Reservoir computing with self-organizing neural oscillators

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Abstract

Reservoir computing is a powerful computational framework that is particularly successful in time-series prediction tasks. It utilises a brain-inspired recurrent neural network and allows biologically plausible learning without backpropagation. Reservoir computing has relied extensively on the self-organizing properties of biological spiking neural networks. We examine the ability of a rate-based network of neural oscillators to take advantage of the self-organizing properties of synaptic plasticity. We show that such models can solve complex tasks and benefit from synaptic plasticity, which increases their performance and robustness. Our results further motivate the study of self-organizing biologically inspired computational models that do not exclusively rely on end-to-end training.

Introduction

Reservoir computing is a computational framework that combines a recurrent network of interacting units (reservoir) with a single trainable layer that interprets the reservoir's activity. Inputs are given to the reservoir, whose dynamics transform them into more interpretable, high-dimensional outputs processed by a trainable linear layer (Schrauwen et al., 2007). Different types of reservoirs have been studied over the years (Tanaka et al., 2019), since their energy efficiency and easy training make them attractive as a computational paradigm. Moreover, their study can offer insights into more fundamental questions about the nature of computation.

Given the prominence of biological neuronal networks as the standard for computational efficiency, biologically inspired reservoirs have been widely studied, mostly in the form of liquid state machines (LSM) that utilise a recurrent spiking network as a reservoir (Maass, 2010). One of the primary features of such networks is their ability to self-organize through a combination of various forms of synaptic plasticity (Effenberger et al., 2015; Raghavan et al., 2020). This ability has been shown to significantly boost the computational capabilities of LSMs (Lazar et al., 2009).

Here, we examine whether the self-organizing effect of biological plasticity can be extended to a rate-based neural reservoir. Specifically, networks of coupled oscillators representing neural populations have been proposed as an computationally tractable alternative to large simulations of spiking networks (Giannakakis et al., 2020). Moreover, networks of oscillators have been suggested as a possible candidate for an efficient reservoir (Yamane et al., 2015).

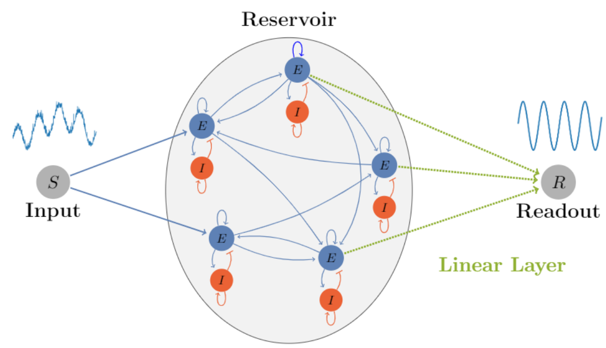

Figure 1: A schematic of the network. The reservoir consists of a network of sparsely connected Wilson-Cowan oscillators and its output is processed by a linear readout layer.

To uncover the effects of self-organization in such a model, we use as a reservoir a network of Wilson-Cowan oscillators. This network is a well-known model, whose dynamical properties have been widely studied (Ahmadizadeh et al., 2016; Maruyama et al., 2014). We investigate how the introduction of local inhibitory plasticity (Vogels et al., 2011), which has been shown to have a self-organizing effect in such networks (Hellyer et al. (2014)), affects the model's performance in a demixing task.

Model & Performance

Our reservoir is a network of 300 Wilson-Cowan oscillators with sparse connections (0.95 sparsity) between the excitatory populations. The parameters of each oscillator are the same, with the exception of the timescale τ that is sampled from a log-normal distribution. The input signal is generated by summing up two sinusoidal waves of different frequencies, amplitude and phases. The aim of the network is to

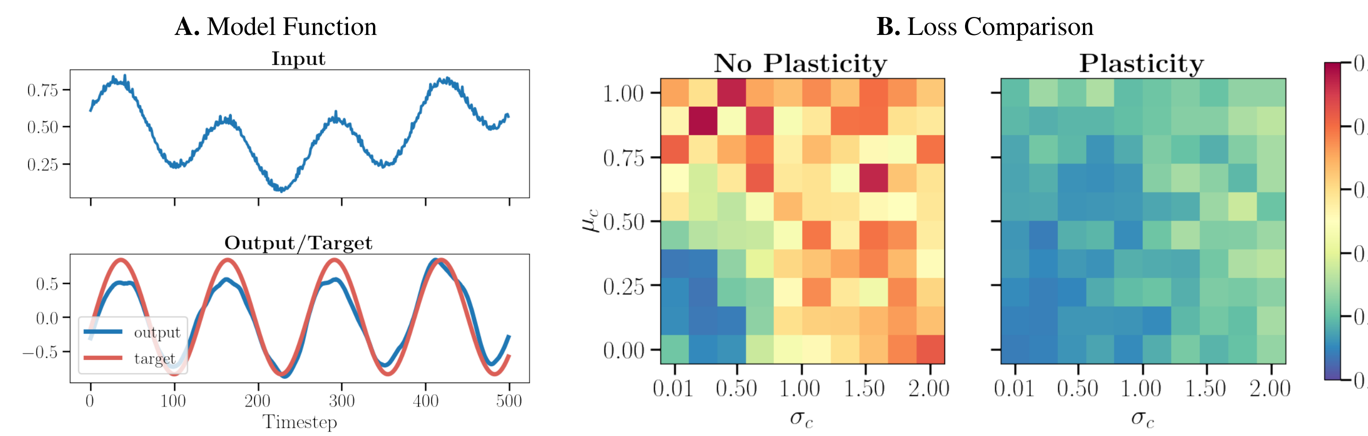

Figure 2: Plasticity improves performance of the reservoir **A**: The input and output signal compared with the target signal. The network reconstructs the target fairly accurately. **B**: A comparison of the model's loss for connectivity matrices drawn from Normal distribution with varying μ and σ. With self-organization by plasticity, the network performs similarly well for all connectivities, while without plasticity, the loss becomes very large outside a small range of distributions

reconstruct the higher-frequency sinusoidal wave, similar to a task that has been used to test reservoir models previously Otte et al. (2016). The signal is fed into a set of read-in neurons in the reservoir and the read-out is generated from a trainable linear read-out layer (Figure 1).

The read-out weights are trained via gradient descent using the mean square error $(1/N \cdot \sum_i^N (y_i - \hat{y}_i)^2)$ between the target and output sequences. All other connection weights in the reservoir are fixed and sampled from a Normal distribution. The model is written and trained using the PyTorch library. Before training, we allow the network to self-organize via an internal plasticity mechanism that adjusts the internal inhibitory to excitatory ($I \rightarrow E$) connection of each Wilson-Cowan node, without affecting the network's global connectivity. The strength of the $I \rightarrow E$ connection is modified according to a classic plasticity rule (Vogels et al., 2011):

$$\Delta w_{ie} = c \cdot I \cdot (E - \rho_0), \tag{1}$$

that adjusts inhibition to keep the average activity of the excitatory population (E) close to a set target rate (ρ_0). This adjustment prevents the network's nodes from converging to a fixed point and instead keeps them oscillating throughout the training period. The target rate for each node is sampled from a uniform distribution: $\rho_0 \sim \mathcal{U}(0.1, 0.25)$.

The network manages to accurately reconstruct the target signal (Figure 2A). The performance of the network strongly depends on the size of the reservoir and the distribution of the timescale parameter τ (larger reservoir and wider distribution improve performance). Additionally, when the network is not tuned via synaptic plasticity, the distribution of inter-node connection weights strongly affects the network's performance (wider distributions lead to diminished performance). However, the inclusion of inhibitory tuning allows the network to self-organize to a balanced state. This, in turn, enables the network to be agnostic to its inter-node connectivity and leads to near-optimal performance for all connectivity parameters (Figure 2B).

Discussion

The state-of-the-art machine learning techniques rely on end-to-end training and precisely defined objective functions. In contrast, biological learning systems utilise distributed, energy-efficient, and robust computational paradigms, as well as the ability to self-organize without explicit training. These features are increasingly sought after in artificial systems both in software and hardware implementations, and therefore, frameworks like reservoir and neuromorphic computing are becoming more mainstream.

Here, we introduce a reservoir of neural oscillators and show that it is capable of performing complex tasks. Additionally, we demonstrate that the ability to self-organize via a biological plasticity mechanism improves its robustness and performance. Further research into the dynamics and behaviour of such systems is needed in order to fully understand their computational capabilities. A better understanding of the function of biological reservoirs might offer an alternative path to studying biological computation as well as developing novel learning algorithms.

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