INFORMATION CODING IN NEURAL MODELS OF SPIKING ELEMENTS WITH EXTERNAL FORCING

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Different encoding schemes are applied in neural network modelling at the level of a single neuron.

(1) **Fine temporal coding**. The fine temporal structure of neuronal spiking is used as a basis for coding and information processing (Mainen & Sejnowski, 1995).

(2) **Rate coding**. A single neural spiking rate is used as a code. This encoding scheme is rough because the temporal pattern of spiking is neglected and small variations of spike times do not change the rate code (Shadlen & Newsome, 1998).

(3) **Phase-frequency coding**. There is experimental evidence that neurons have frequency preference due to a resonance between the input signal and internal oscillations of the neuronal membrane potential (Hutcheon & Yarom, 2000). This approach to neuronal coding seems to be very promising both from neuroscientific and mathematical/computational points of views.

Neural information coding can be implemented not only at the level of individual neurons but also at the level of activity of neural assemblies. The ideas about information coding by neural populations are similar to those of individual neurons:

(1) **Spatio-temporal coding**. The characteristics of spatio-temporal patterns of neural activity determine the code. Time and space variation of dynamics of neural activity defines functional correlates of information processing. For example, the synchrony of spike trains is related to learning and memory.

(2) **Population rate coding**. The rate/activity at time t is determined as the average number of firing neurons in a given population per a time unit (or as the average membrane potential of neurons at the moment t).

(3) **Phase-frequency coding in oscillatory neural networks**. The phases of oscillations and the natural frequencies of oscillators are characteristic variables of this approach to neuronal coding.

The above-mentioned coding schemes can be realized in the frames of the following theoretical construction. A coding system is implemented by a network (or a single neuron) of dynamically interacting elements supplied by a set of inputs (which deliver the information about a stimulus to the network) and a set of outputs (which transmit the results of coding to other information processing systems). Depending on the type of coding, the elements of the network simulate in different detail the functioning of individual neurons, neural populations (excitatory and inhibitory), or neural structures.

As the input signals, both constant and changing continuous signals can be used, as well as stochastic or deterministic sequences of spikes. The signals at different inputs can be identical to each other or can vary from one input to the other. In this paper we consider the most general case when the input signal is a modulated renewal process and the modulation of this process is the informative component.

The output signals are spike trains, or the average activity of coding elements, or the phases of oscillations. An adequate mathematical description of the coding system dynamics in the case of spike trains is a multidimensional stochastic point process with interactive components and its computational realisation by an advanced integrate-and-fire model. In the case of average activity or oscillatory phase description we deal with dynamical system models with discrete or continuous time. Typically, a coding system has the capability to learn by experience, that is the parameters of the system elements and the strength of connections are supposed to be modifiable. This may lead to the modification of the dynamics of the system while different stimuli are supplied to it. New ideas about oscillatory memory are presented in our recent papers (Borisyuk et al., 2000, 2001) where an oscillatory neural model of novelty detection in the hippocampus (based on frequency adaptation and the resonance) has been developed.

The formulated concept emphasizes the importance of studying the dynamics of encoding networks that arises as a result of the presentation of different stimuli. Not only the final state of the system that appears as a result of stimulation but the whole spatio-temporal dynamics of the system properly reflect what kind of coding is accomplished (Kryukov et al, 1990; Arbib et al., 2000). Many investigations confirm that oscillatory dynamics of neural activity and its synchronisation should play a key role in the models of information processing in the brain (see, e.g., Singer 1999, Castelo-Branko et al. 2000).

In this paper we study an oscillatory neural network composed of enhanced integrate-and-fire elements with external forcing. We study the dynamical properties of the network related to different types of external stimulations. We consider three types of stimuli: periodic, random, and modulated stochastic processes. We show that the model of a single neuron is computationally sufficient because this model demonstrates the same dynamical respond to the stimulus as the recorded neuron during experimental recordings with the same experimental conditions. On the basis of simulations we suggest some new experimental setting and predict a result of this experiment.

We show that the model of interactive populations with different connection types demonstrate a broad spectrum of different dynamics. In particular, we are interested in persistent states of neural activity as well as in coherent/synchronous patterns, which appear under stimulation by different types of external input. We estimate the performance of the encoder by the amount of information in the input signal that one can extract from the output signal. This approach gives us the possibility to compare different types of encoding schemes. An oscillatory neural network of enhanced integrate-and-fire neurons is a convenient tool for this study because we can determine spike trains as well as average activity of different neural populations and the phases of oscillations.

On the basis of available experimental evidence and the results of our modelling we hypothesize that different coding schemes are used preferably during different stages of information processing. For early stages, the temporal code is preferable. For example, the earliest stages of visual information processing (LGN) are based on spatio-temporal coding (Jones et al, 2000). At the next stages when the information includes a mixture of different modalities, another coding scheme is applied. This is the rate-coding scheme which is rather typical for the neocortex. At the top/control level of information flow the phase-frequency coding scheme seems to be most powerful. For example, information coding in the hippocampus and the cerebellum seems to be of a phase-frequency type. This complies with the fact that the medial septum, which is an input structure to the hippocampus, has endogenous pacemakers with preferable frequency band in the theta rhythm region

(Vinogradova 1995). The neurons of inferior olives, which is an input structure to the cerebellum, have frequency preference in a similar frequency band (4Hz).

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