Dynamical Systems and Accurate Temporal Information Transmission in Neural Networks

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Abstract We simulated the activity of hierarchically organized spiking neural networks characterized by an initial developmental phase featuring cell death followed by spike timing dependent synaptic plasticity in presence of background noise. Upstream networks receiving spatiotemporally organized external inputs projected to downstream networks disconnected from external inputs. The observation of precise firing sequences, formed by recurrent patterns of spikes intervals above chance levels, suggested the build-up of an unsupervised connectivity able to sustain and preserve temporal information processing.

1 Introduction

The embryonic nervous system is initially driven by genetic programs that control neural stem cell proliferation, differentiation and migration through the actions of a limited set of trophic factors and guidance cues. After a relatively short period of stable synaptic density, a pruning process begins: synapses are constantly removed, yielding a marked decrease in synaptic density due to apoptosis – genetically programmed cell death – and selective axon pruning [1]. Overproduction of a critical mass of synapses in each cortical area may be essential for their parallel emergence through competitive interactions between extrinsic afferent projections [2]. Furthermore, background activity and selected patterns of afferent activity are likely to shape deeply the emergent circuit wiring [3]. Synapses can change their strength in response to the activity of both pre-, and post-synaptic cells following spike timing dependent plasticity (STDP) rules [4]. This property is assumed to be associated

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R. Wang, F. Gu (eds.), *Advances in Cognitive Neurodynamics (II)*,
DOI 10.1007/978-90-481-9695-1_8,

with learning, synapse formation and pruning. In cell assemblies interconnected in this way some ordered and precise – in the order of few ms – interspike interval relationships, referred to as "spatio-temporal firing patterns" or "precise firing sequences", may recur within spike trains of individual neurons and across spike trains recorded from different neurons [5].

In this study we assume the existence of functional correlates of spatio-temporal neural coding, such that one would expect that the same temporal pattern of firing would be observed whenever the same information is processed in a network [6]. The relationship between the input and output spike trains is characterized by highly nonlinear transfer functions [7] and we investigate to which extent precise temporal information may be preserved assuming that each afference can carry only part of the overall information.

2 Methods

In the present study we simulate the activity of interconnected neural networks undergoing neural developmental phases. The output spike trains of the networks were scanned to detect precise firing sequences, simply referred below as "patterns", using the Pattern Grouping Algorithm (PGA) [8]. The structure and dynamics of the detected patterns were analyzed and compared with the results obtained for the single simulated networks in presence and in absence of stimuli. An underlying dynamical system attractor, if any, was searched following a technique of "denoising" the spike trains using the detected patterns [9]. The overall description of the simulation framework and parameters cannot be inserted here due to editorial space limitation and has been published elsewhere [10]. These characteristics naturally geared the modeling framework towards the analysis of spike trains recorded in a network of hierarchically organized neural networks.

3 Results

Appearance and disappearance of patterns was due to developmental changes shaped by STDP in the network connectivity underlying the process of temporally organized input activity. In absence of an external input more units survived at the end of the simulation run but less patterns were found in proportion to the number of active cells. Moreover, the ratio of detected patterns vs. active cells was larger in the downstream than in the upstream network. Figure 1 shows extreme cases of onset dynamics of a single-unit pattern: in one case a triplet appeared early in the network maturation and disappeared after $t \approx 35,000$ ms (Fig. 1a, b). The single-unit pattern <148C, 148C, 148C; 191±0.9, 698±1.0> was composed by spikes produced by unit #148C. This notation means that a precise firing sequence started with a spike of unit #148C, followed 191±0.9 ms later by a second spike of the same unit, and followed by a third spike 698±1.0 ms after the first. In the opposite case another pattern (a quadruplet in this example) appeared only at a later stage of maturation after

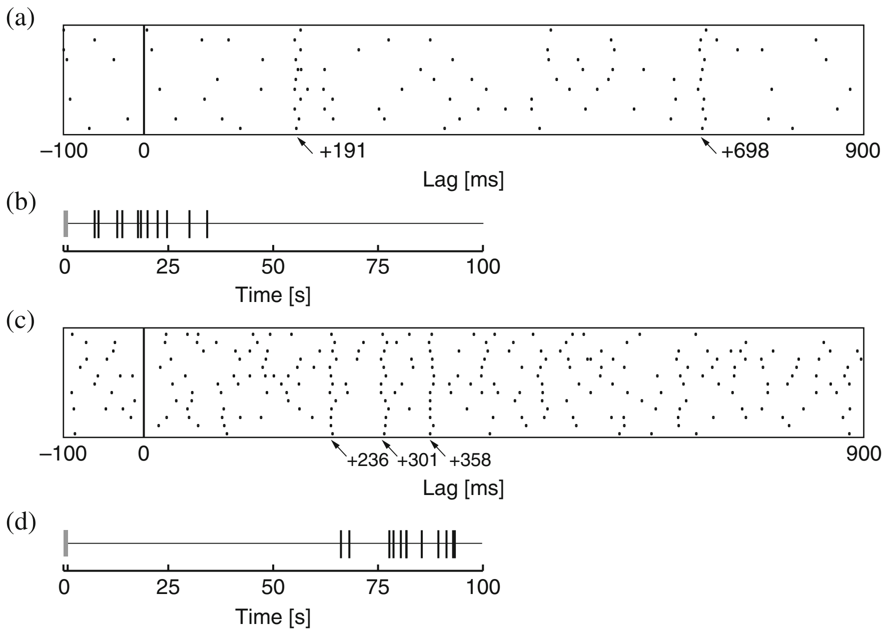

Fig. 1 Firing pattern $< 148C, 148C, 148C; 191 \pm 0.9, 698 \pm 1.0 >$ that repeated 11 times (mean firing rate = 4.0 spikes/s). **a** Raster plot of the patterns aligned on the pattern start. **b** Raster plot of pattern onsets: each vertical tick corresponds to the onset time of each pattern occurrence; Firing pattern $< 554, 554, 554, 554; 236 \pm 0.7, 301 \pm 0.8, 358 \pm 0.6 >$ (mean firing rate = 13.1 spikes/s). **c** Raster plot showing 13 repetitions; **d** Raster plot of pattern onsets

$t \approx 65,000$ ms (Fig. 1c, d). The nonlinear dynamic deterministic structure (attractor) embedded in the upstream afferent spike train was retrieved in the downstream spike train depending on the level of noise and also on parameters of the neuron model. We consider here the filtering effect produced by a cell assembly. Each neuron received only a fraction of a temporal information generated by a deterministic nonlinear dynamical system (Fig. 2). We used an input time series derived from the Zaslavskii map [9] and we observed that a distributed activity was much more efficient in transmitting the precise afferent temporal structure through the neural networks.

4 Discussion

Despite the fact that in downstream networks fewer cells were surviving at the end of the simulation run we found more firing patterns [11]. Downstream networks took more time to build-up the internal dynamics underlying the emergence of the patterns particularly in case of divergent and stronger connectivity towards the downstream network [12]. It is particularly interesting to note that when the external

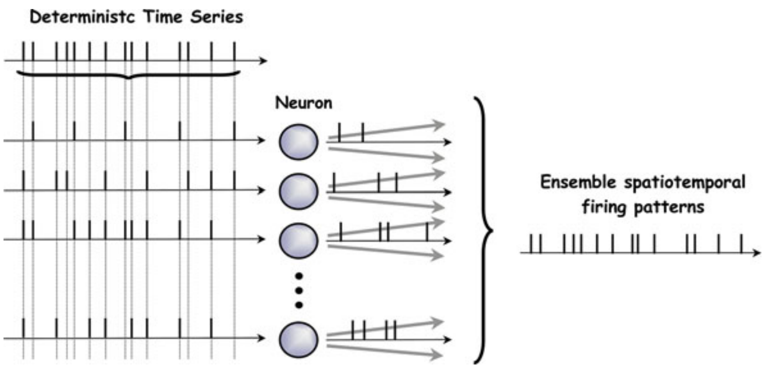

Fig. 2 The precise temporal information distributed in a cell assembly

input fed into the upstream network has en embedded complex temporally organized structure the temporally organized activity is distributed across the network and preserved throughout the downstream network and can be recovered by the analysis of reconstructed spike trains [13]. We suggest that specific neuronal dynamics characteristic of certain brain areas or associated to specific functional neuronal states play an essential role in the efficacy of transmitting a temporal pattern in a neuronal network. This feature is critical to determine the encoding and decoding processing that might be carried out by a single neuron and by the network and the extent of a distributed population coding scheme.

Acknowledgments The authors ackowledge the support by the EU FP6 grants #034632 PERPLEXUS and #043309 GABA.

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