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 of a population of neurons considerably enhances the discrimination accuracy as well, in comparison with the firing rate of a single neuron.

Key words: Discrimination, Firing Rate, Input Noise, Population

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 ([6]) 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 depends both on the input category and on the decision of the monkey. We implemented a neural network model for this task and measured the firing rate (FR) both from a single and from a population of neurons, which enabled us to model a discrimination within a biologically realistic time scale. We compared the discriminative performance 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.

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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 [6,7]. 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 p_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 [8]. 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 FR 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, eg the FR be bigger than the criterium when the movement is downwards. This mimics an error of 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" [6]. 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 Integrate-and-Fire (IF) model [3,9]. We simplistically assumed that each synapse receives a poisson process which rate is proportionally linked to the direction of one moving dot on the screen. So for n_c dots that move coherently, the n_c synapses that receive coherent inputs are correlated by a constant c, that reflects the correlation of activity of different synapses as studied in Feng,2001 and in Zohary, 1994,[4,12]. Using the diffusion approximation as in Tuckwell,1988 [9] we reach the simplified following description of the dynamics of our discriminating neuron, with V as the membrane potential:

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

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

- 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): $N_{cell} = 100$.
- $\lambda(j)$ is the direction of the jth dot.
- The time decay parameter: $\gamma = 20ms$.
- The time step for the integration: dt=0.01 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.
- The resting membrane potential: $V_{rest} = 0$ mV.
- The threshold membrane potential: $V_{threshold} = 20$ 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. Generating hundred spikes with hundred 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 Firing rate (FR) measure, in a visual system that only has time for "one spike per neuron" as argued in (Van Rullen, 2000) [10]. All the neurons of the population, modelled as above, receive independent inputs with the same rates.

Increasing the input noise. We can interpret the equation of the dynamics of the membrane potential of the Integrate-and-Fire model (3) as a leaky neuron $(-\frac{Vdt}{\gamma})$ whose synapses receive a poisson input of rate μ $(+\mu dt)$, perturbed by a stochastic noise ($\sigma N\sqrt{dt}$). Since this stochastic perturbation is proportional to $(1 + r)$ and the mean is proportional to to $(1 - r)$, the stochastic effect of the synapse increases with r, the ratio between inhibitory and excitatory inputs. As explained in Feng, 2001 [4], 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 [2] has 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 (Zohary et al., 1994) [12] 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 are confirmed by the following simulation results.

4 Simulation results

A performance criterium: Total Probability of Misclassification (TPM).
The firing rates distribution can be fitted as a Gaussian, where σ^2 is the variance of the sample of firing rates and μ its mean: $G(x) = \frac{1}{2\pi\sigma^2} \exp^{-\frac{(x-\mu)^2}{2\sigma^2}}$. In order to tell the motion direction based upon the efferent FR, we compare it to the 'discrimination boundary'. This boundary value is the rate were the two firing rates distributions meet, when plotted on the same graph. The (TPM) is the number of misclassifications divided by the total number of classifications:

$$TPM = \frac{\int_{-\infty}^{b} G_{up}(x)dx + \int_{b}^{\infty} G_{down}(x)dx}{\int_{-\infty}^{\infty} G_{up}(x) + G_{down}(x)dx}$$

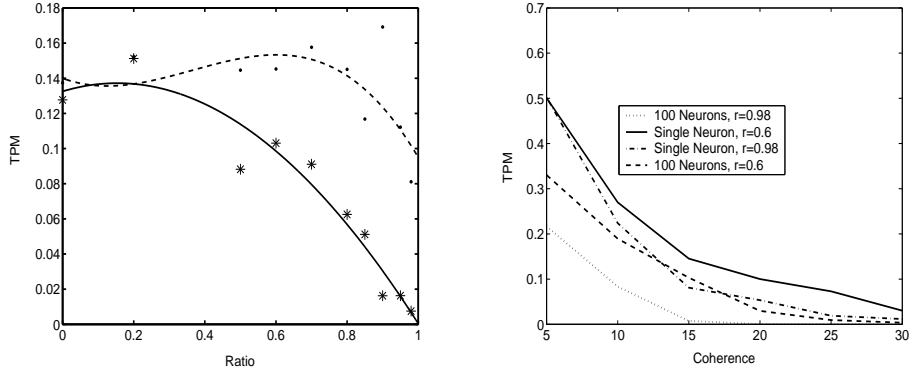where b is the boundary rate, G_{up} and G_{down} the fitted distributions.

Fig. 1. Comparison of the TPM of one single neuron and of a population, for various r and coherences, using a hundred spikes. In the first figure, the continuous line represents the population, and the dashed line the single neuron.

Discriminating with a hundred 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.

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The peak of errors attained at around $r = 0.7$ for the single neuron and the better performance of the population can be explained together as follows: In the population approach, we use the first hundred spikes of a hundred neurons to measure the FR, which means that we use on average one spike per neuron, long interspike intervals are unlikely to be produced. The hundred spikes will be attained before a neuron will have generated a spike with an interspike interval longer than twice the mean interspike interval. Those longer interspike intervals increase significantly the variability of the efferent firing rates: this is the reason for the larger TPM of the single neuron around $r = 0.7$.

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 ($r \simeq 1$).
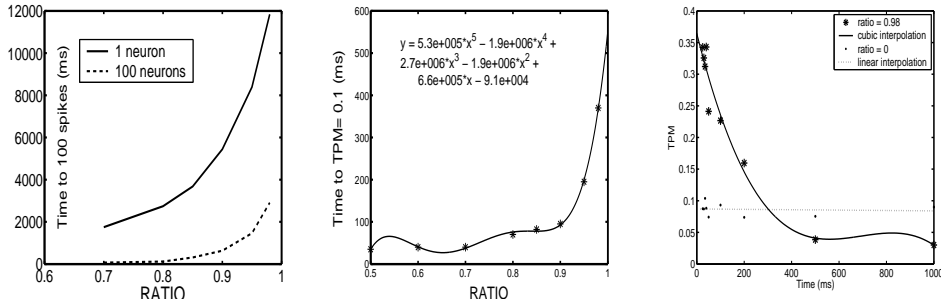

Fig. 2. *Coherence* = 15%. Left: Time to get a hundred spikes versus r, with a population of a hundred neurons and with a single neuron. Middle: Illustration of the numerical estimation of the time to reach an acceptable discrimination performance ($TPM = 0.1$). Right:Comparison of the evolution of the 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

5 Conclusions

We have shown that measuring the firing rate of a population of neurons enables us to overcome the time scale impossibilities often associated with the firing rate approach. Although augmenting r, ie 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 firing rate of a population with exclusively excitatory synapses. Those very good performances are achieved at the cost of a very long reaction time. 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 Wang, [11] and Shadlen, [7]

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