# Single-Unit Recordings Revisited: Activity in Recurrent Microcircuits

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We investigated the relevance of single-unit recordings in the context of dynamical neural systems with recurrent synapses. The present study focuses on modeling a relatively small, biologically-plausible network of neurons. In the absence of any input, the network activity is self-sustained due to the resonating properties of the neurons. Recording of single units reveals an increasingly complex response to stimulation as one proceeds higher into the processing stream hierarchy. Results suggest that classical analysis methods, using rate and averaging over time, fail to describe the dynamics of the system, and instead hide the relevant information embedded in the complex states of the network. We conclude that single-unit recordings, which are still extensively used in experimental neuroscience, need to be more carefully interpreted.

## 1. Introduction

For a long time, single-unit recordings have been the only available method of recording in experimental neuroscience. Technical difficulties imposed constraints on the experimental setups, such that recording with only a single electrode has already posed tremendous challenges for experimentalists. By using one electrode however, one can record spikes from only one cell (in the case of intra-cellular recording), or, at best, from a few cells separated by spike-sorting (when recording with an extra-cellular electrode). Only relatively recently, multi-unit recording has been introduced and used on a larger scale [9,10].

When recording from a single unit, one reliable way of analyzing the spiking activity is to observe the firing rate of the neuron. In the absence of any other information about the spiking of neurons in the surrounding populations, it seems plausible to characterize the response of single cells in terms of rate-responses to stimulation [3]. Within this framework, many categories can be defined depending on the response properties of a cell ("stimulus-presence" cell, "delayed-stimulus-presence" cell, "don't care" cell, etc).

To compensate for the variability of the spike-trains, a frequently used method is to average the response of the cell over multiple trials, thereby characterizing its response properties in terms of the average response. However, this method assumes a stationary response embedded into a randomly fluctuating signal (noisy signal). As we shall see, in the case of ongoing, non-random, history-dependent activity, the assumption of stationary

responses is not holding anymore, especially for cells strongly coupled with populations less driven by the input (especially cells strongly modulated by feed-back).

We investigate a model network of 40 neurons in analogy to single unit recording by tracing the activity of only one member of the simulated network at a time. Although we do not claim that our model is completely biologically relevant, the results suggest that single-unit recordings have to be very carefully interpreted for a class of systems similar to our model. This might indicate that describing the dynamics of a recorded piece of cortex, consisting of a large population of cells, by a single rate response profile is a very poor approximation.

## 2. The model

The artificial neural system consists of a microcircuit composed of 4 layers of neurons interconnected in a recurrent fashion and an additional stimulation "input" layer of neurons (Fig. 1). Each layer contains 10 neurons, "resonate-and-fire" neurons [4] and "chattering" neurons [6]. The resonance properties of the neurons facilitate the self-sustained activity of the network, even in the absence of any input (there are no nonspecific background currents used). Although resonating neurons have been considered in only a few simulation studies so far, there is accumulating evidence that some types of real neurons exhibit resonance properties [2]. One important aspect to keep in mind is that the microcircuit activity is self-sustained without being stimulated with random non-specific background currents, so there is no added external noise.
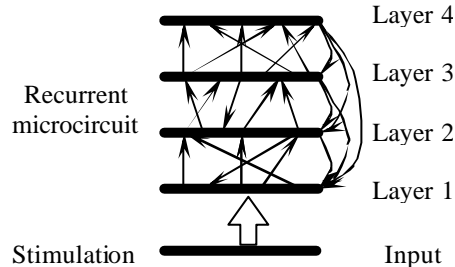


**Fig. 1.** The model consists of a 4-layer microcircuit with recurrent synapses and a stimulation "input" layer. Each layer is composed of 10 neurons randomly connected to higher-, lower- and same-layer neurons, with certain distributions.

The properties of the system can be summarized as follows:
  1. The system has a recurrent hierarchical neural architecture.
  2. The synaptic connectivity is mainly retinotopic (for ascending fibers), but lateral connectivity is also present. A neuron in one layer is connected via random synapses to higher-, lower- and same-layer neurons, within a local neighborhood. For feedback synapses, there is no neighborhood constraint.
  3. The receptive-field sizes increase from early to late stages of processing.
  4. The neural system never rests; even in the absence of stimulation, there is spontaneous self-sustained activity.

5. Synaptic connections and strengths are randomly distributed to match the retinotopic criteria. Post-synaptic currents are modeled as exponentially decaying alpha functions, with time constants in the range of 10-20 ms.
6. The neural dynamics are mainly characterized by subthreshold oscillations near an Adropov-Hopf bifurcation [5].
7. Neuron parameters were chosen to fit cortical neuron dynamics with a distribution of 80% resonator and 20% chattering neurons (see ref. [6] for details).
8. The input signal consists of a fixed firing frequency (50 Hz) mapped onto the "input" layer (see Fig. 2).
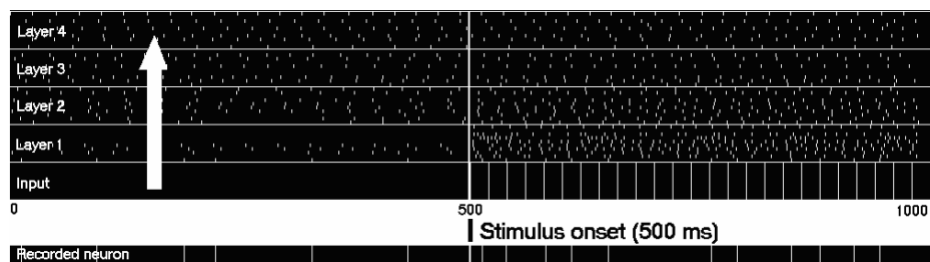


**Fig. 2.** A plot of the system's dynamics. The top 4 spike rasters show the activity in the 4 layers of the microcircuit. The "Input" raster displays the activity of the "input" layer, whereas the lower spike raster plots the activity of a recorded neuron from the microcircuit. In the first 500 ms, the system has self-sustained dynamics. Then, at 500 ms it is stimulated with a regular input spike-train of 50 Hz. Please note that the system has always ongoing activity, such that the time of 0 ms in the plot corresponds to 500 ms before stimulus presentation (not a real simulation time).

The dynamical system contains only 40 neurons having non-trivial dynamics (activity cannot be described in terms of classical filter responses). An important observation is that the complexity of neural activity increases with the size of the network (by complexity we mean the irregularity of the rate response). Connections are random; 80% are excitatory and 20% are inhibitory. Reversal potentials at synapses are 0 mV for excitatory and –90 mV for inhibitory synapses. Resting potential is around –70 mV, however, the thresholds are dynamic, depending on the history of stimulation (see [6]). Neurons show adaptation, occasional bursting, post-inhibitory rebound, synchronization, and other interesting biologically-plausible behavior. The simulation is continuous; between 2 stimulations, the system is not shut down, but allowed to evolve freely, self-sustained. During recording, a one second window is chosen and the stimulus is presented at the half time (500 ms). Stimulation lasts for 1500 ms, then the system is allowed to evolve for at least 2 seconds between two stimulations (to avoid short-term memory effects). The microcircuit is more realistic than other models in the sense that it "lives" between experiments/stimulations (i.e. the system has self-sustained activity), and the activity ceases only after the circuit is "killed".

For one particular microcircuit experiment, we stimulate and then record one neuron at a time, systematically from all layers, choosing the targets at random. The firing rate of the target neuron is estimated by convolving the spike train with a gaussian kernel (sd = 15 ms) [1]. Each neuron is recorded during at least 10 trials and the mean rate-activity is computed. Analysis reveals many important aspects both on the measured effects and on the method-dependence of the results, as will be shown next.

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## 3. Results

The activity in the first layer (analogous with V1) is strongly dependent on the input and the responses are quite sharp, with little delay. The activity is mainly driven by the input (Fig. 3).
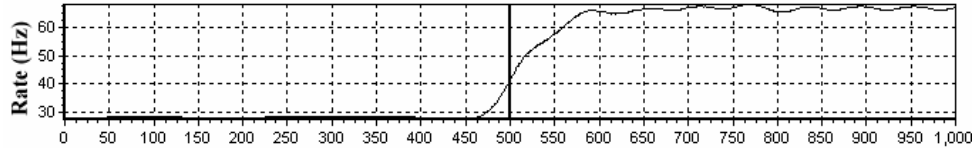


**Fig. 3.** Mean firing rate of neuron #4 in layer 1. The response to the input is sharp although the neuron is strongly modulated by feedback and has quite an elevated spontaneous activity.

A small percentage of the neurons in the primary layers can show more complicated dynamics which cannot be described in terms of stimulus-locked rate increase, mainly due to the strong coupling with the higher layers and lateral interaction (Fig. 4).
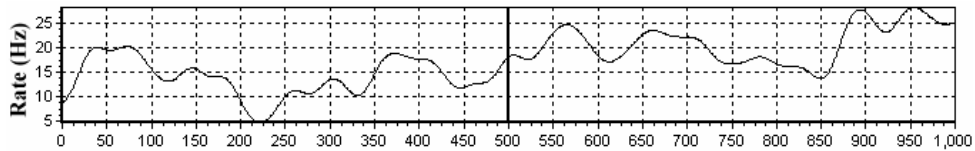


**Fig. 4.** Mean firing rate of neuron #1 in layer 1. In analogy with experimental data, the input has a modulatory rather than driving effect. This cell is involved in highly-dynamic processing and, averaging over many trials seems to hide the dynamic computation that is going on (recording observation).
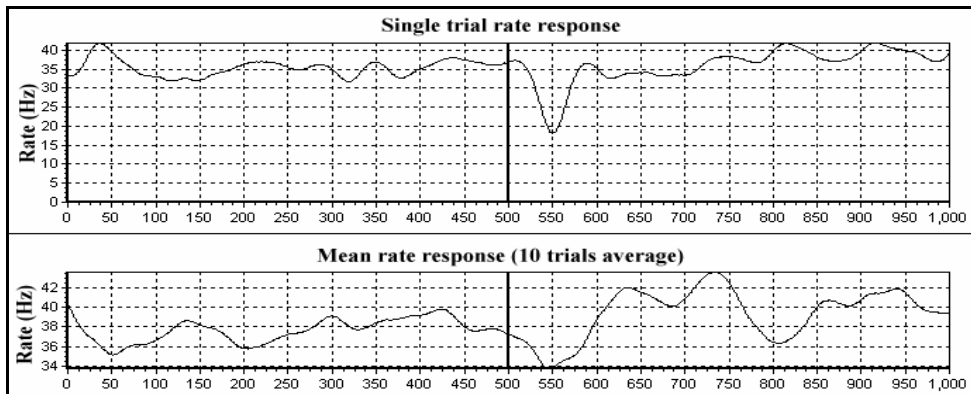


**Fig. 5.** Trial #10 (top) and average over 10 trials (bottom) rates for neuron #1 in layer 2. Analysis of the average rates over 10 trials reveals an inconsistent transient response (between 550–800 ms) which is only obtained by averaging over certain trials. The averaged rate strongly depends both on the number of trials that are averaged (10 being a statistically low number of trials) and on the delay between two stimulations, which is reflecting a strong dependence on the history of the system. The sharp inhibition at 550 ms is either present or totally absent in different trials. Its presence in the averaged rate is only due to the fact that in the 10-trial-average, this inhibition peak was more frequent, although in a 15-trial-average experiment it may vanish for example.

As we proceed to the higher layers, other phenomena can be observed. A smaller number of cells still have a sharp signaling profile (similar to Fig. 3). However, another type of cell emerges: the "dynamical computation" cell. These cells do not have a significant or sharp change in the rate response when the system is stimulated (Fig. 5). It seems that the worst way of analyzing their activity is to average over different trials. This is because the stationary response assumption is not fulfilled, making averaging ineffective. These cells have more a non-stationary, phase/rate variable response to the stimulation. Interpreting the averaged activity in Fig. 5 is probably a misleading method of analysis since sharp peaks and high fluctuations with variable phase are all averaged together. In single trial measurements however the cell's activity is obviously not changed but merely modulated.

As the neural dynamics get more and more complex, measuring the averaged rate is a less and less reliable method of analysis. We might classify the cell in Fig. 5 as a "don't care" cell, expressing that there is no obvious link between the input and the cell's rate response. However, experiments on the model show that shutting down such neurons can dramatically affect the dynamics of the entire system and its response to the stimulus. It might be that either rate is not a relevant parameter to measure for such neurons or that the activity of the neuron was critical for the overall processing performed by the population, thus indirectly influencing the response to the stimulus.

An enormous diversity of neural responses can be found in the later stages of processing due to the complexity of neural interactions (Figs. 6-8).
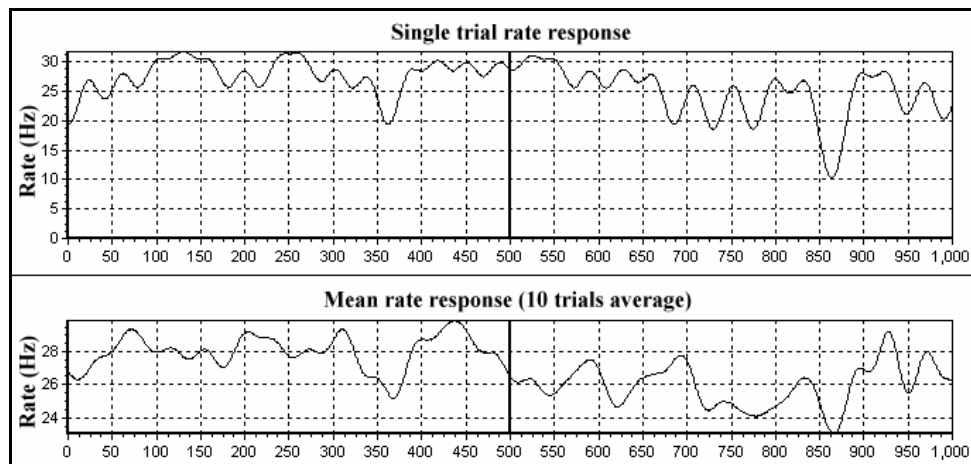


**Fig. 6.** Complex dynamics of an apparently "don't care cell" in layer 3. Again, the mean rate is totally irrelevant for the type of processing at the cell. It can only be inferred that the cell receives some inhibitory delayed effects from another population of neurons.
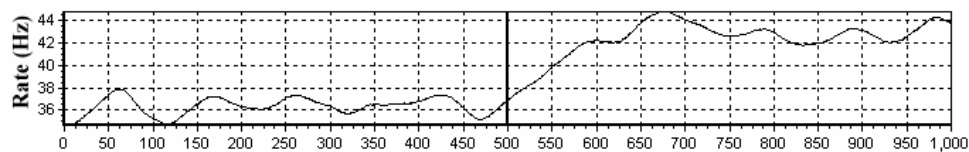


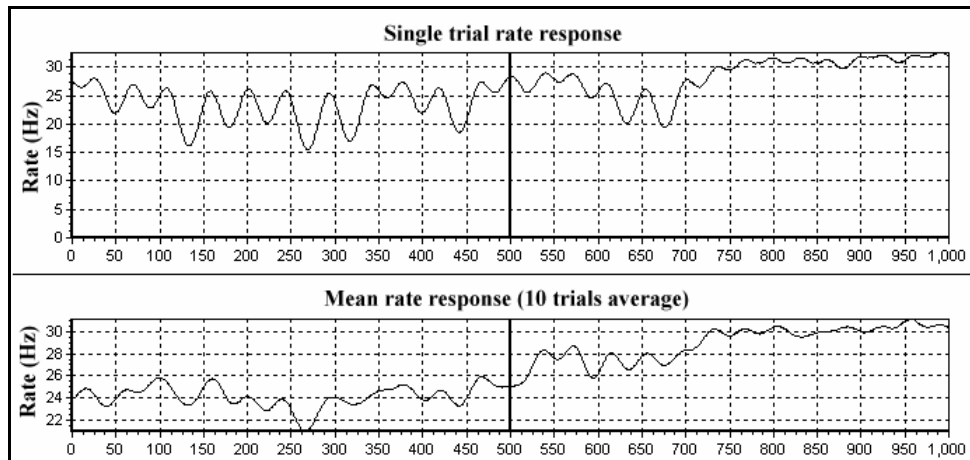**Fig. 7.** Delayed signaling cell in layer 3

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**Fig. 8.** An interesting cell in layer 4 that can be classified as an intermediate cell between inputs and later stages. Understanding its function from a rate analysis seems elusive.

## 4. Discussion

Average rate response and function are an elusive pairing for complex neural interactions. It seems like rate analysis and individual neuron recordings are potentially misleading as one tries to explain activity in higher areas where activity is complex. When the system has nontrivial dynamics, which is the case for the neocortex, single-unit recordings and function interpretation seem to be incompatible. On one hand, averaging does not emphasize a stable rate response since fluctuations are not random and independent but related to the network dynamics and history. On the other hand, in many cases, even single trial rate responses might reveal no obvious link to the function of the neuron.

For the complex activity that is going on in high visual areas like V4, we need novel methods of analysis. Complex interactions among neurons cannot be simply assumed to execute certain functions unless we understand the entire picture. As an example, a simple readout neuron (connected to a recurrent high-dimensional microcircuit) can be trained to respond in a stable manner to the highly complex patterns of activity whenever a stimulus is presented, although understanding the highly complex dynamics of the individual neurons in the microcircuit seems elusive [7]. Moreover, it seems like such systems are highly effective computational "devices", and the key to the power of processing is the micro-level cellular and synaptic diversity [8].

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