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Modelling a visual discrimination task

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Abstract

We study the performance of a spiking network model based on integrate-and-fire neurons when performing a benchmark discrimination task. The task consists of determining the direction of moving dots in a noisy context. By varying the synaptic parameters of the integrate-and-fire neurons, we illustrate the counter-intuitive importance of the second-order statistics (input noise) in improving the discrimination accuracy of the model. Surprisingly, we found that measuring the firing rate (FR) of a population of neurons considerably enhances the discrimination accuracy as well, in comparison with the firing rate of a single neuron.

Keywords: Discrimination; Firing rate; Input noise; Population

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1. Introduction

Discriminating between inputs is a fundamental task for the visual system. In most cases, the accuracy of the discrimination is directly linked to the reaction time: this is expressed as the Fitts law. Experiments with random dots stimuli are classical ways to study it, Newsome and Shadlen [5] have experimented on this discrimination process in Macaque monkeys. Specifically, they have studied neurons from the lateral intraparietal (LIP) area of the cortex, whose behavior

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depends both on the input category and on the decision of the monkey. So, those neurons are typical of sensorimotor decision processes, neither completely determined by the stimuli nor completely independent from it. Recently, interesting relations between reaction time (RT) and discrimination accuracy have been shown. We implemented a neural network model for this discrimination task using integrate-and-fire (IF) neurons, so that we could model the time course of spike generation. Even if the model takes simplistic assumptions, this simplicity renders the obvious phenomenon it exhibits. We measured the firing rate (FR) both from a single and from a population of neurons, which enabled us to model a discrimination task within a biologically realistic time scale. We compared the discriminative accuracy of the population model to the performance of the single neuron, relatively to the number of emitted spikes and to the processing time. In our model, the role of inhibitory inputs and input noise can account for the Fitts law.

2. The discrimination task

We have implemented a detailed model of the LIP neurons that take part in the decision of the monkey during the two choices discrimination task set up by Newsome et al. in for example [5,6]. In this set of experiments, the monkeys had to watch a display of dots, a certain percentage of them moving consistently in one direction or its opposite, and the rest of the dots appearing at random places on the screen as a perturbing noise. Then they had to signify the direction by an eye movement. The difficulty of the task was controlled by modifying the percentage of coherently moving dots. We assume that the discriminating neurons receive synaptic inputs composed of an actual signal perturbed by noise. If a percentage n_c of dots moves coherently in one direction, the same percentage of synapses receives coherent input. Furthermore, we assume that the spike trains arriving to those synapses are correlated. The rest of the synapses receive randomly distributed inputs. The synaptic inputs are modelled as Poisson processes. It has been shown that the motion detectors of area MT and MST that are involved in the decision process of the monkey [1] are constituted of columns of neurons, and a model has been proposed for this organization [7]. So, it is probable that the neurons encoding for the same direction are close to each other and thus fire synchronously. The outputs of the discriminating neurons are spike trains whose FRs are related to the input of the movement, so that we can crudely model that this FR being bigger or smaller than a criteria means a command for the eye to move respectively up or down. Since there is a variation in the output FR, this command can be erroneous, e.g. the FR is bigger than the criterium when the movement is downwards. This mimics an error made by the monkey, and follows the behavior of the real LIP neurons that suggest that "the decision might be embodied in direct transformations between the relevant sensory and motor systems" [5]. Of course, the clearer the stimulus, the more widely separated the efferent spike trains, and thus the less errors the model makes.

3. Model description

The discriminating neuron model used here is the classical IF model [4,9]. We simplistically assumed that each synapse receives a Poisson process whose rate is proportionally linked to the direction of one moving dot on the screen, but independent on the velocity. So, for n_c dots that move coherently, the n_c synapses that receive coherent inputs are correlated by a constant c, and reflect the correlation of activity of different synapses as studied in [3,11]. Using the diffusion approximation as in [8,9], we reach the simplified following description of the dynamics of our discriminating neuron, with V as the membrane potential:

$$dV = -\frac{V dt}{\gamma} + \mu\, dt + N\sigma\sqrt{dt}, \quad \text{where } \mu = \sum_{j=1}^{N_{\text{cells}}} (1 - r)\lambda_j,$$

and

$$\sigma^2 = \sum_{j=1}^{N_{\text{cells}}} (1 + r)\lambda_j + \sum_{i=1}^{n_c} \sum_{j=1, j \neq i}^{n_c} c(1 + r)\sqrt{\lambda_i \lambda_j}.$$

- The ratio between inhibitory inputs and excitatory inputs: r is variable.
- The number of incoming synapses (corresponding to the number of dots in the experiments): $N_{\text{cell}} = 100$.
- λ_j is the direction of the jth dot.
- The time decay parameter $\gamma = 20\,\text{ms}$.
- The time step for the integration $dt = 0.01\,\text{ms}$.
- The correlation coefficient between coherent motion $c = 0.1$.
- The number of coherent inputs n_c is variable. Coherent inputs are dots that move consistently in one direction. Thus, the coherence is defined as n_c/N_{cell}.
- The resting membrane potential $V_{\text{rest}} = 0\,\text{mV}$.
- The threshold membrane potential $V_{\text{threshold}} = 20\,\text{mV}$.
- N is a normally distributed random variable, $N\sqrt{dt}$ is the Brownian motion.

Instead of using only one neuron, we can measure the FR of a whole population. On average, generating 100 spikes with 100 neurons only requires the time for one neuron to generate one spike; increasing the population enables us to generate as many spikes as we want in a very short time. This rehabilitates the FR measure, in a visual system that only has time for "one spike per neuron" as argued in [8]. All the neurons of the population, modelled as above, receive independent inputs with the same rates.

3.1. Increasing the input noise

We can interpret the equation of the dynamics of the membrane potential of the IF model (3) as a leaky membrane ($-Vdt/\gamma$) that receives an input $\mu(+\mu\, dt)$, perturbed by a stochastic noise ($\sigma N\sqrt{dt}$). Since this stochastic perturbation is proportional to $(1 + r)$ and the mean is proportional to $(1 - r)$, the stochastic effect of the synapse increases with r, the ratio between inhibitory and excitatory inputs. As explained in [3], an increase in the coefficient of variability in the input will increase the coefficient of variability of the efferent spike train of the neuron. Thus, intuitively, it should be more difficult to discriminate between two inputs from their efferent FR. However, Feng and his colleagues [2] have formally proven that this is not the case when the coherent inputs (those upon which we discriminate) are correlated. More precisely, he obtained the following conclusion: when the correlation is positive, the accuracy of the discrimination increases with r. We use a correlation coefficient of 0.1, for synapses that receive the coherent input. It has been shown [11] that in area V5 of the visual cortex of the monkeys, the level of correlation is 0.1 and although being weak, has a significant impact on the global behavior. The theoretically counter-intuitive results that the larger the coefficient of variation (CV) of the input, the better the discrimination which is confirmed by the following simulation results.

4. Simulation results

4.1. A performance criterium: total probability of misclassification (TPM)

For each set of parameter values, we perform 100 discrimination trials, for each direction, and measure the FR each time. The FR is the number of emitted spikes divided by the time window. The experimenter uses the FR as decisive evidence: if the FR is larger than a ‘discrimination boundary’, than the movement is classified upward, if the FR is smaller, then the movement is classified downward. This discrimination boundary depends on the FR values, thus it is optimal for each set of parameter values.

4.2. Discrimination with a 100 spikes

Extensive simulations over the range of r, and over the range of input coherence (percentage of coherently moving dots), produced the following results, summarized in Fig. 1:

- Obviously, the TPM decreases when the coherence increases: the more separated the inputs are, the easier the discrimination task is.
- The TPM decreases when r increases. This decrease is not monotonic. For the single neuron, the better performance achieved by increasing the input noise occurs only for $r > 0.7$.
- The population performs much better, for almost one order of magnitude, than the single neuron, and its TPM decreases steadily with r.

The better performance of the population can be explained as follows. In the population approach, we use the first 100 spikes of a 100 neurons to measure the FR, which means that we use on average one spike per neuron. Long interspike intervals (ISI) are unlikely to be produced, because there will be hundred spikes produced

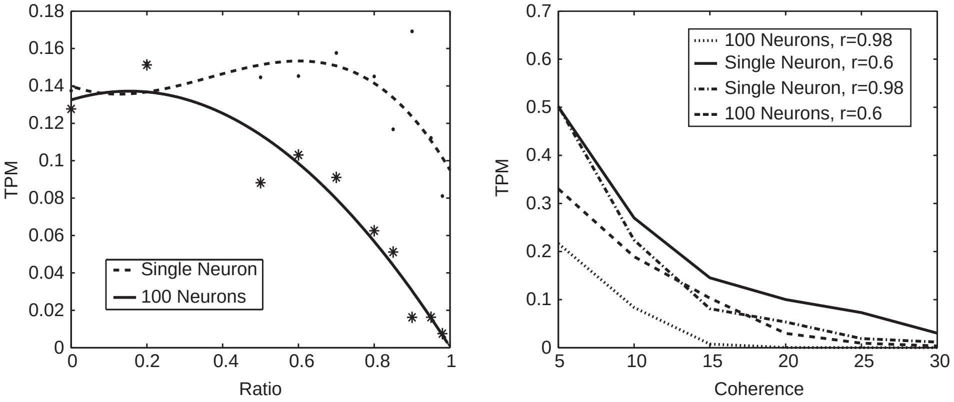

Fig. 1. Comparison of the TPM of one single neuron and of a population, for various r and coherences, using 100 spikes. Left panel, coherence = 15%. The time window needed to collect these 100 spikes varies a lot with parameter values, especially it increases dramatically with r. We will evaluate the effect of time in Fig. 2.

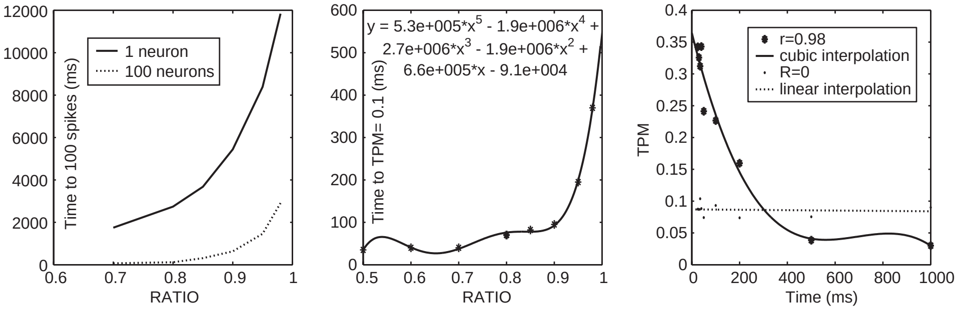

Fig. 2. Coherence = 15%. Left: time to get a hundred spikes versus r, with a population of a hundred neurons and with a single neuron. Middle: Illustration of the numerical estimation of the time to reach an acceptable discrimination performance (TPM = 0.1). Right: comparison of the evolution of the TPM for long time windows, reaching to one second, with $r = 0.98$ and $r = 0$. When we wait for one second, the TPM for $r = 0.98$ is 0.03 and the TPM for $r = 0$ is 0.09.

before a spike following a long ISI will ever occurs. These longer ISIs increase significantly the variability of the efferent FR, thus increasing the TPM. This is the reason for the better performance of the population.

4.3. Time related performance

For most biological systems, the absolute performance must take into account not only the accuracy at realizing the task, but also the time spent to achieve it. The time to generate spikes varies a lot when r increases. In fact, when $r = 1$, the only postsynaptic input is noise, and the FR is very low. We see in Fig. 2 that generating a number of spikes sufficient to reliably measure an FR increases dramatically the processing time. The population approach partly solves this problem, but, in order to put the TPM in perspective, we have to measure the evolution of the quantity of errors with the size of the time window during which we collect the spikes. Those time considerations undermine the advantage gained with increasing the input noise; as we see in Fig. 2, it is much quicker to achieve an acceptable performance with exclusively excitatory inputs. However, the performance of the system can be much better, over a long time window, with balanced excitatory and inhibitory inputs ($r \simeq 1$).

5. Conclusions

We have shown that measuring the FR of a population of neurons enables us to overcome the time scale impossibilities often associated with the FR approach. Although augmenting r, i.e. the input noise, increases the performance per spike, it increases the reaction time dramatically. The probability of misclassification decreases much quicker for smaller ratios. However, we have seen that only ratios close to one can reach a certain level of performance unreachable by the FR of a population with exclusively excitatory synapses. Those very good performances are achieved at the cost of a very long RT. This phenomenon of increased accuracy with a longer processing time in living organisms is known as the Fitts law. Furthermore, the fact that inhibitory inputs play a central role in a discrimination task is in agreement with biological data as reported in [10,6].

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