Brain dynamics promotes function

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Abstract. Dynamical structure in the brain promotes biological function. Natural scientists look for correlations between measured electrical signals and behavior or mental states. Computational scientists have new opportunities to receive 'algorithmic' inspiration from brain processes and propose computational paradigms. Thus a tradition which dates back to the 1940s with neural nets research is renewed. Real processes in the brain are 'complex' and withstand trivial descriptions. However, dynamical complexity need not be at odds with a computational description of the phenomena and with the inspiration for algorithms that actually compute something in an engineering sense. We engage this complexity from a computational viewpoint, not excluding dynamical regimes that a number of authors are willing to label as chaos. The key question is: what may we be missing computation-wise if we overlook brain dynamics? At this point in brain research, we are happy if we can at least provide a partial answer.

Key words: Brain dynamics; spatiotemporal dynamics; chaos; computation.

1 Natural computing

Natural computing is regarded as belonging to two strands: computation taking place in nature and human-designed computation inspired by nature [1]. Our work takes the understanding of the former as a starting point, and aims to contribute to the latter by proposing abstractions leading to computing paradigms or actual analog devices.

2 Natural neurons and artificial neural networks

Classical neural nets research has emphasized the structure and the role of the individual neuron, either through trying to infer the formal function that would be best approximated by a given biological neuron, or through using synaptic adaptation as inspiration for automatic learning procedures in computation [2].

This lead to a bottom-up engineering approach, and quite naturally to initial examples of emergent behavior in artificial networks. Such emergence or self-organization is most evident in recurrent networks, which are believed to mimic the structure of the biological brain better than non-recurrent ones.

3 Dynamics

Despite researchers having studied processes involving neural populations, the dynamical aspects thereof have been viewed as somewhat secondary in artificial computation. The dynamics has mainly consisted in periodic cycles of synchronized populations, or in transients to equilibrium states. A modern stream of research goes one step further by considering the so-called dynamical complexity as revealed e.g. by the measurement of the brain's electrical activity [3–8]. Inspired by such experiments with the biological brain, our own work and that of others tries to assess the computational role of the brain's complex dynamics, as well as to obtain inspiration for possible artificial computing paradigms. In this extended abstract we refer the reader e.g. to Refs. [9–11] and references therein. Here we briefly point out a few interpretations of the so-called dynamical state of the brain, providing as many implementation ideas for the computer scientist. The definition of dynamical state is left somewhat open. The approach evolves from viewing dynamics as a tag, up to viewing it as a structural explanation or a functional necessity.

The dynamical state is a label

Under this 'passive' view, the dynamical state labels what the animal is able to process at a given time, which can be related to anticipation or predisposition. It can also label whatever the animal is already computing in a broad sense. Either way, the observed dynamics is regarded as an epiphenomenon, secondary to some other, deeper, process which is taking place and which is what really matters in terms of computation.

The dynamical state is a substrate

Freeman and co-workers [12] have identified amplitude and phase modulation patterns over a spatiotemporal wave of electrical activity in the animal's brain. The underlying wave is a so-called carrier wave. The identified modulation patterns convey meaning, e.g., by identifying particular odors that are being sensed.

The dynamical state modulates attention

With enough control available, a seemingly complex dynamics —or mixture of dynamical regimes— can be driven into a particular state, which is specialized in a processing task, or class of tasks. In biological terms, we would say that the animal (or the bio-inspired device) is 'attentive' to input data with certain characteristics [9].

The dynamical state provides an operator for input data

Input data can itself generally be described as a function of time and space. Several scenarios can be envisaged whereby external input data perturbs an internal dynamical state [9–11]. The way in which the internal state is perturbed depends on its own details and on details of the input data.

The dynamical state is the output of a computation

Traditionally, the concept of computation implies that some output is read out. An observed dynamics can constitute such a readout, or 'result' of the computation. Output functions need not be as complicated as full spatiotemporal waves of activity, and the reduction of complexity can happen at several levels [9].

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