Synchronization and memory in neural networks beyond their fixed point

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Random neural networks (RNN's) are a popular choice to approximate biologically realistic recurrent neural networks, where the synaptic neural links are Gaussian distributed [1–4]. Despite the fact that connectivity inside the brain cannot be assumed to be fully random [5;6], there is experimental evidence supporting the assumption that some parts of the brain are described by a stochastic architecture [7–9]. Although interactions inside RNN's are governed by random connections, these networks can still achieve highly coherent collective dynamics [10;11]. Among others, they exhibit phase synchronized dynamics which have an important role in biological memory processes, neural communication and plasticity [12]. Therefore phase synchronization plays a crucial role in biological neural networks information processing.

Spatiotemporal patterns of self-organization can be found in homogeneous [13] and heterogeneous [14;15] artificial neural networks. Depending on system parameters, such spatiotemporal patterns include global synchronization or clustering. This suggests that such cooperative behaviour is potentially an universal phenomenon found in neural networks. The computational capabilities of RNN's have been widely studied in the machine learning community. For machine learning purposes the initial state of the neural network can be set to stable [16] or transitory (regular-to-chaotic) dynamics [17]. Hence, regardless of how regular the RNN's autonomous dynamical state is, it is always capable to process information as long as input information and memory are preserved. Consequently, how global dynamical properties are harnessed by the RNN for information processing has to be considered.

In this work, we show a RNN designed with a periodic nonlinear function with several extrema. For higher values of the bifurcation parameter μ the network is able to maintain highly regular spatiotemporal patterns, despite chaotic behavior of the individual neurons. We found that some of the most synchronous spatiotemporal patterns are related with non-chaotic responses of the network's neurons, among with we can find steady states and periodic solutions. Such regions offer a lower degree of complexity, which can be harnessed for information processing. For machine learning purposes, we have introduced a xy-system capable to emulate the temporal evolution of a given chaotic system, i.e. to predict the future time-steps of the Mackey Glass chaotic system [18].

The way how these networks memorize information is addressed by three different methods, which can be interpreted as complexity indices for machine learning based on dynamical systems. At first, we studied the spatial synchronization of the network, where the highly synchronous regular regimes were related to good prediction performances. However, spatially synchronized chaotic responses were not capable to keep the important features of the input dynamic, resulting in a low prediction performance. Maximal Lyapunov exponents and memory capacity were found to behave inversely proportional respect to each other. Memory capacity therefore decreases when λ_{max} increases. As the complexity of the RNN increases with μ, the network is less efficient by memorizing the input information.

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