Networks of Neurons that Emit and Recognize Signatures

Antonio Tristán, Francisco de Borja Rodríguez, Eduardo Serrano, Pablo Varona

GNB. Dpto. de Ingeniería Informática. Escuela Politécnica Superior. Universidad Autónoma de Madrid. 28049 Madrid. Spain.

Abstract

Recent experiments have revealed the presence of neural fingerprints in the activity of several neurons of the pyloric central pattern generator of crustacean. These signatures consist of specific spike timings in the bursting activity of the neurons. The existence of cellular mechanisms to identify the origin of individual neural signals, and the study of information processing based on this identification have been neglected in the context of theoretical approaches to the nervous system. In this paper we present a simple model to study the ability of a neural network to process information based on the emission and recognition of neural signatures.

Key words: Neural signatures, processing based on signal identification.

1 Introduction

Neurons of the stomatogastric central pattern generator (CPG) of the lobster (5) have specific neural signatures in the form of characteristic interspike intervals at the beginning of each burst (6). These neuron-specific firing patterns depend on the synaptic organization of the network (6; 1; 4) and can be reconfigured by neuromodulatory action. These facts raise several intriguing questions: Does the nervous system have mechanisms to generate neuron signatures and the ability to process information using these fingerprints? Do neuron signatures enhance the capacity of a network to perform a given task?

Email addresses: `Antonio.Tristan@ii.uam.es` (Antonio Tristán), `Francisco.Rodriguez@ii.uam.es` (Francisco de Borja Rodríguez), `Eduardo.Serrano@ii.uam.es` (Eduardo Serrano), `Pablo.Varona@ii.uam.es` (Pablo Varona).

As a first step to answer this last question we have developed a simple network of neurons that are able to emit and recognize specific neural fingerprints. We have studied the self-organizing properties within this network. Fast transitions of the collective activity emerge as a function of a stimulus introduced in a few neurons within the network. Information processing based on the identification of specific neural signatures can be a general and powerful strategy for neural systems.

2 Neuron and Network models

As a first approach to study information processing with neuron signatures, we have built a network of binary neurons. Each neuron in the network responds to the recognition of two signatures (A and B). When A or B signatures are recognized, the neuron emits the same signature to its neighbors with a probability equal to 0.8. If no signature is recognized, the neuron emits another signature, C, with a probability equal to 0.05. A schematic representation of this behavior can be seen in Figure 1 (panels A-C). We have built a square (50x50) network of such units with periodic boundary conditions. Each neuron is connected to its eight nearest neighbors as shown Figure 1, panel D.

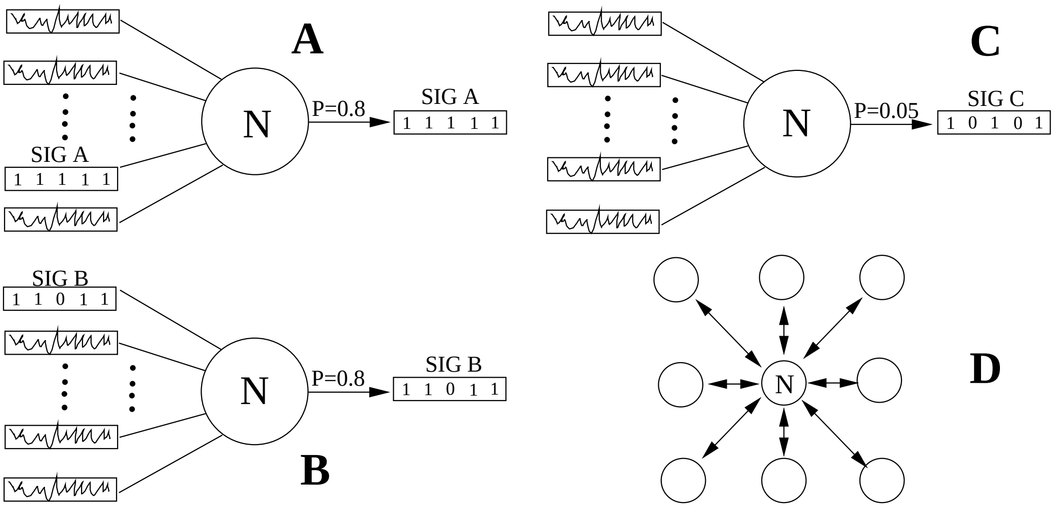

Fig. 1. Representation of the signature recognition process in the neuron model (A-C). Signature C represents the spontaneous activity of the neurons. A schematic representation of the connections established by each neuron is shown in panel D.

Each signature consists of a sequence of ones and zeros (5 bits). Signature A is (1,1,1,1,1), signature B is (1,1,0,1,1) and signature C is (1,0,1,0,1). This last signature could be considered as the spontaneous activity of the cells.

Each neuron keeps a record of its previous inputs for five time steps. Neurons check the recognition of a signature using this record in every time step. The eight connection channels are always checked in the same order. The first recognition of an input signature triggers the emission of the response signature. In the model, another channel is used to introduce an external stimulus into a few units. The recognition through this channel has also a probability of success of 0.8.

After emitting a signature, neurons have a refractory period of 10 time steps during which neither emission nor recognition is made.

3 Results

Initially, the neurons are silent and no stimulus is given to the network. At time step 5000, signature A is introduced in eight neurons chosen randomly within the network. This stimulus is kept for 10000 time steps. The network evolves freely for 5000 time steps. Then signature B is introduced as the external input to the network. These sequence is repeated once more with both signatures.

Figure 2 shows the number of neurons emitting a particular signature at each time step (panels corresponding to N_A, N_B, N_C). Bottom panel shows the overall number of neurons emitting any signature as a function of time. Without any stimulus, the activity of the network evolves to a stationary state due to the spontaneous emission of signature C. At time step 5000, signature A is introduced. The number of neurons emitting signature C drops almost instantaneously, while the number of neurons that recognize signature A grows quickly. This number oscillates around a steady level until signature B is introduced in the network. In this case, the time needed to reach a steady level in the number of neurons that emit signature B is longer than the previous transition time between signature C and A. This is due to the competition established between signatures A and B, which have the same probability of recognition. Eventually signature B wins this competition since no stimulus with signature A is sustained any longer.

The presence of a steady mean level in the emission of signatures A or B is due to the presence of a refractory period in the activity of the neurons and the network architecture used. This level is approximately the same for A and B signatures since we use the same emission probability for both. The emission level does not depend on the time during which the stimulus is sustained, once one of the competing signatures disappears from the network. Note that the time to reach each steady level of signature emission is different in each episode in which a stimulus is introduced.

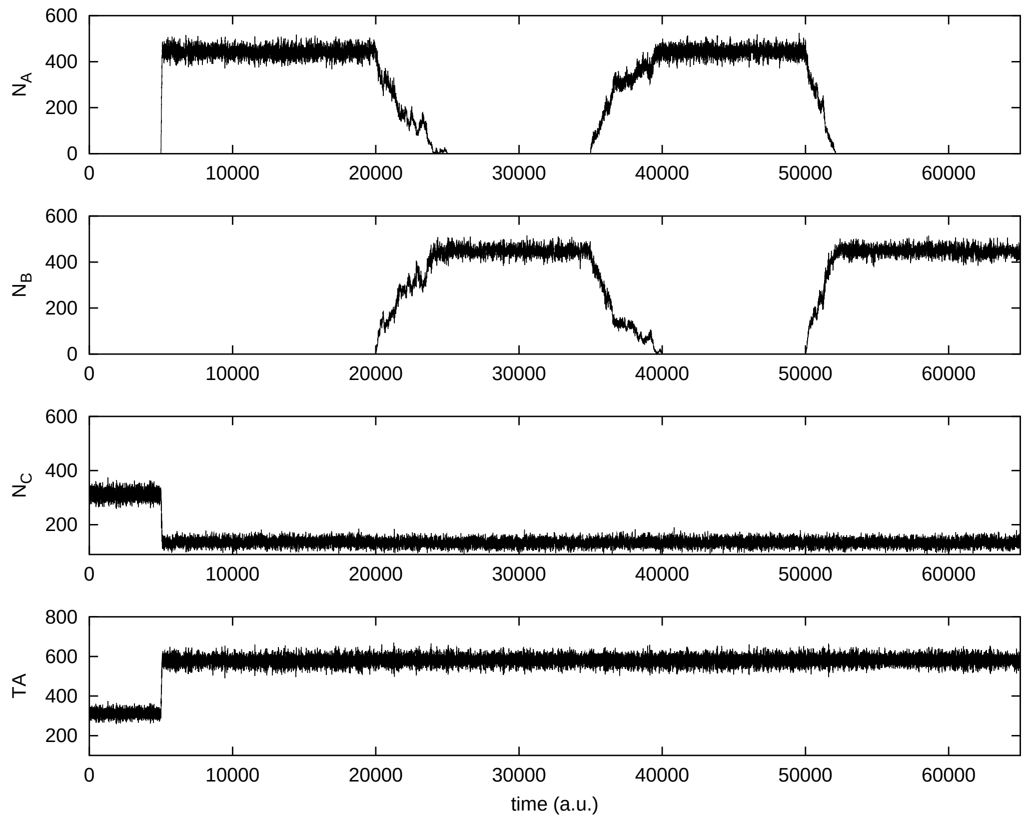

Fig. 2. Evolution of the number of neurons that emit a given signature in the network. From top to bottom, panels correspond to the emission of signature A, B, and C. Signature C represents the spontaneous activity of the neurons. Bottom panel displays the total activity (TA): the total number of neurons that emit a signature (A, B or C) at any time.

This figure also shows that the overall number of neurons emitting the spontaneous activity (signature C) is constant over time. The transition to a lower level at time 5000 is obviously caused by the spreading of signature A at that time. After that, the level is kept constant because signature B completely replaces A at each episode.

We have repeated the experiments using other sizes for up to 4 signatures (A,B,C,D) but keeping the same network architecture. Depending on the size of the signatures, the network evolves in different ways (see Figure 3). The longer the signature, the higher the total level of activity in the network. The level of spontaneous activity (signature C) grows with the signature length, since longer signatures are more difficult to recognize. The spontaneous activity is emitted if no other signature is recognized. However the level of each signature in the network decreases with increasing signature lengths. There are several regimes in which different signatures can coexist in the network (e.g. note the regions of competing B/A, B/D and D/A signatures in the panel that corresponds to length 7).

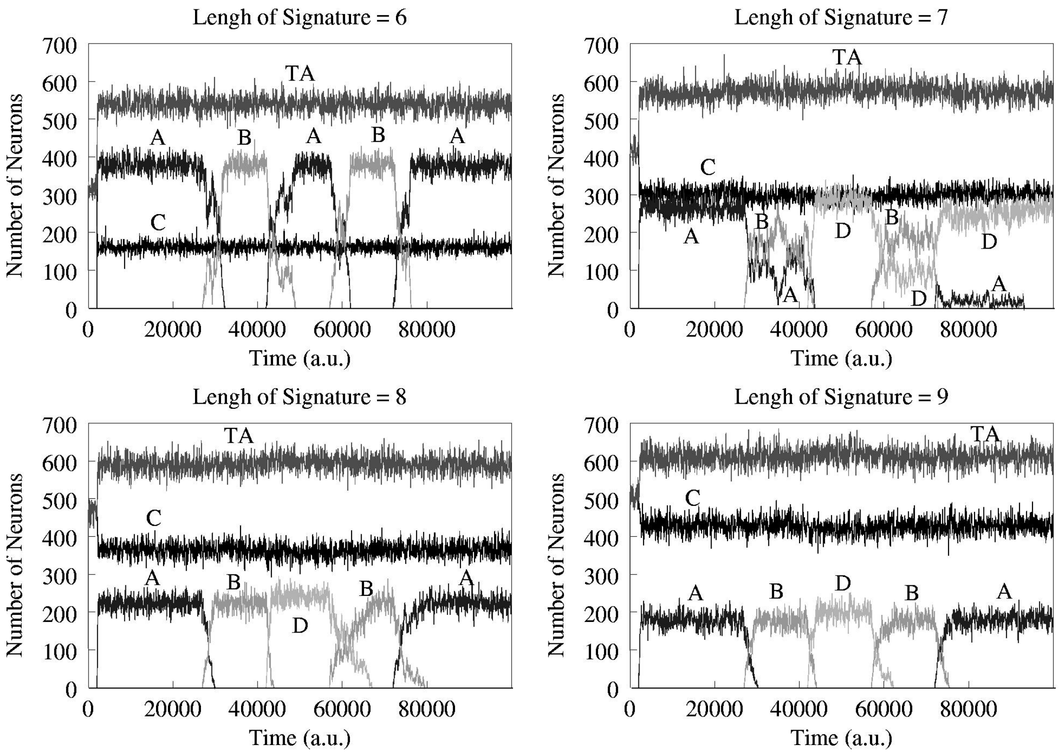

Fig. 3. Evolution of the network depending on the length of the signatures (6-9 bits). TA: total activity. Signatures for size 6 were A=(1,0,0,1,1,1), B=(1,1,1,0,1,1), and spontaneous activity C=(1,0,1,0,1,1). Signatures for size 7–9 were set by adding 1's at the end of the 6-bit signatures. In these cases we introduced an additional signature D. The sequence of inputs was A-B-D-A. For size 7, D=(1,1,1,1,1,1,1) and longer D signatures just contained additional 1 bits.

4 Discussion

Characteristic interspike interval signatures have been found in several cells of the pyloric central pattern generator of crustacean. These neuron fingerprints may play an important role for fast and fine tuning of CPG rhythms. Recent neurophysiological experiments show that modulatory inputs can modify CPG neuron signatures (6). In model experiments we have seen that the characteristic CPG triphasic rhythm evolves to other types of rhythms when signatures are changed (2). Thus, dynamic changes in the neuron signatures can have functional meanings for the pyloric CPG and other related stomatogastric circuits. The gastric CPG receives signatures from several pyloric cells, and so do muscles innervated by pyloric motoneurons. Recent evidence shows that some muscles reflect fine changes in the temporal pattern of pyloric neurons (3). Thus, both gastric cells and muscles may be able to read these signatures to perform different tasks in response to the multifunctional signals from each pyloric CPG cell. Neural fingerprints can be a general mechanism to encode temporal information in other neural networks of the nervous system.

A simple network of model neurons that have the ability to recognize several signatures displays complex self-organizing properties. In this paper, we have shown that the arrival of an specific but minor stimulus in the network induces an alternation of activity in the whole ensemble. This is just one example of what a network of neurons that emit and process signatures can do. Information processing based on recognition of signatures can make use of this recognition to:

- completely decide the output of the cells;
- weight the decision about the output based on the recognition of the signature and the content of rest of the signal;
- emit a new signature in the output based on the recognition of the incoming signature;
- in the case of a motoneuron signature, send a specific neuron fingerprint that can be read by the muscles.

A realistic spiking model for the activity of the neurons, or a more elaborate model of discrete states, can introduce higher capacity of signature information processing in the network.

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