The effect of correlations in the background activity on the information transmission properties of neural populations

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Abstract

Recently the information transmission properties of populations of neurons with independent noise inputs were examined and it was shown that noise can improve the transmission of sub-threshold signals. Information transmission is maximized at a certain noise level which, in general, depends on the population size. In the central nervous system of higher animals, however, the noise is likely to be correlated. In this paper we therefore investigate the effect of correlations between neurons on the information transmission properties of populations of neurons. We show that correlations in the noise inputs of neurons not only decrease information transmission but also immediately reduce the optimal population noise level to that of the single neuron. Hence, information about the population size does not need to be made available to the single neuron and therefore local adaptation rules as suggested in [1] suffice.

Key words: Stochastic Resonance, Population coding, Local adaptation

1 Introduction

It is well established that background activity can influence the information transmission properties of cortical neurons [2] as, for example, in a stochastic resonance setting [3]. The term *stochastic resonance* is used for the phenomenon, that in a nonlinear dynamical system noise can improve the information transmission to a certain fraction (see [4] for a review), and has been extensively studied in the context of single neurons [5]. However, in the central nervous system of higher animals single neurons rarely matter, and information is likely to be coded by populations of cells. In a recent study we have shown, that the optimal noise level of a population of neurons with mutually

Preprint submitted to Elsevier Science *20 August 2004*

independent noise inputs depends on the population size [6]. If the dependency on the size is strong, a single neuron would need to process the information about the population size in order to establish optimal information transmission. If the dependency is weak, the neuron could instead use local quantities to calculate the proper noise level as suggested in [1]. In this paper we show that if correlations between neurons are considered, the optimal noise level of the population immediately reduces to that of the single neuron, which means that optimal information transmission can be achieved by a simple adaptation principle, for which only local information is needed. The assumption of correlated noise between neurons is reasonable from a biological point of view, because nearby neurons share a certain fraction of their input [7].
This paper is organized as follows. First we introduce our model which consists of a population of leaky integrate-and-fire neurons and we briefly describe how information transmission through the population is estimated. In section 3 we present the numerical results and we show, how correlations in the background activity alter the information transmission properties of the neural population. Section 4, finally, concludes with a short discussion.

2 The model

2.1 The neural population

We consider a population of N leaky integrate-and-fire neurons as displayed in Fig. 1. The total input to each neuron i is the sum of the input signal I_{stim} and the individual correlated noise input $\frac{dW(t)}{dt}$. The entire output of the population is generated by summing over all individual outputs Y_i (called pooling in neurophysiological terminology) in every time step Δt.
The membrane potential V of the leaky integrate-and-fire neuron changes in time according to the following differential equation

$$C_m \frac{dV(t)}{dt} = -g_L(V(t) - E_L) + I_{stim}(t) + \sigma \frac{dW_i(t)}{dt}, \tag{1}$$

where $C_m = 0.5\,nF$ is the membrane capacitance, $g_L = 25\,nS$ the leak conductance of the membrane, $E_L = -74\,mV$ the reversal potential, I_{bias} a constant bias current, and $I_{stim}(t)$ an aperiodic Gaussian stimulus, which is generated by a Fourier transform of a band-limited white noise power spectrum with a cut-off frequency of $f_c = 20\,Hz$. Once the membrane potential reaches the threshold $V_{th} = -54\,mV$, a spike is immediately generated and the membrane potential is clamped to a reset value $V_{reset} = -60\,mV$ for an absolute refractory period $T_{ref} = 1.8\,ms$. Throughout this paper we used a bias current of $I_{bias} = 0.3\,nA$ and the standard deviation of the stimulus was equal to $0.05\,nA$

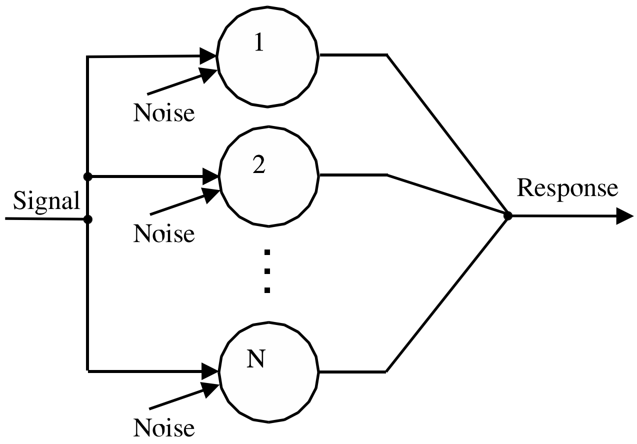

Fig. 1. A population of leaky integrate-and-fire neurons. Each neuron receives the same input signal and correlated Gaussian noise with zero mean and correlation matrix C. The entire output of the population is generated by summing over all individual outputs Y_i in every time step Δt.

(constant signals below $0.5\,nA$ are sub-threshold). The background activity is modeled by Wiener processes. The noise process $W_i(t)$ of each neuron is generated from N independent Wiener processes, which we multiply by a matrix A, so that the resulting processes $W_i(t)$ are correlated with a given correlation matrix C. The matrix A can be obtained from C with a method called cholesky decomposition. For all simulations we used a correlation matrix C, where the correlation factor c between any pair of neurons is the same.

$$C = \begin{pmatrix} 1 & c & c & \cdots & c \\ c & 1 & c & \cdots & c \\ c & c & 1 & \cdots & c \\ \vdots & \vdots & \vdots & & \vdots \\ c & c & c & \cdots & 1 \end{pmatrix} \tag{2}$$

2.2 Measuring the information transmission

We calculated a lower bound on the information transfer with a method called *reverse reconstruction* [8]. Starting from the observed spike train, a reconstruction method is used to obtain an estimate to the stimulus, so that that the mean square error between the stimulus and its estimate is minimized. The mutual information between the stimulus and the population response is then estimated by calculating the information between the stimulus and its estimate. This bound is close to the real information if the noise is approximately Gaussian distributed and the reconstruction algorithm extracts all the information about the stimulus from the response. In the following we used the common method (*linear filtering*) for reconstruction, because it has

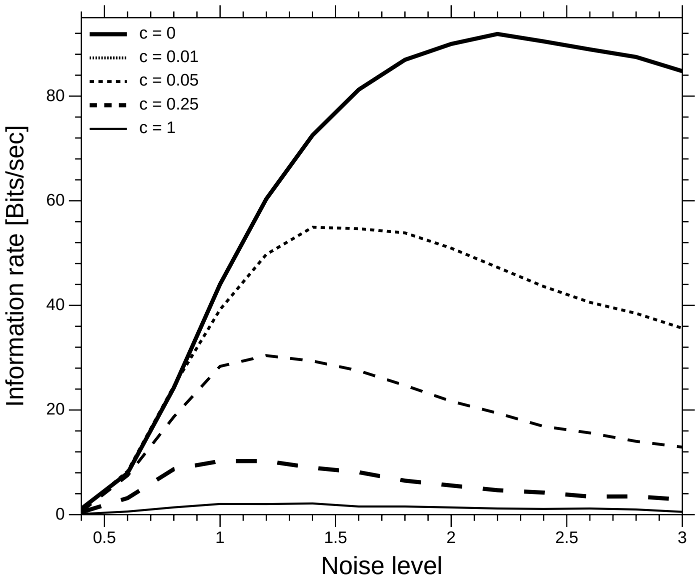

Fig. 2. a) displays the information rate of a population with $N = 1000$ neurons. Different curves show different levels of correlations between pairs of neurons. From low correlations (top) to correlations about one (bottom). The information rate was calculated from simulations of approximately $500\,sec$ duration ($\Delta t = 0.5\,ms$).

been shown that neural populations can act as linear readout mechanism [9]. Alternatively, one could estimate the information transfer directly, but this is difficult in the case of time dependent stimuli, because the data collection is limiting (see [8] for a review). In the following we used well developed signal processing methods to obtain the information rate from the equation

$$R_{info} = \int_0^\infty \log_2(1 - \gamma^2) df. \tag{3}$$

where γ^2 is the magnitude squared coherence

$$\gamma^2 = \frac{\langle S(f)^* R(f) \rangle \langle S(f) R(f)^* \rangle}{\langle S(f)^* S(f) \rangle \langle R(f) R(f)^* \rangle}, \tag{4}$$

which measures the correlation between the signal S and the response R at a given frequency f.

3 Simulation results

Fig. 2a shows the information rate plotted against the noise level for a population of 1000 neurons. The top curve indicates the case of independent noise.

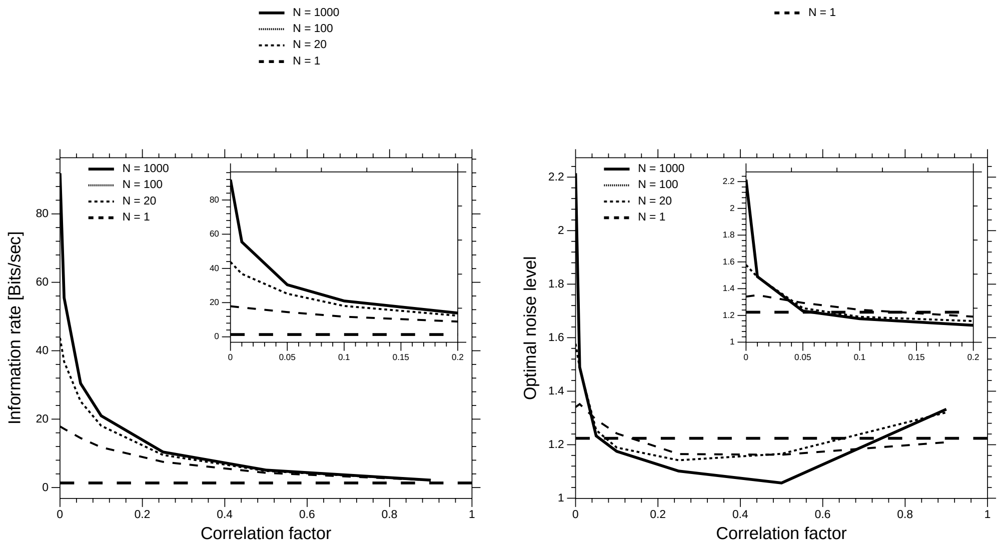

Fig. 3. a) The maximum of the information rate plotted against the correlation factor for different population sizes. b) The optimal noise level of the populations plotted against the correlation factor. The dotted line displays the corresponding value for the single neuron. For clarity, the inset in both figures provides an enlargement of the range $c \in [0, 0.2]$.

By introducing correlations between the pairs of neurons as described in chapter 2.1, the maximum of the information rate curve decreases with increasing correlations in the noise. We find a substantial decrease of the maximum even for small correlations in the noise. In addition, the figure shows that not only the maximum of the information rate curve is reduced, but also the optimal noise level decreases with increasing correlations.
The role of the noise in this system is twofold. On the one hand it allows the transmission of sub-threshold signals and on the other hand it corrupts the information in the response. At the optimal noise level these two effects balance. In the case of correlated noise a smaller fraction of the noise can be averaged out by pooling, which leads to the observed decrease in information transmission and thus to a smaller optimal noise level. In the extreme case of a correlation factor $c = 1$, all noise processes are identical, which means that every neuron in the population gets the same input and will produce therefore exactly the same output. In this case the information transmission curve of the population is the same as that of the single neuron. Thus, the optimal noise level and the maximum of the information rate, reduce for increasing correlations in the noise to the corresponding single neuron values (dotted line), as shown in Fig. 2a and 2b, respectively. Remarkably, the optimal population noise level decreases faster to the value of the single neuron than the maximum of the information rate does. Even a small correlation factor of $c = 0.1$ leads to an optimal noise level which is approximately that of the single neuron, meanwhile the maximum of the information rate is still much higher. Hence, the dependency of the optimal noise level on the population size diminishes and the single neurons can use local adaptation rules to optimize the overall information transmission.

4 Discussion

We showed that even small correlations in the background activity alter the information transmission through populations dramatically. In the extreme case of identical noise inputs the information rate of the population reduces to that of the single neuron. Interestingly, the optimal noise level, relative to the maximum of information rate, decreases much faster to that of a single neuron. Although correlations in the background activity reduce the maximum of the information rate, a population of neurons could still benefit from such correlations, because individual neurons could use local adaptation rules to optimize the information transmission.

Supported by the DFG (SFB 618).

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