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Stimulus processing and unsupervised learning in autonomously active recurrent networks

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Abstract. Strongly recurrent neural nets may show a continuously ongoing self-sustained activity, as it is the case for the brain. A new paradigm for learning is needed for neural nets being such autonomously active, since standard Hebbian-style online learning would result in uncontrolled reinforcement of accidental activity patterns.

Here we propose that autonomously active neural networks processing a time series of stimuli adapt whenever a stimulus successfully influences the ongoing internal dynamics. In this case the incoming stimulus corresponds to a novel signal. We then show, that the network performance results in an unsupervised non-linear independent component analysis of the input data stream. We propose this paradigm to be of relevance for stimulus processing in both natural and artificial neural nets.

1 Introduction

The self-generated internal neural activity has a central functional role for the brain, and presumably also for prospective advanced artificial cognitive systems. New experimental evidences, and theoretical considerations, indicate that this eigendynamics is important for regulating the overall cognitive processing of the brain. This spontaneous internal dynamics is influenced, but in general not forcefully driven, by the sensory input signals. In other words, the brain is not a generalized input-output calculator. In this context we study on one side possible working principles for the self-sustained internal dynamics of autonomous neural nets and on the other side its interaction with the input data stream.

For the self-sustained neural activity of the recurrent net we will use transient-state dynamics, motivated by an increasing flux of experimental results [1, 2, 3, 4, 5], indicating that the spontaneous neural activity in the cortex has often the form of quasi-stationary states. These states are not accidental in general, their semantic content being related to the informational content of the sensory data.

We propose that semantic correlations between the external stimuli and the internal transient-state activity of the autonomously active recurrent net are built up whenever the sensory signals lead to an unexpected modulation of the internal dynamics, corresponding to a novel event. We have implemented this paradigm algorithmically and tested the resulting system with the bars problem. We found it capable to perform a non-linear independent component analysis (IDA) on its own, being all the time continuously and autonomously active.

2 Quasistationary states in recurrent neural nets

Isolated dynamical systems have very characteristic long-term behaviors [6], such as chaotic orbits or trajectories approaching normal or strange attractors or limiting cycles. A special class of limiting cycles denoted 'transient-state dynamics' [7], refers to limiting cycles composed of a series of quasistationary plateaus of dynamical activity, as illustrated in Fig. 1. We note, that the individual transient states turn into stable attractors when the length of the plateau becomes extended in time [8]. Transient state dynamics is intrinsically competitive in nature. When the current transient attractor turns unstable the subsequent transient state is selected by a competitive process. Transient-state dynamics is a form of 'multi-winners-take-all' process, with the winning coalition of dynamical variables suppressing all other competing activity.

Similar processes have been proposed to be relevant for various neural functionalities in the brain. Edelman and Tononi [9, 10] argue that 'critical reentrant events' constitute transient conscious states in the human brain. These 'states-of-mind' are in their view semi-stable global activity states of a continuously changing ensemble of neurons, the 'dynamic core'. This activity takes place in what Dehaene and Naccache [11] denote the 'global workspace'. The global workspace serves, in the view of Baars and Franklin [12], as an exchange platform for conscious experience and working memory. Crick and Koch [13] and Koch [14] have suggested that the global workspace is made-up of 'essential nodes', i.e. ensembles of neurons responsible for the explicit representation of particular aspects of visual scenes or other sensory information.

3 Model

We have formulated a continuous-time neural network model showing well behaved transient state dynamics in terms of 'associative thought processes' [7, 8]. With

$$\dot{x}_i = \left\{ \begin{array}{rl} (1-x_i)\, r_i & (r_i > 0) \\ x_i\, r_i & (r_i < 0) \end{array} \right. \tag{1}$$

one can quite generally define the growth rates r_i for the neural activity-levels $x_i \in [0,1]$ of neuron i. Typical time series of growth rates r_i as obtained from numerical simulations are illustrated in Fig. 1. When the $r_i > 0$ the respective neural activity x_i increases, approaching rapidly the upper bound, as illustrated in Fig. 1; when $r_i < 0$ it decays to zero. The model is specified [7, 8], by providing the functional dependence of the growth rates with respect to the set of activity-states $\{x_j\}$.

During the transition periods most growth rates r_i acquire small absolute values and enter the competition process for the next winning coalition, as illustrated in Fig. 1. The system has then a 'sensitive period' during the transition periods, at which point it becomes sensible to the influence of external sensory signals.

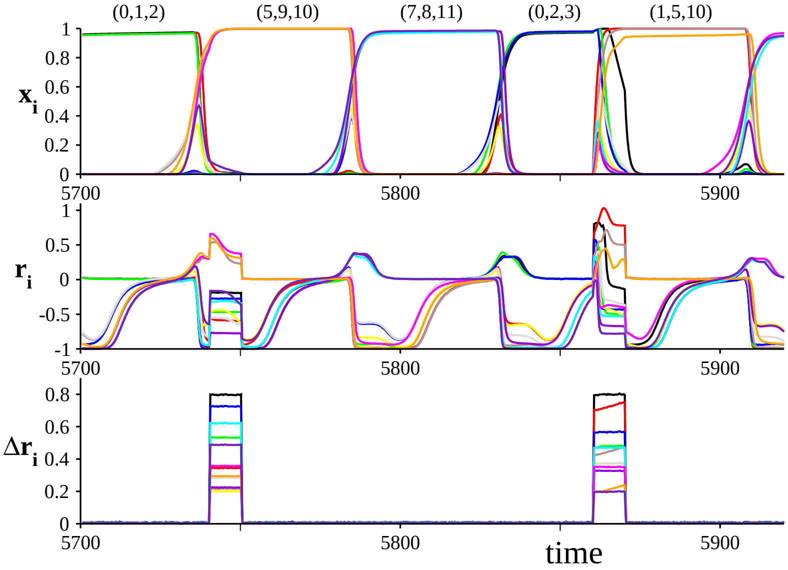

Fig. 1: Results (color coding) for the activities $x_i(t)$, the growth rates $r_i(t)$ and the input signals $\Delta r_i(t)$ from a simulation of a network containing $N = 12$ sites (topologically an icosahedron). The time series of winning coalitions is given at the top. The first input signal does not influence the neural activities x_i qualitatively, the second input signal does however modulate the ongoing transient-state dynamics.

3.1 Sensitive periods and learning

The sensory input signals contribute to the growth rates r_i of the individual neurons via

$$r_i \;\to\; r_i^{(int)} + \Delta r_i \;, \tag{2}$$

where $r_i^{(int)}$ is the internal contribution to the growth rate and where Δr_i encodes the influence of the input signals. Homeostatic self-regulation, inherent to the model [8], leads to typical input-signal strength of the order

$$\Delta r_i \simeq \left\{ \begin{array}{rl} 0.5 & \text{(active input)} \\ 0 & \text{(inactive input)} \end{array} \right. . \tag{3}$$

The input signal will therefore not destroy an active transient state, but it will enter into the competition for the next winning coalition during a sensitive period. This situation is exemplified in Fig. 1, where we present simulation-results for a system containing $N = 12$ neurons subject to two sensory inputs $\Delta r_i(t)$. The self-generated time series of winning coalitions is not redirected for the case of the first input signal, compare Eq. (3). The second input signal does however overlap with a sensitive period and the strongest components of the input influence the neural competition for the next winning coalition.

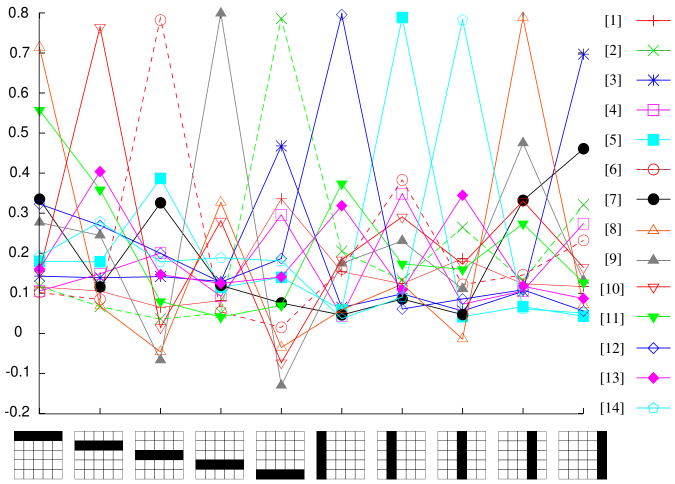

Fig. 2: For the bars-problem the response, see Eq. (5), of the 14 winning coalitions with respect to the ten reference patterns, *viz* the 5 horizontal bars and the 5 vertical bars of the 5 × 5 input field.

The model has therefore well defined time-windows suitable for the learning of correlations between the input signal and the intrinsic dynamical activity, namely during and shortly after a transition period, alias the sensitive period.

3.2 Novelty signals

A cognitive system should build up correlations between the sensory input and the neural activity patterns of the self-sustained dynamical activity only when it receives a non-trivial information, *viz* when something novel happens. Technically we define a global signal $S(t)$. It is activated whenever any of the input signals Δr_i changes the sign of the respective growth rates,

$$\dot{S} \;\to\; \left\{ \begin{array}{ll} >0 & (r_i>0) \text{ and } (r_i^{(int)}<0) \\ <0 & \text{otherwise} \end{array} \right. \quad . \tag{4}$$

The input signal Δr_i successfully modulates the internal process, making a qualitative difference, when Eq. (4) is fulfilled. The novelty signal $S(t)$ is a global signal and a sum $\sum_i$ over all dynamical variables is therefore implicit on the right-hand side of Eq. (4).

It is desirable that the interlayer connections v_{ij} (with i being an internal neuron and j a sensory input) do neither grow unbounded with time (runaway-effect) nor disappear into irrelevance. Suitable homeostatic normalization procedures are therefore implemented [15].

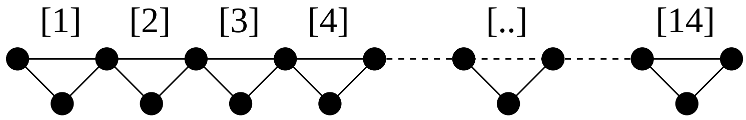

Fig. 3: The geometry of the neural net as a linear chain of triangles (3-site cliques). The winning coalitions $[i]$ $(i = 1, .., 14)$ are numerated and correspond here to the individual triangles.

4 The Bars Problem

In order to evaluate the performance of the network we selected the bars problem [16], a standard non-linear task in the domain of independent component analysis [17]. The input layer is an $L \times L$ matrix. Basic patterns are the L vertical and the L horizontal bars. The individual input patterns are made-up of a non-linear superposition of the $2L$ basic bars, containing with probability $p = 0.1$ any one of them. For the simulations we presented to the system about $N_{patt} \approx 5 \times 10^3$ randomly generated 5×5 and 10×10 input patters [15].

The results for the simulations are presented in Fig. 2 for the case of the 5×5 bars problem. For the geometry of the network we used for simplicity a chain containing 15+14=29 sites and 14 potential winning coalitions, as illustrated in Fig. 3. The winning coalitions are here 3-site fully interconnected clusters, i.e. the cliques in math terminology. In Fig. 2 we present the response

$$\frac{1}{S(C_\alpha)} \sum_{i \in C_\alpha, j} v_{ij} x_j^\beta \qquad \alpha = 1, .., 14, \qquad \beta = 1, .., 10 \tag{5}$$

of the 14 potential winning coalitions C_α to the 10 basic input patterns $\{x_j^\beta, j = 1, .., 25\}$, the isolated bars. Here C_α denotes the set of sites of the winning-coalition α and $S(C_\alpha)$ its size, here $S(C_\alpha) = 3$. The individual potential winning coalitions have acquired, a result of the unsupervised learning, distinct susceptibilities to the 10 bars. The problem is however in this case over-complete, as there are more potential winning coalitions than statistically independent basic patterns. The learning is very fast, in addition, and perfect signal separation cannot be expected.

5 Discussion

We studied the interplay of the eigendynamics of a recurrent neural net, having the form of a time-series of winning coalitions, with the sensory input. We found that the system performs a non-linear feature analysis on its own, with the internal associative thought process acquiring semantic content. We believe that self-active recurrent networks will play a central functional role for future advanced artificial cognitive systems and we hope that this work will stimulate further research in this field.

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