Computational Diversity in a Formal Model of the Insect Olfactory Macroglomerulus

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Abstract

We present a model of the specialist olfactory system of selected moth species and the cockroach. The model is built in a semi-random fashion, constrained by biological (physiological and anatomical) data. We propose a classification of the response patterns of individual neurons, based on the temporal aspects of the observed responses. Among the observations made in our simulations a number relate to data about olfactory information processing reported in the literature, others may serve as predictions and as guidelines for further investigations. We discuss the effect of the stochastic parameters of the model on the observed model behavior and on the ability of the model to extract features of the input stimulation. We conclude that a formal network, built with random connectivity, can suffice to reproduce and to explain many aspects of olfactory information processing at the first level of the specialist olfactory system of insects.

Introduction

We study the detection of sexual pheromones by insects, with a view to the more general modeling of the olfactory pathway. We use the known anatomical data of the olfactory system, and retain the level of detail we deem necessary to produce biologically relevant behavior. Thus, we do not attempt to represent the particulars of dendritic passive propagation, or the precise local input-output functionality of individual synapses. We model them by simple ingredients such as propagation delays and activation thresholds. Precise biological data on the wiring is not available, therefore we introduce randomness in the connectivity.

A variety of approaches to the modeling of olfactory systems have been presented thus far: the pioneering work of Rall and Shepherd (1968) exploits a wealth of detail concerning the precise shape of mitral cell dendrites in order to compute electrical potentials; Wilson et al (Wilson & Bower 1988; Wilson & Bower 1989; Haberly & Bower 1989) replicate certain basic features of responses by extensive simulations of larger cell sets exploiting the same data; Lynch and Granger (Lynch et al. 1989; Lynch & Granger 1989) study associative memory and synaptic adaptation in piriform cortex, including considerable detail about synaptic processes, and a Hebb-type learning rule; Li and Hopfield (1989) attempt to abstract a set of relevant parameters from the biological details of the olfactory modular organization, with a highly simplified model: interneurons are lumped into single variables. In contrast, we study the individual and collective behavior of neurons whose dendrites make contacts within the so-called *macroglomerulus* (or macroglomerular complex MGC), which is responsible for sexual pheromone recognition. The aim of our work is to analyze the emergence of the responses necessary for odor recognition and localization.

Biological background

In the olfactory system of insects, two sub-systems process behaviorally important odor classes: the *specialist* subsystem detects sexual pheromones, while the *generalist* subsystem recognizes food odors (for a review see (Masson & Mustaparta 1990)). In the following, we focus on the specialist subsystem. It receives information from *sensory neurons*, which are sensitive to non overlapping molecule spectra ("labelled lines"). The axons of sensory neurons project onto the antennal lobe *local interneurons*, which possess no axons, and onto the antennal lobe *projection* or *output neurons*. The latter transfer signals to other centers for further integration with other sensory modalities. The huge convergence between pheromone sensitive and projection neurons, which Ernst and Boeckh (1983) estimate as 5000:1 in the cockroach, leads to a characteristic spatial organization of all synaptic connections in sub-assemblies termed *glomeruli,* which are identifiable and species-specific. In the case of interest to us, (e.g. in certain moth species and in the cockroach), this reduces to a single MGC (Figure 1).

We use data pertaining to the moth species *Manduca sexta* and to the cockroach *Periplaneta americana* (for reviews see (Christensen & Hildebrand 1987a; Boeckh & Ernst 1987)). The complex responses to stimulation by pheromone blends, as observed intracellularly in projection neurons, indicate that integrative processes take place in the

MGC. In the moth, the depolarization of a local interneuron can cause inhibition of background activity in a projection neuron. There is also evidence that *local* interneurons are responsible for much or all of the inhibitory synaptic activity (Christensen & Hildebrand 1987b). Furthermore, the long-latency excitation exhibited by some projection neurons suggests that polysynaptic pathways are present between pheromone-responsive primary afferent axons and the projection neurons. In fact, it has been demonstrated, in the cockroach, that the receptor axons synapse mainly with local interneurons (Boeckh et al. 1989; Distler 1990).

The formal model

Neurons may be at rest (x=0) or above firing threshold (x=1). They are probabilistic neurons with memory: the probability $P[x_i(t)=1]$ that the *state* $x_i(t)$ of neuron i at time t is 1 is given by a sigmoid function of the neuron *membrane potential* $v_i(t)$ at time t :

$$P[x_i(t)=1] = \frac{1}{1+e^{-[v_i(t)-\Theta_i]/T}},$$

which is biased by a positive threshold Θ_i, and where T is a parameter, called temperature, which determines the amount of noise in the network (random fluctuations of the membrane potential).

In discrete time, the fluctuation of the membrane potential around the resting potential, due to *input* $e_i(t)$ at its postsynaptic sites, is expressed as:

$$v_i(t) = (1 - \frac{\Delta t}{\tau_i}) * v_i(t-\Delta t) + \frac{\Delta t}{\tau_i} * e_i(t-\Delta t)$$

where τ_i is the membrane time constant, and Δt is the sampling interval, with:

$$e_i(t) = \Sigma\ [w_{ij} * x_j(t - r_{ij})]$$

where w_{ij} is the weight of the synapse between neuron j and neuron i, and r_{ij} is its delay. The weights are binary. The value of the transmission delay associated with each synapse is fixed but chosen randomly; it is meant to model all sources of delay, transduction and deformation of the transmitted signal from the cell body or dendro-dendritic terminal of neuron j to the receptor site of neuron i. The mean value of the delay distribution is longer for inhibition than for excitation: we thereby take into account approximately the fact that IPSC's usually have slower decay than EPSC's, and may accumulate to act later than actually applied.

We consider three types of neurons: receptor, inhibitory and excitatory. Two types of receptor neurons (A and B) are sensitive only to input A or B, where A and B represent two odor components. For all A (resp. B) type receptor neurons, we have $e_i(t) = A(t)$, (resp. $B(t)$), where $A(t)$ is the concentration of component A. Receptor neurons may make axo-dendritic ($r_{ij} = 0$), excitatory synapses with both types of interneurons.

Interneurons may make dendro-dendritic synapses ($r_{ij} \neq 0$) with any other interneuron, but the connectivity c will be sparse.

Results

To analyze the behavior of such network, we first introduce a classification of the possible response patterns of the neurons, which has been found useful for the analysis of olfactory response patterns (Meredith 1986; Kauer 1974; Fonta et al. 1991).
In the network under investigation[1], which exhibits a typical distribution of response patterns, we observe three classes of patterns: purely excitatory, purely inhibitory, and mixed (both inhibitory and excitatory) responses. Excitation and inhibition are defined in relation to the neuron spontaneous activity. The mixed response patterns subdivide into three groups, according to the relative durations of the inhibition and excitation phases (Figure 2A, 2B).
We analyze the behavior of the network in response to four characteristics of the input patterns (pure odors, A or B, and mixed odors, A and B), which are behaviorally important (see (Kaissling & Kramer 1990)): (1) amplitude, (2) stimulus shape, (3) frequency of stimulus presentation, (4) ratio of the components in mixed odors. The behavior of the model network exhibits several characteristics that agree with biological data: selective neurons respond to only one of the two odor components, non-selective neurons respond to both components. The neurons exhibit a limited number of response patterns, most of them a combination of excitation and inhibition (Figure 3A, 3B).
The recognition of the concentration ratio of odor components is of behavioral importance, but it is not known whether the detection of a precise ratio is achieved at the level of the glomerulus or at higher olfactory centers. Here, we observe amplitude and temporal variations of the response patterns of individual interneurons as a function of the concentration ratio. Interneurons with oscillatory responses code, by temporal changes in their response patterns (Figure 4A), for ratio variations of the input stimulation. In addition, pairs of neurons respond simultaneously to mixed input of a specific input ratio: in contrast, the first spikes of the responses to other ratios are separated by 25-50 ms; thus, the response latency could be one of the response parameters which indicate ratio detection (Figure 5).

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[1] 50 neurons; connectivity c=10% (190 synapses); synaptic strength w_{ij}=+1/ -1; 30% receptor neurons, 30% excitatory interneurons, 40% inhibitory interneurons; sampling step Δt=5 ms, which is enough to study the maximal physiological spiking frequencies (Christensen et al. 1989a); membrane time constant τ_j=25 ms; synaptic delays are chosen from a uniform distribution between 10 ms and 50 ms for excitatory synapses, and between 10 and 100 ms for inhibitory synapses; the parameters of the sigmoids are T=1 and Θ=1 for receptor neurons, T=0.375 and Θ=1.5 for the others.

The odor plume formed downwind from the calling female possesses a highly variable structure. Pulsed stimulation improves a male moth ability to orient towards an odor source (Baker et al. 1985; Kennedy 1983). We have therefore observed the behavior of the interneurons in response to pulsed stimulation. We find that some interneurons cannot follow pulsed stimulation beyond a specific cut-off frequency (Figure 4B). The ability of these neurons to detect a certain frequency range depends on their response pattern; the cut-off frequency of each neuron depends on the duration of the stimulation and on the interstimulus interval. Neurons that respond with mixed excitation and inhibition show irregular responses and cannot follow high frequency stimulation. Neurons that respond with excitation mostly respond continously to high frequency stimulation. These behaviors depend mainly on the relations between the stimulation frequency, the interstimulus interval, and the temporal parameters of the model. Synaptic delays determine the behavior of mixed responses, while membrane time constants determine the behavior of excitatory responses.
The stimulus profiles (rise and fall times of the odor signal) indicate — irrespective of the stimulus concentration — the distance between the location of odor perception and the odor source. We observe a number of interneurons that reflect the profile of the stimulation irrespective of its concentration. This depends again on the response patterns; neurons that exhibit purely excitatory responses reflect the input profile by response latency and response duration, whereas neurons that exhibit an oscillatory response have completely different temporal response patterns as a function of the input profile (Figure 4C).

In this section, we have shown that the response patterns of individual neurons reflect various characteristics of the input pattern. Selective neurons indicate the presence, amplitude, and stimulus profile of one component (depending on their response pattern); non-selective neurons indicate the presence, amplitude, and stimulus profile of the mixture of the two components. Some non-selective neurons also reflect the quality of the mixture, that is, the ratio of the components.

Influence of the distribution of neurons and synapses

The number and the diversity of the response patterns depend on the total number of neurons, on the distribution of excitation and inhibition in the network, on the number of connections and feedback loops, and on the temporal parameters (i.e. synaptic delays, membrane time constants).
The diversity of response patterns grows with the percentage of synapses in the network (all other parameters remaining unchanged). At connectivity $c<2\%$, afferent synapses cause purely excitatory responses (R1); around $c = 2\%$, simple mixed responses (R2) and

inhibitory responses (R6) appear; at about c = 8%, the majority of the interneurons respond mainly with excitation (R1 and R2). The full diversity and distribution of response patterns described above is observed for most networks around c = 10%. With an increasing number of synapses, the number of response patterns decreases. Due to an increasing network activity, the response patterns tend to oscillate, and the network saturates.

Similarly, increasing the inhibitory synapse number beyond fifty percent introduces oscillations, the total activity in the network decreases. Beyond 60% inhibition, only R3 responses (phasic burst followed by a long inhibitory period) survive. If there is too much excitation in the network (more than forty percent excitatory neurons or more than forty percent receptor neurons), the network becomes unstable and saturates .

Discussion

In this section, we discuss the relevance of the results to the specialist system of insects. The model exhibits several behaviors that agree with biological data, and it allows us to state several predictive hypotheses about the processing of the pheromone blend.

In the model, we observe two broad classes of interneurons: selective (to one odor component) and non-selective neurons. The fact that a distinct representation of pheromone components in parallel pathways coming from the antenna is preserved by some antennal lobe neurons (local interneurons and projection neurons), but not all of them, has been reported in several species: in moths (Manduca sexta (Christensen & Hildebrand 1987a, 1987b, 1989b)), (Bombyx mori (Olberg 1983)), and in the cockroach Periplaneta americana (Boeckh 1976; Burrows et al. 1982; Boeckh & Selsam 1984; Hösl 1990).

Selective neurons and non-selective neurons exhibit a variety of response patterns, which fall into three classes: inhibitory, excitatory and mixed. Such a classification has indeed been proposed for olfactory antennal lobe neurons (local interneurons and projection neurons) in the specialist olfactory system in Manduca (Christensen et al. 1989a; Christensen & Hildebrand 1987a; 1987b). Similar observations have been reported for Bombyx mori (Olberg 1983) and for the cockroach (Burrows et al. 1982; Boeckh & Ernst 1987).

In our model we observe a number of local interneurons that cannot follow pulsed stimulation beyond a neuron-specific cut-off frequency. This frequency depends on the neuron response pattern and on the duration of the interstimulus interval. These results agree with data pertaining to antennal lobe neurons (interneurons and projection neurons) in Manduca sexta (Christensen & Hildebrand 1988) and in Heliothis virescens (Christensen et al. 1989b). In both species, some antennal lobe neurons follow pulsed input with phasic bursts up to a cut-off frequency

Physiological evidence in several species (Christensen & Hildebrand 1987b; Burrows & et al 1982) has led to the hypothesis that some projection neurons (or local interneurons), may code for pheromone concentration and quality by measuring differences in response latency and duration, instantaneous spike frequency, and total number of spikes. Furthermore, the overall response to the correct blend of pheromones may be qualitatively different from the response to some other ratio of pheromones (Christensen & Hildebrand 1987b). Our model exhibits characteristics (Figure 4A, 5) which could substantiate these suggestions. They will be analyzed and discussed in more detail in a forthcoming publication.

Conclusion

We have presented an original model of olfactory information processing in the macroglomerulus of insects. This model incorporates very simple ingredients; its connectivity is chosen randomly, from distributions which take into account complete, albeit approximate, biological knowledge. From these simple assumptions, a variety of neuronal responses emerge, some of them strongly resembling those observed in living systems. Our model performs feature extraction on the signal represented in separate input lines. A number of features concerning the single odor components as well as their blend are represented in parallel lines by the interneuron network. These results agree with the hypothesis that there are "separate but parallel lines of olfactory information flow between the antennal lobe and the protocerebrum, each line carrying information about different aspects of a pheromonal stimulus" (Christensen et al 1989a). The use of random connectivity and synaptic delays gives us a means to study the conditions under which such feature extraction can arise, and the diversity of output patterns that are thereby exhibited. Thus, a model built with random connectivity suffices to explain, reproduce and predict a number of signal processing properties on the olfactory specialist sub-system. The variation of random distribution parameters and delays gives insights into the means whereby natural neural nets may be modulated by higher control mechanisms, be they genetic, adaptive or instructive.

Acknowledgements

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FIGURE CAPTIONS

Figure 1: Schematic representation of the specialist olfactory system. In the macroglomerulus, receptor cell axons connect with local interneurons (restricted to the antennal lobe), and with projection neurons, which convey information to higher centers.

Figure 2A: Response patterns: the amount of activation and inactivation is shown as a function of the stimulation (there $\Delta t = 5$ ms).

- R1: Activation for the duration of the stimulation. The spiking frequency varies as a function of the amplitude of the input.
- R2: The activation is followed by an inactive phase after the end of the stimulation.
- R3: Phasic burst, followed by an inactive phase of the same duration as the stimulus.
- R4: Phasic burst, followed by a tonic phase of diminished activation or by a phase of non-response, and by a short inactive phase after the end of the stimulation.
- R5: Phasic burst, followed by several phases of inactivation and activation (oscillatory response).
- R6: Inactivation during the application of the stimulation. The amplitude of the negative potential is a function of the amplitude of the stimulation.

Figure 2B: Neurons responding with R1 - R6 (duration of each stimulation: 200 ms).

Figure 3: Responses of selective (3A) and non-selective (3B) neurons to stimulation with one and both odors (duration of each stimulation: 200 ms).

Figure 4: Responses of selective and non-selective neurons with varying response patterns to stimulation with varying input characteristics:

4A: Stimulation with varying ratios of the input components, the sum of the amplitudes of the two components being constant. Several neurons respond with varying temporal response patterns to changing ratios (duration of each stimulation: 50 ms).

4B: Neuron 7 responds with phasic bursts to stimulation at low frequencies, and responds continually to stimulation at the same frequency but with shorter inter-stimulus intervals, because the interstimulus interval approches the membrane constant of the neuron (upper diagram: stimulation duration 30ms, interstimulus interval 20ms; middle diagram: stimulation duration 40ms, interstimulus interval 10 ms; bottom diagram: stimulation duration 20ms, interstimulus interval 10ms).

4C: Stimulation by input with varying profiles, the rise and fall times vary from 10 ms to 50 ms (stimulation duration 100ms).

Figure 5: Importance of response latencies for ratio detection (stimulation duration 50ms).

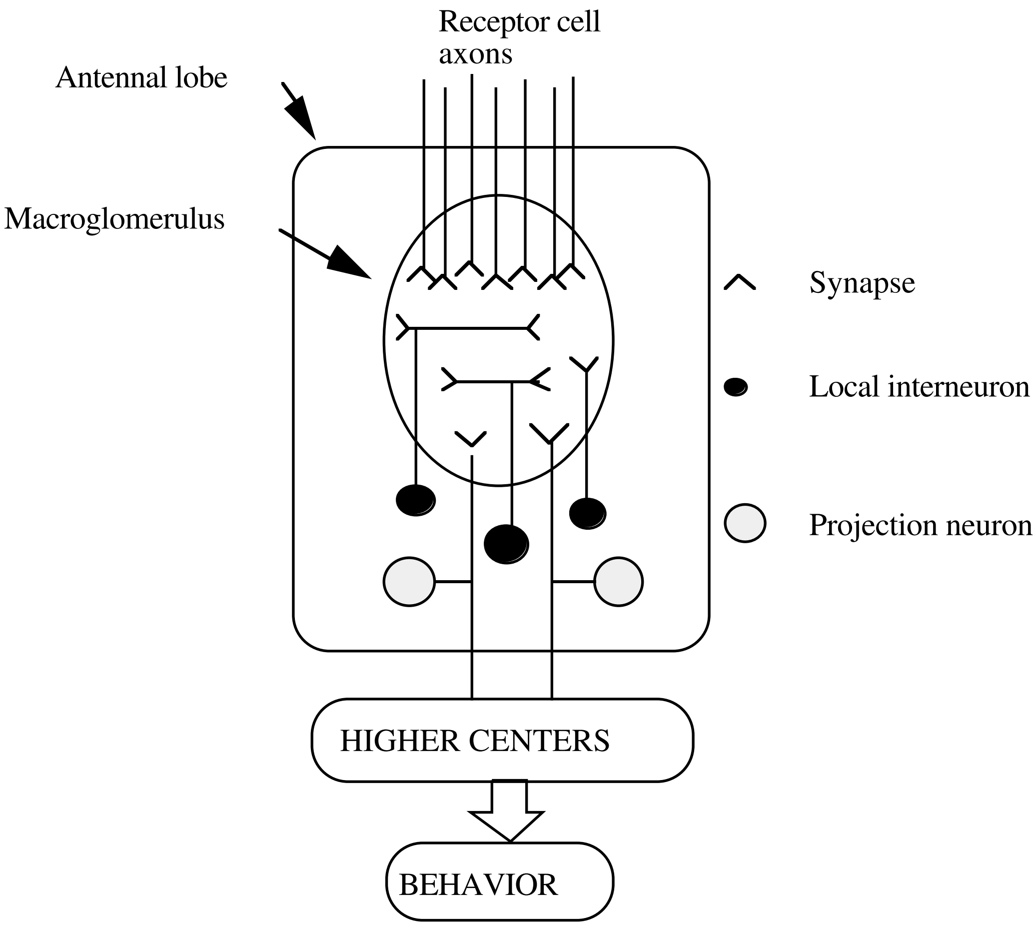
Receptor cell
axons
Antennal lobe
Macroglomerulus
Synapse
Local interneuron
Projection neuron
HIGHER CENTERS
BEHAVIOR

FIGURE 1

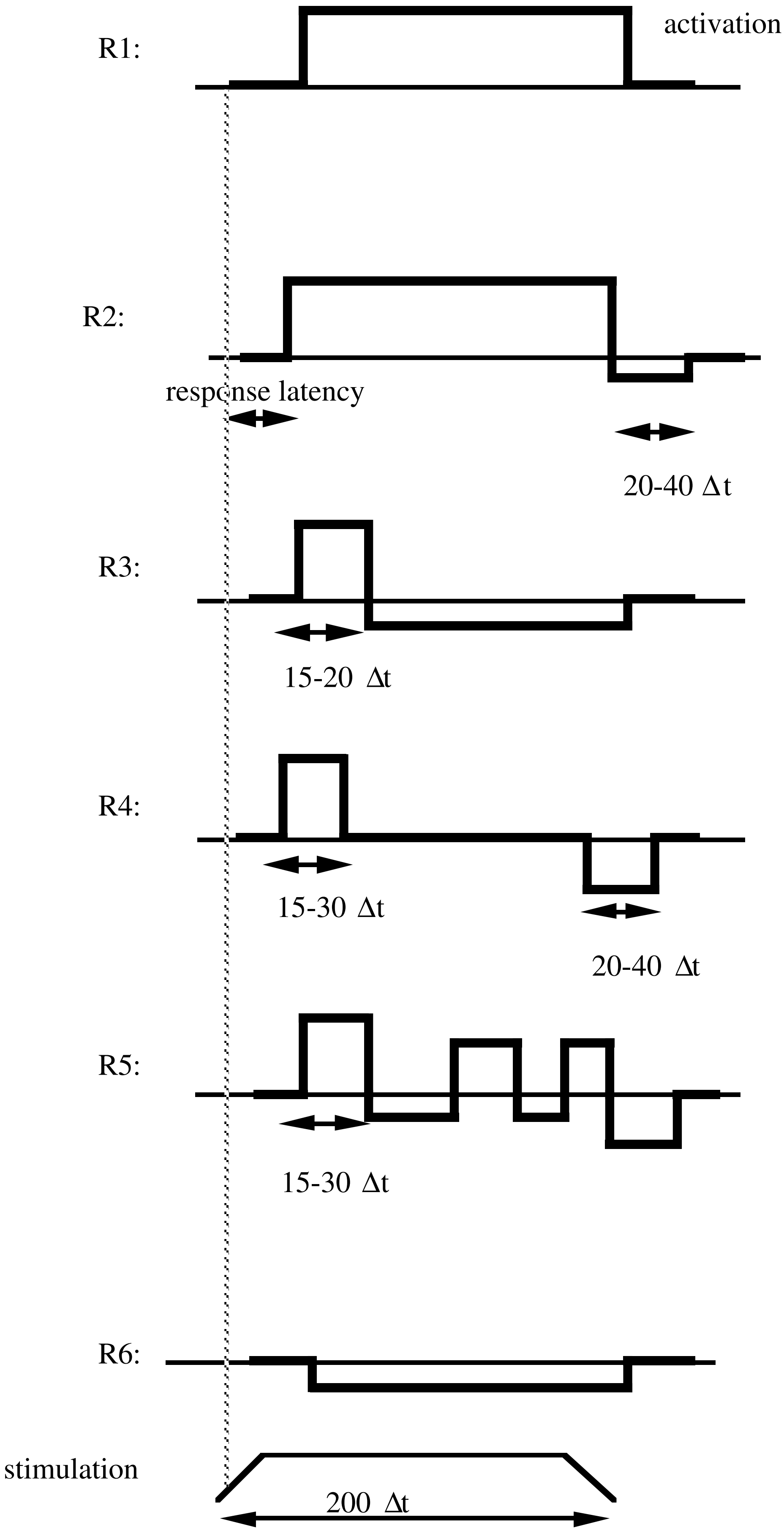
R1:
activation
R2:
response latency
20-40 Δt
R3:
15-20 Δt
R4:
15-30 Δt
20-40 Δt
R5:
15-30 Δt
R6:
stimulation
200 Δt

FIGURE 2A

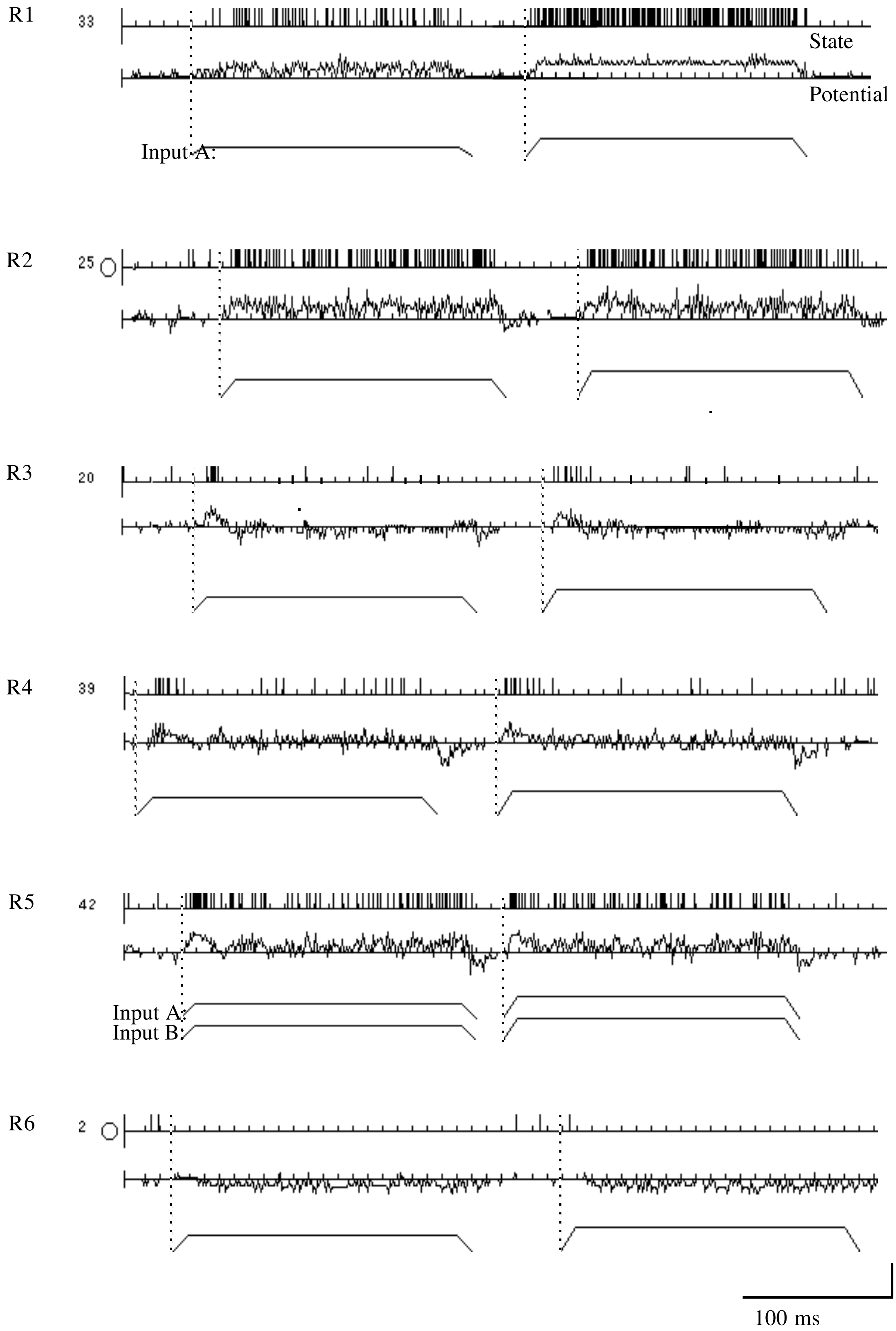
R1
33
State
Potential
Input A:
R2
25
R3
20
R4
39
R5
42
Input A:
Input B:
R6
2
100 ms

FIGURE 2B

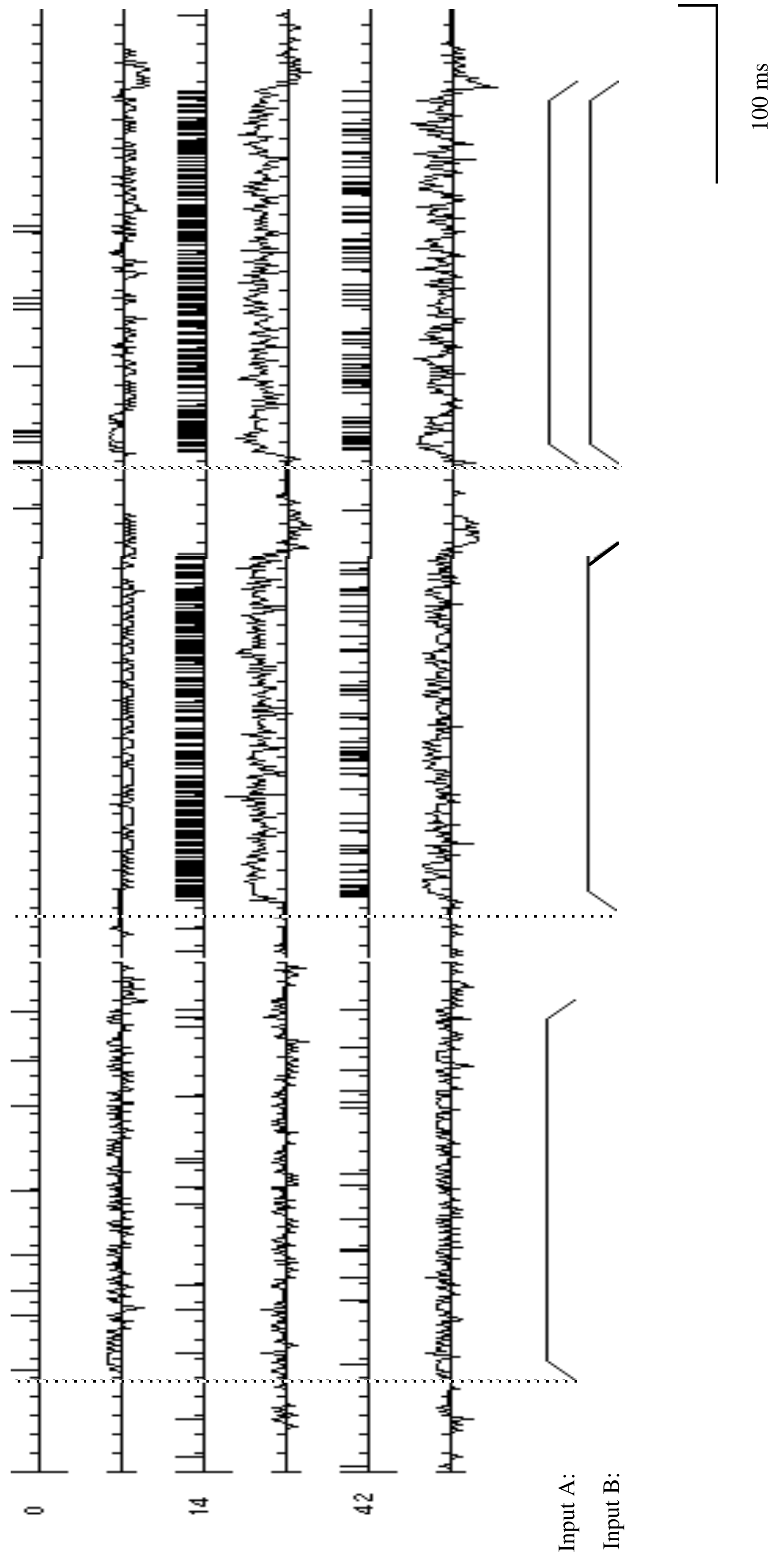

FIGURE 3A

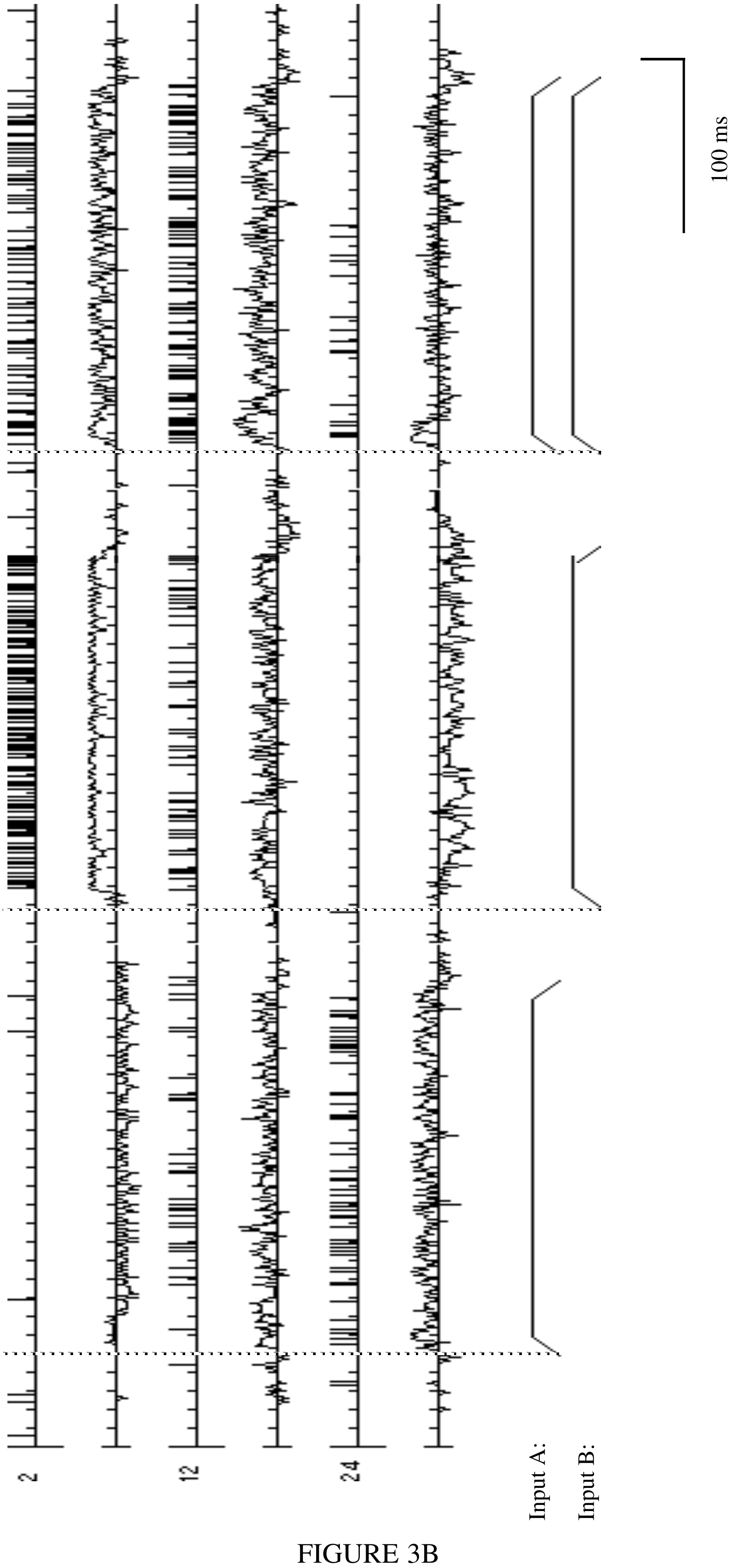

FIGURE 3B

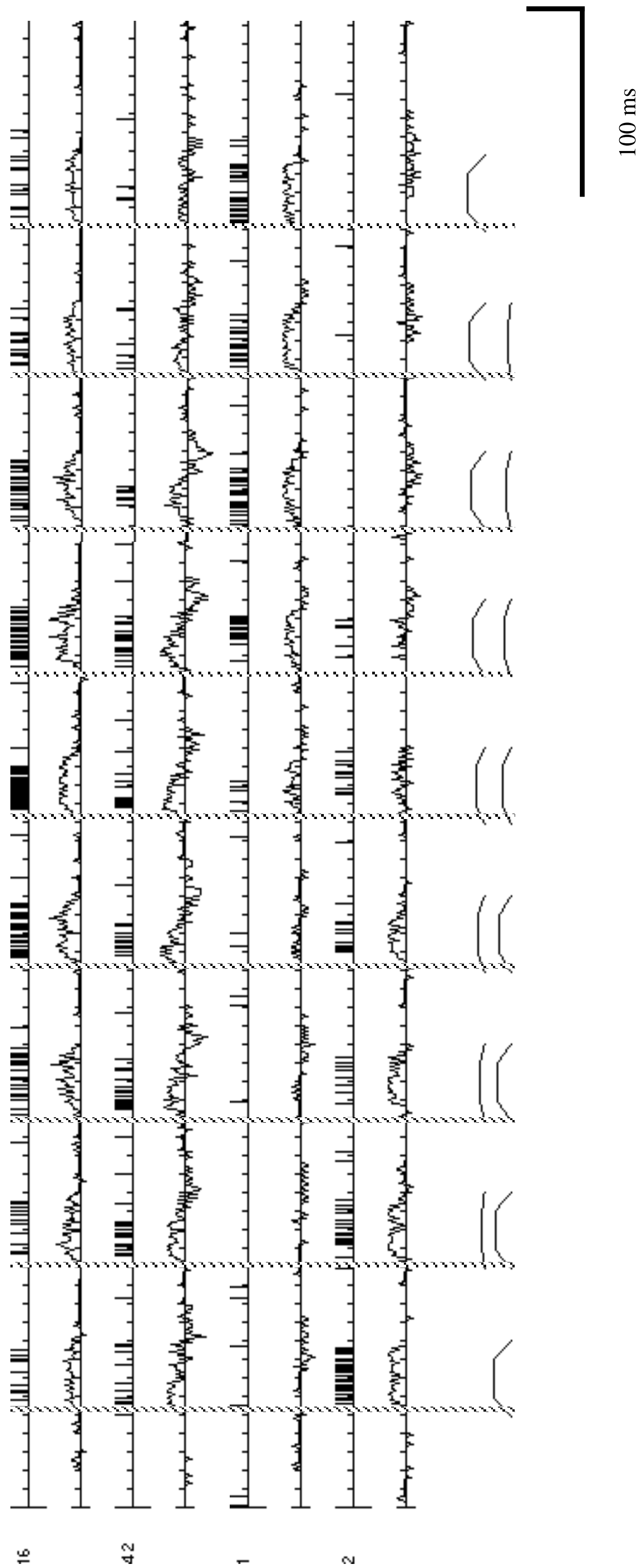

FIGURE 4A

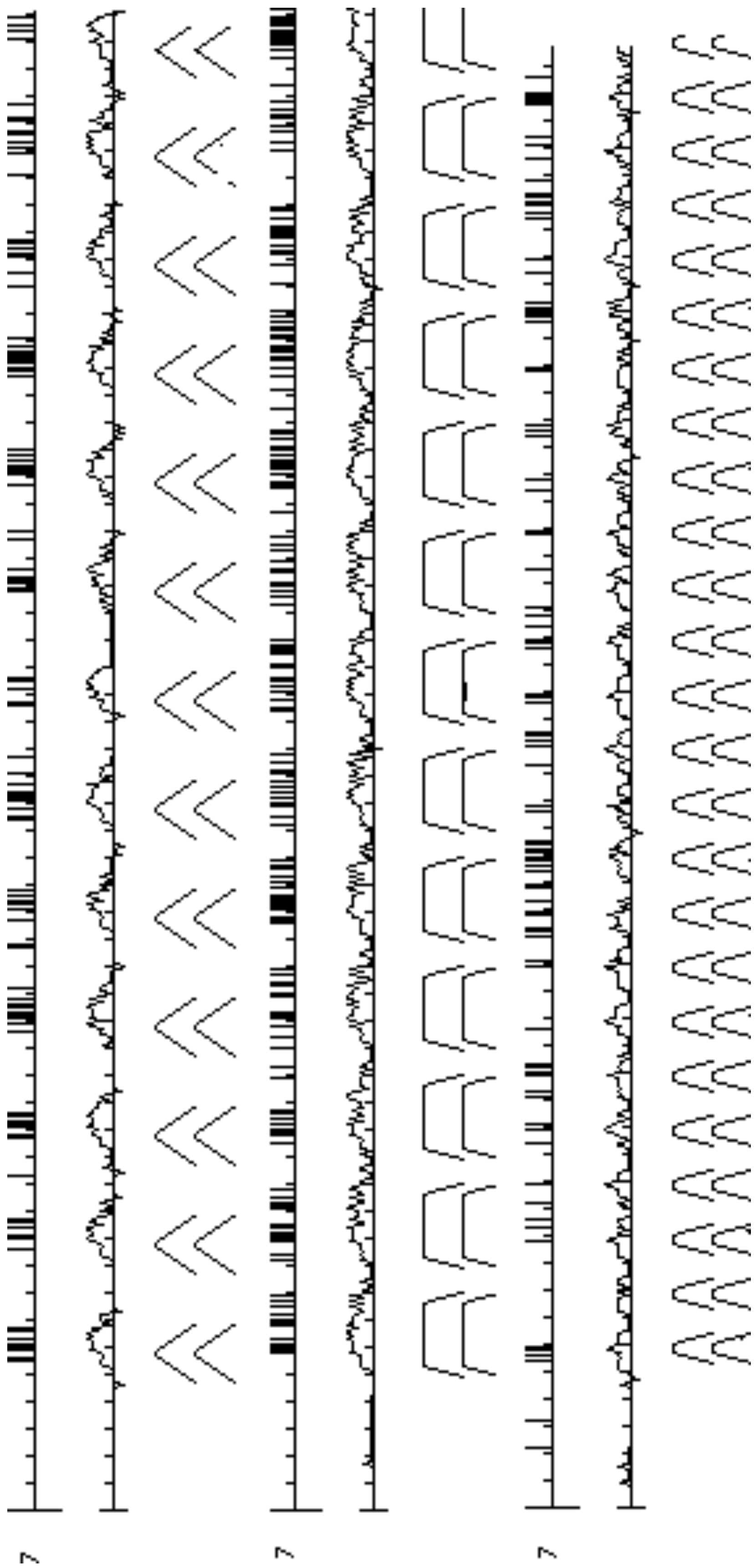

FIGURE 4B

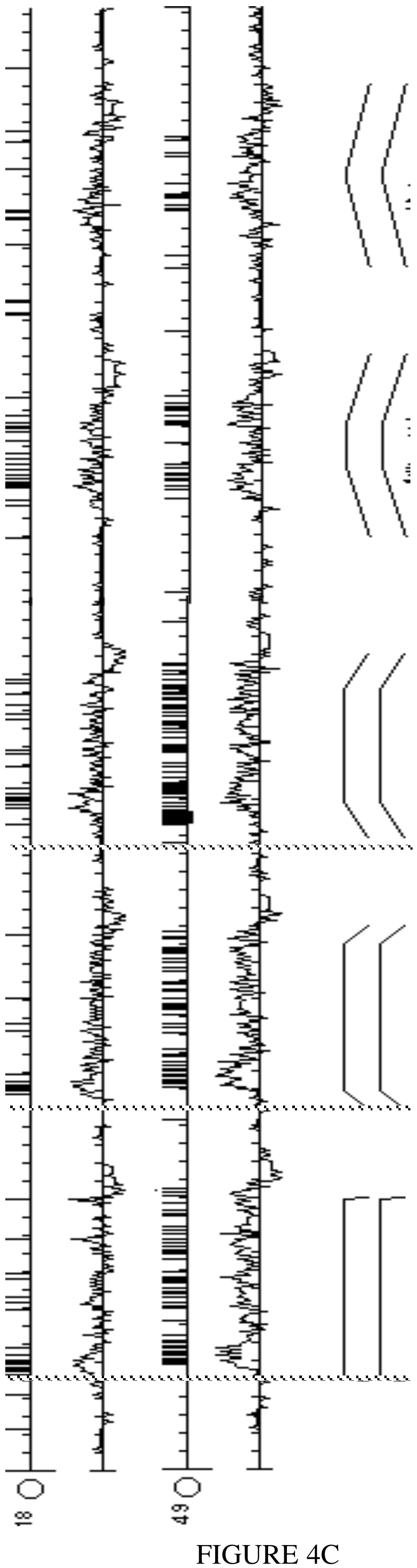

FIGURE 4C

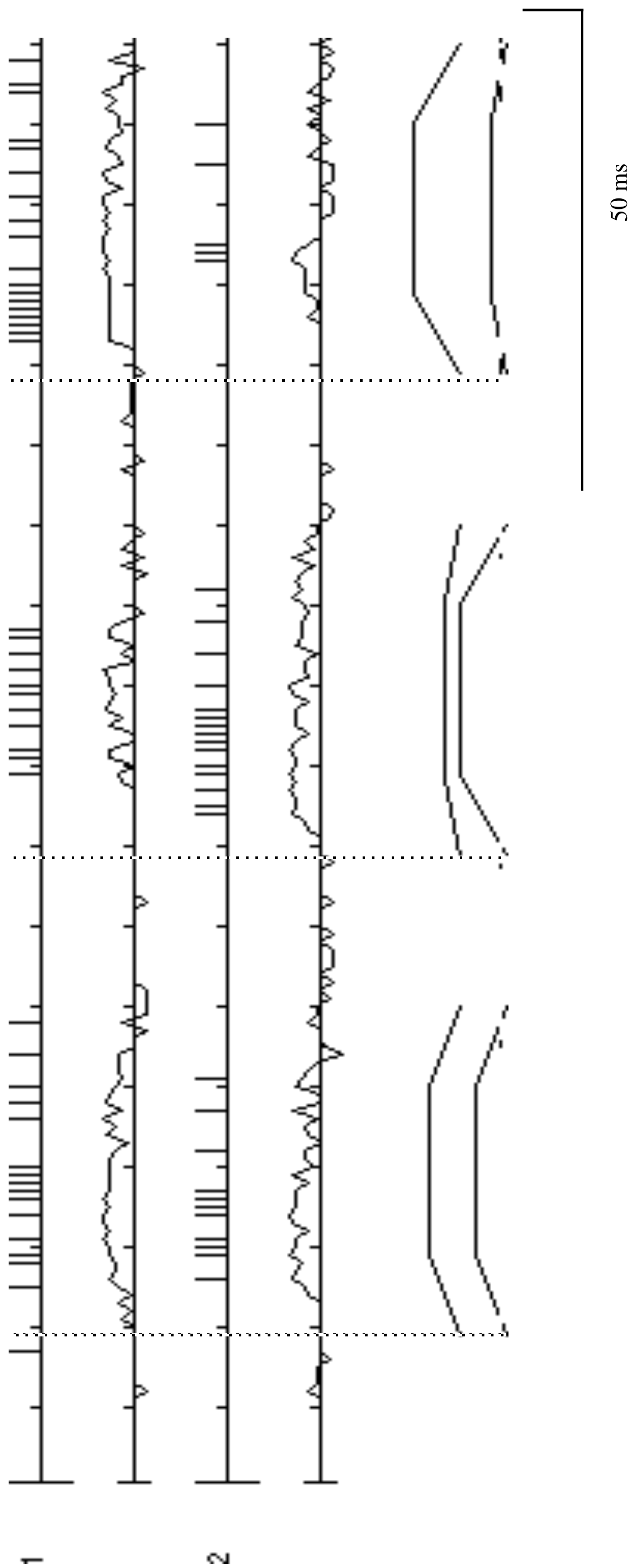

FIGURE 5