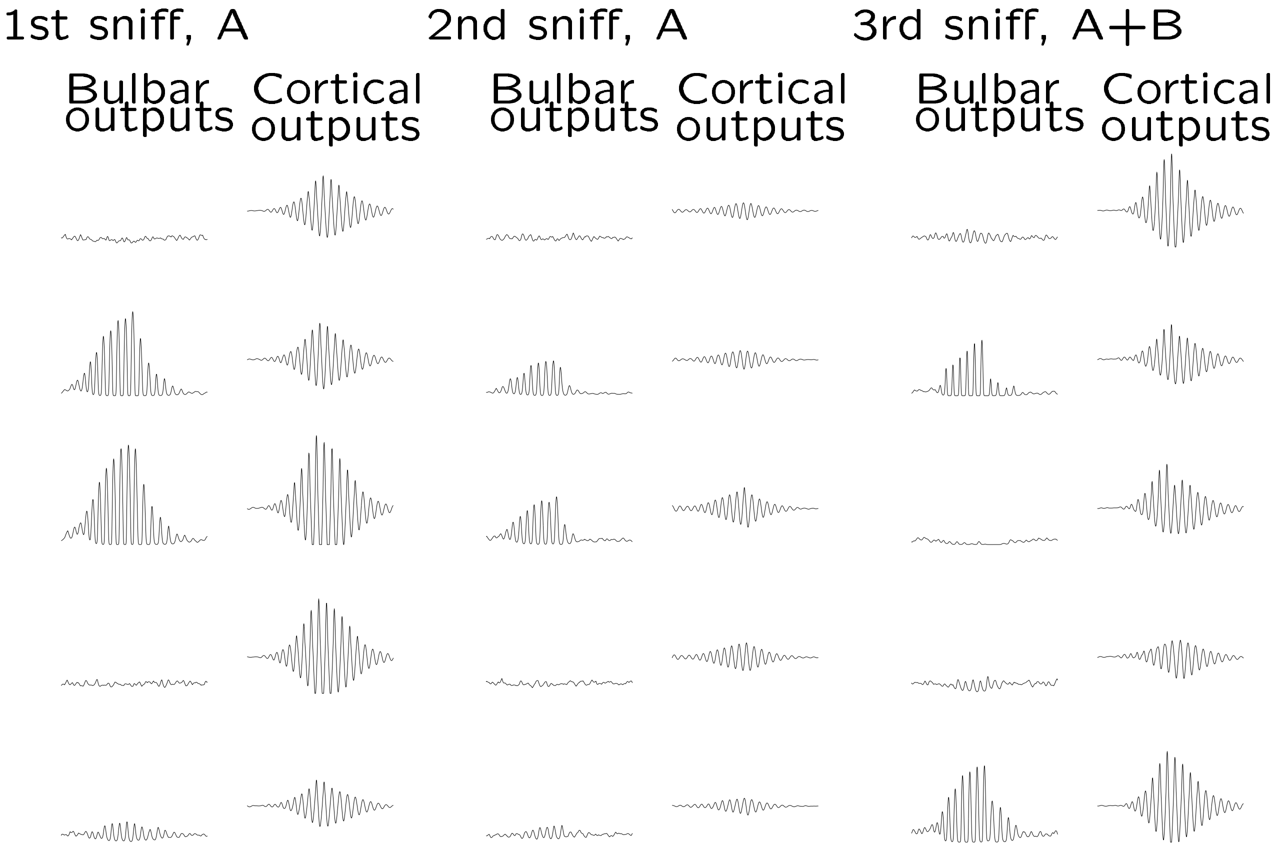
(1) Transforming the AC outputs to slow DC like signal. (2) (Approximately Linearly) Transform it to the desired feedback signal.

Simulation results — odor adaptation



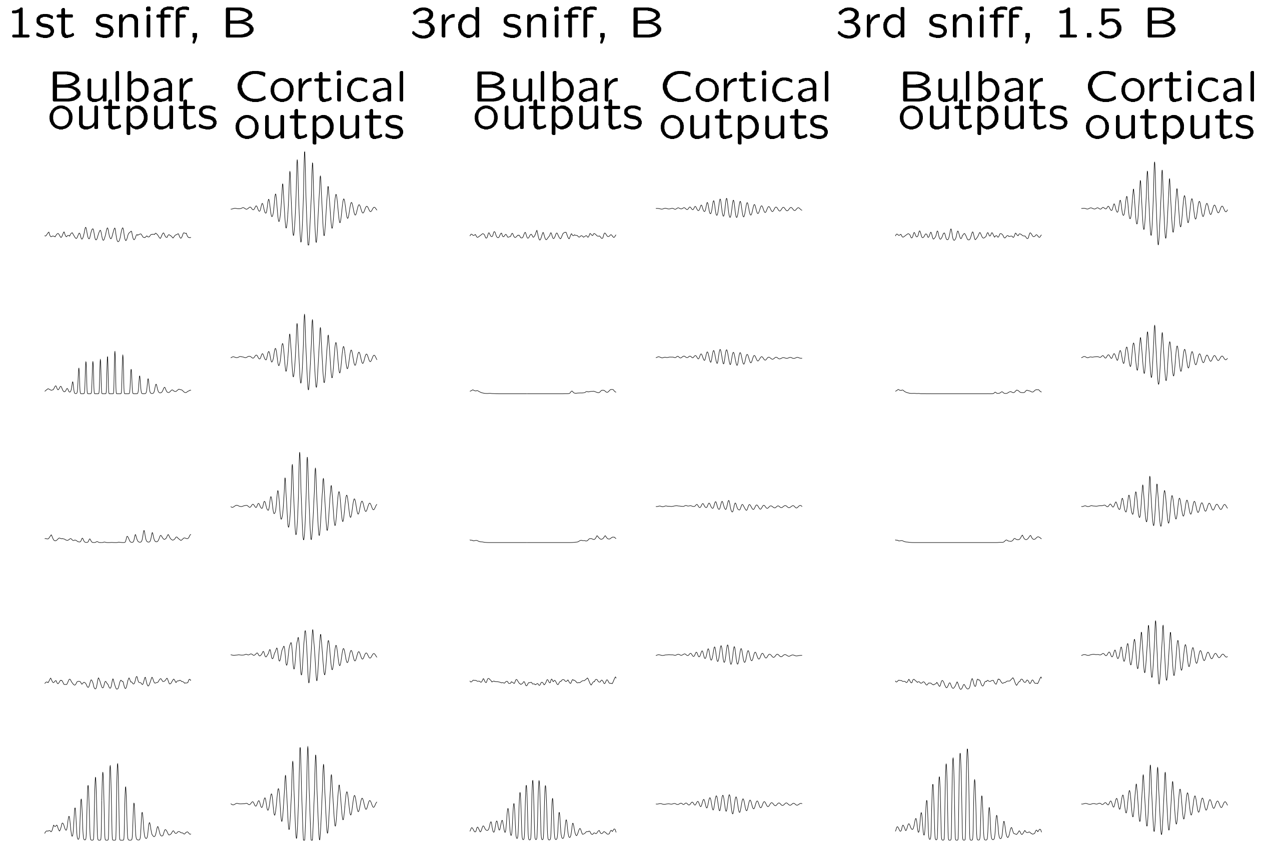
Bulbar and cortical response patterns to the 1st, 2nd, and 3rd sniff of odor A.

Simulation results — odor segmentation



Bulbar and cortical responses to odor A in the first and second sniff, and odor A+B in the third sniff.

Simulation results — cross adaptation

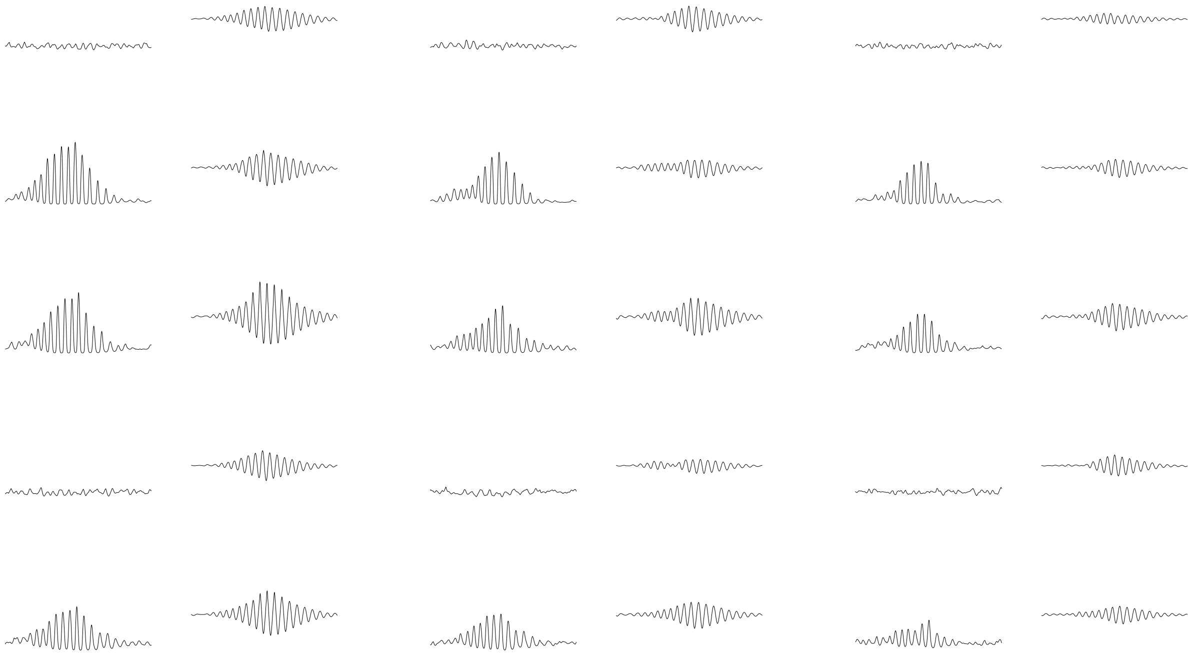


Bulbar and cortical responses to odor B (or 150% of B) with or without 2 previous sniffs to odor A.

Simulation results — responses to odor mixture (A+B)/2, adaptation is less effective

1st sniff　　2nd sniff　　3rd sniff

Bulbar outputs　Cortical outputs　Bulbar outputs　Cortical outputs　Bulbar outputs　Cortical outputs



Bulbar and cortical responses to (A+B)/2, in the 1st, 2nd, and 3rd sniffs.

Recognition — capability of adaptation

Summary

- Bulb — Odor detection and coding by oscillation
- Odor recognition by cortical resonance.
- Odor memory stored in the cortex.
- Odor segmentation by cortex-to-bulb feedback.

Predictions to be tested

- Higher center feedback to bulb is
  (1) odor dependent,
  (2) increase with odor input strengths,
  (3) have the breathing cycle time scale,
  (4) and are distributed.

- Adaptation to novel odors may be slower than adaptation to familiar odors.