Reservoir computing allows recovering hidden network dynamics

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***Abstract*—In this study, we examined reservoir computing (RC)as a tool for predicting the macroscopic dynamics of a subset of oscillators in a network based on the macroscopic dynamics of other parts of it. As a model network, we utilized a network of 300 Kuramoto oscillators with adaptation. Our results demonstrate that reservoir computing effectively addresses this task. Additionally, a similar reservoir computing model was applied to experimental neurovisualization data and exhibited high accuracy in reconstructing damaged EEG channels compared to classical methods like spatial interpolation.**

***Index Terms*—Brain adaptation, fNIRS, Sternberg paradigm, short-term memory**

I. Introduction

In recent decades, RC has been actively researched and applied in various fields of artificial intelligence and machine learning. This approach represents a powerful tool for analyzing and predicting complex dynamic systems where hidden network processes play a crucial role. It is well known that RC excels in predicting the complex dynamics of chaotic systems such as the Rössler system, Lorenz system, and others, as well as effectively reconstructing the structure of their attractors [1]–[3]. In our recent work, we explored the possibility of predicting the behavior of complex systems with limited information using RC [4]. We demonstrated that to improve the quality of prediction of chaotic signals, it is necessary to expand the feature space and determine the appropriate embedding dimension.

In real life, forecasting and recovering the macroscopic dynamics of complex networked systems are of paramount importance. The main challenge lies in the fact that signals from multiple different elements are combined into a single macroscopic signal through complex communication structures, reducing the system's dimensionality and making it challenging to analyze. In most real-world networked systems, the connections between elements change over time, which increases the complexity and unpredictability of macroscopic dynamics. A good example of a macroscopic signal is the signals produced by various neuroimaging techniques such as EEG, fNIRS and fMRI, which are actively used in neurophysiological research [5]–[12].

In this study, we examined the dynamics of a network consisting of 300 Kuramoto oscillators with adaptation, similar to the work referenced [4], [13], [14]. We divided the oscillators into 6 equal groups and calculated the macroscopic signal obtained from each of these groups. Then, we trained our reservoir model to predict the dynamics of one of the macroscopic signals based on the dynamics of the others. For reservoir computing, we used the package [15].

II. Results

We optimized the hyperparametersof the reservoir (leak rate, spectral radius, reservoir connectivity, input connectivity) using Monte Carlo method. Optimization of hyperparameters was performed in the following ranges: leak rate from 0.01 to 0.9; spectral radius from 0.001 to 2; reservoir connectivity from 0.05 to 0.9; input connectivity from 0.05 to 0.9. To evaluate the prediction quality, we estimated the standard deviation attributable to the maximum spread of the target signal amplitude. The maximum prediction accuracy was 0.056. Figure 1 shows the reconstructed state (blue) of the reservoir and the actual trajectory (red) of one of the 6 macroscopic signals of the Kuramoto adaptive network. The figure clearly shows that the reconstructed signal well repeats the real macroscopic signal. Also in this work, we have considered the possibility of using RC to repair damaged channels on neurophysiological recordings.

III. Conclusions

In this paper, we applied RC to recover the hidden macroscopic dynamics of a subset of oscillators in a network based on the macroscopic dynamics of other parts of the network. We used a network of 300 Kuramoto oscillators with adaptation as a model network. We have shown that reservoir computing can

This work was supported by Saint Petersburg State University, project ID: 94034465. A.A. was supported by the Council on Grants of the President of the Russian Federation (Grant MK-2142.2022.1.2).

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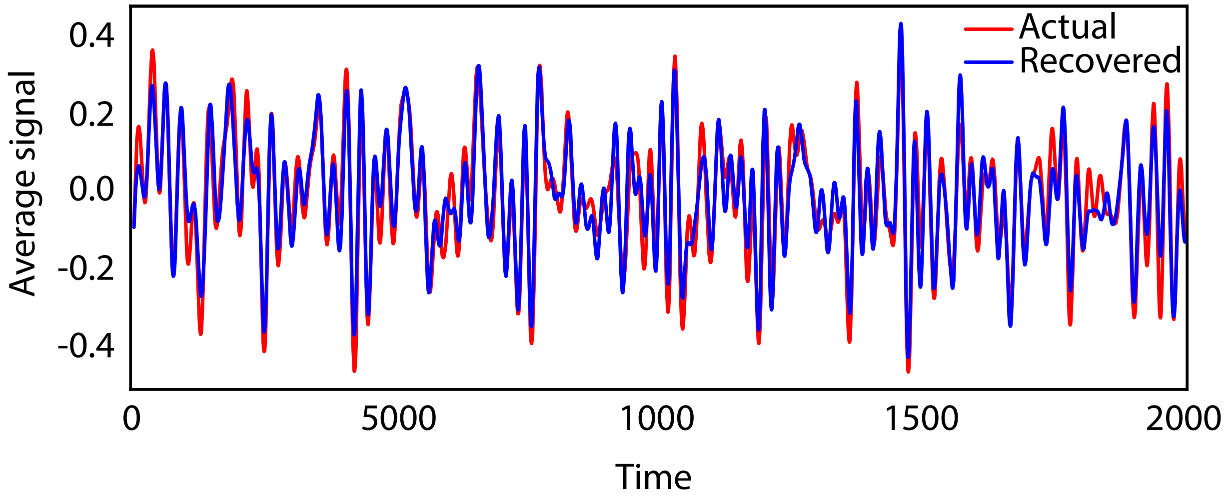

Fig. 1. Recovered state (blue) of the reservoir and the actual trajectory (red) of one of the 6 macroscopic signals of the Kuramoto adaptive network.

solve this problem with high accuracy. In addition, we used a similar reservoir computing model to recover damaged EEG channels and found that the accuracy of recovering damaged EEG channels outperforms classical recovery methods such as spatial interpolation. Also in this paper we considered the possibility of applying RC to hemodynamic neurophysiological signals.

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