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Forecasting of adaptive network's dynamics

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***Abstract*—We investigate the possibility of forecasting the dynamics of the adaptive network, which topology changes in time, by using Reservoir Computing (RC). As an input signal, we use a signal averaged over 100 Kuramoto oscillators. Such macroscopic signal has a similar nature with EEG signal which is a macroscopic signal of a group of neurons that connections adapt in time. We find the optimal values of RC's parameters for achieving maximal correlation between the output and the target signal.**

***Index Terms*—Adaptive network, nonlinear dynamics, forecasting, reservoir computing**

I. Introduction

Forecasting complex systems dynamics is a complicated and important task. Complex systems are characterized by multiple, interacting spatiotemporal scales that challenge classical numerical methods for their prediction and control. In real life, we face the challenges of predicting the dynamics of different natures like weather, climate, economic trends, etc [1]. One of the interesting tasks here is forecasting neurophysiological signals to diagnose and react in time to a negative phenomenon, like epilepsy seizure [2]. To study brain activity researchers investigate dynamics of electroencephalographic (EEG) [3]–[10], magnetoencephalographic (MEG) [11]–[14], functional near-infrared spectroscopy (fNIRS) [15]–[17] signals, modulate neural network's dynamics [18]–[22], use artificial neural networks (ANN) for analysing big neurophysiological data [23]–[26].

Recurrent Neural Networks (RNNs) offer a potential method for addressing these challenges. The most promising type of RNN for solving this task is Reservoir Computing (RC) [27]–[30]. RC has shown significant success in modelling the full-order space dynamics of high dimensional chaotic systems. In addition, reservoir computers have also been realized physically as optical feedback systems, which can perform chaotic system forecasting at a very high rate.

In this work, we address the question of using RC to forecast the dynamics of the adaptive network of Kuramoto oscillators, which topology changes in time, and the averaged signal of the network is evolving. A similar process is going in the brain's neural network, and an EEG signal is a macroscopic signal of a group of neurons that connections adapt in time.

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II. Methods

As an input signal for forecasting we use a signal averaged over 100 Kuramoto oscillators with the adaptation of the couplings. The model and the adaptation mechanism are described in [31]. To generate the signal we use $N = 100$ oscillators and $M = 1$ layer with characteristic memory time $T_m = 100$ and intralayer coupling strength $\sigma = 1.0$. We solve the system of differential equations using the Runge Kutta 4th order method with time step $\Delta t = 0.1$ ms for $T = 4000$ ms.

To increase the dimension of the signal, we use delayed signals and reconstruct a phase space.

We use an RC construct known as an echo state network, which uses a network of nodes as the internal reservoir [32]. Every node has inputs drawn from other nodes in the reservoir or from the input to the RC, and every input has an associated weight. Each node also has an output, described by a differential equation. The output of each node in the network is fed into the output layer of the RC, which performs a linear operation of the node values to produce the output of the RC as a whole. The regularization constant $\beta = 10^{-8}$ discourages overfitting by penalizing large values of the fitting parameters.

We use the reservoir with $D = 1000$ nodes and investigate RCs with different number of input nodes. The number of output nodes in each case is the same as the number of input nodes. The first part of the signal is used for learning and the second one for testing.

III. Results

We investigate the correlation r between the output and the target signal versus the parameters of the reservoir (spectral radius R, nodes degree D, input scaling σ_{input}). We calculate r for different time intervals: 100, 200 and 2000 ms (see Fig. 1).

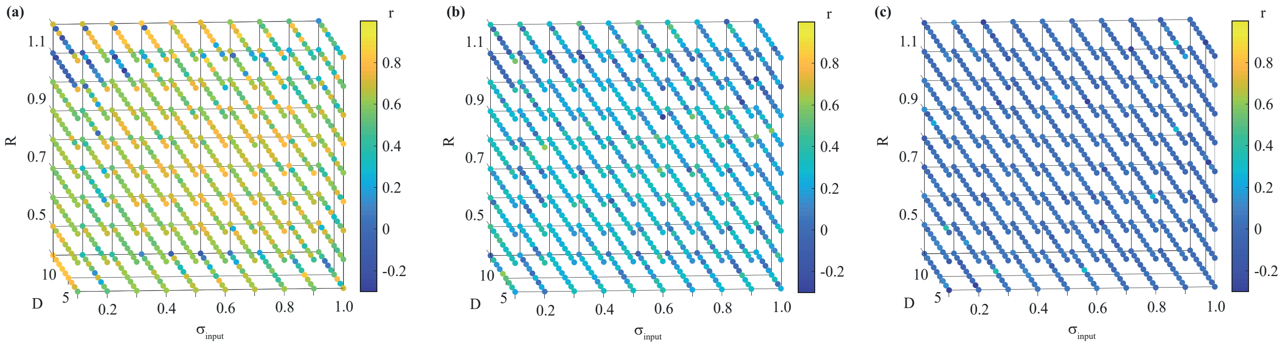

Fig. 1. The correlation r between the output and the target signal versus the parameters of the reservoir (spectral radius R, nodes degree D, input scaling σ_{input}) for different time intervals: (a) 100, (b) 200 and (c) 2000 ms.

TABLE I
OPTIMAL RC'S PARAMETERS FOR ACHIEVING THE MAXIMAL CORRELATION BETWEEN THE OUTPUT AND THE TARGET SIGNAL.

Parameter	***Value***		
	100 ms	200 ms	2000 ms
Maximal correlation r	0.863	0.603	0.386
Spectral radius R	1.1	0.9	0.6
Nodes degree D	8	2	3
Input scaling σ_{input}	0.6	0.2	0.1

We find the optimal parameters of the reservoir to achieve a maximal correlation r (Table 1). As one can see, better correlation is achieved for shorter time because of non-stationary complex dynamics of the signal. Low values of input scaling σ_{input} and high values of spectral radius R lead to low correlation (Fig. 1(a)).

To increase the capability of RC to forecast the signal's dynamics we increase the dimension of the input signal by adding the delays. We find, that it leads to increasing the maximum achievable value of correlation, the valid prediction time, and minimal root mean square error of the predicted signal.

IV. Conclusions

We have investigated the possibility of forecasting the dynamics of the adaptive network, which topology changes in time, by using Reservoir Computing (RC). As an input signal, we have used a signal averaged over 100 Kuramoto oscillators. Such macroscopic signal has a similar nature with EEG signal which is a macroscopic signal of a group of neurons that connections adapt in time. We have found the optimal values of RC's parameters for achieving maximal correlation between the output and the target signal. Increasing the dimension of the input signal by adding the delays leads to increasing the capability of RC to forecast the signal's dynamics.

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