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Performance evaluation of new echo state networks based on complex network

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Abstract

Recently, echo state networks (ESN) have aroused a lot of interest in their nonlinear dynamic system modeling capabilities. In a classical ESN, its dynamic reservoir (DR) has a sparse and random topology, but the performance of ESN with its DR taking another kind of topology is still unknown. So based on complex network theory, three new ESNs are proposed and investigated in this paper. The small-world topology, scale-free topology and the mixed topology of small-world effect and scale-free feature are considered in these new ESNs. We studied the relationship between DR architecture and prediction capability. In our simulation experiments, we used two widely used time series to test the prediction performance among the new ESNs and classical ESN, and used the independent identically distributed (i.i.d) time series to analyze the short-term memory (STM) capability. We answer the following questions: What are the differences of these ESNs in the prediction performance? Can the spectral radius of the internal weights matrix be wider? What is the short-term memory capability? The experimental results show that the proposed new ESNs have better prediction performance, wider spectral radius and almost the same STM capacity as classical ESN's.

Keywords ESN, complex network, time series prediction, short-term memory capacity

1 Introduction

In the past decade, complex networks have aroused a lot of interest [1–4] and have been extensively studied in many fields, including the Internet, social networks, protein networks, ecological networks, transport networks, metabolic networks, power networks, communications networks and so on [5–13]. In a large number of the real-world networks as mentioned above, small-world phenomena and scale-free properties have also been discovered. A small-world network is a network where many nodes are not directly connected to the others, but any node can reach any other node in a relatively few number of steps [14–15]. These small-world networks have a common feature that the degree distribution of the network follows an exponential distribution. Barabási and Albert proposed a scale-free network model [2,16], which pays more attentions to the growth and preferential attachment of the structure and has a power-law degree distribution.

It is well known that complex networked systems abound in both nature and technology, for instance, biological neural systems are typical complex systems, which consist of neurons and synaptic pathways. And many researchers have made several attempts in applying complex network theories to complex systems. Associative memory neural networks with small-world architecture or scale-free topology have been presented [17–20]. The small-world effect and scale-free feature can also make synchronization more efficient [21].

ESN is a new paradigm for using recurrent neural networks (RNN) with a simpler training method [22–23]. It does well in modeling nonlinear dynamic systems, function approximation as well as time series prediction. The classical ESN contains a randomly connected DR as a hidden layer with hundreds or thousands of neural nodes. Just like an ESN's DR, many systems in nature can be modeled by networks or graphs, which would consist of

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nodes and connections. However, for almost a century, there is an implicit assumption that the connections among the nodes of underlying system can be embedded onto a regular or a random connection model. Apparently, modeling systems under such assumption is unreasonable, for most of these real-world networks are neither entirely regular nor totally random [24]. Although the classical ESN has perfect modeling capability, its DR is constructed under the plain assumption above.

And Jaeger et al. pointed out in Refs. [22–23] that the spectral radius of internal weights matrix should be smaller than one in order to guarantee the echo property. But he also mentioned in his report (*The echo state approach to analyzing and training recurrent neural networks*. Available: http://minds.jacobs-university.de/sites/default/files/uploads/papers/EchoStatesTechRep.pdf) that the larger the spectral radius, the faster is the network's response to an impulse input, and the stronger the network's memory capacity. That is to say, there seems to be a contradiction between the spectral radius and the ESN's performance. Does the random topology of DR lead to this contradiction? And can ESN have enhanced performance while using a new paradigm to generate its DR?

So in this paper, we try to introduce the complex network theory into the construction of the ESN's DR. Topologies of these new DRs essentially interpolate between the completely regular networks and the random networks. The small-world ESN (SWESN), scale-free ESN (SFESN) and mixed ESN (MESN) are proposed and applied to the nonlinear autoregressive moving average with exogenous inputs (NARMAX) time series prediction problems. And we also analyze the STM capacity of these ESNs using i.i.d. time series. Amazingly, the experiments show that with the same spectral radius, the proposed ESNs have better prediction accuracies, and with the same prediction accuracy, the proposed ESNs can have wider ranges of spectral radius. In other words, the proposed new ESNs have enhanced performance and better echo properties. And the contradiction between the spectral radius and the performance can also be relieved. As to the STM capacity, the proposed ESNs have almost the same STM value as the classical ESN.

The remainder of this paper is organized as follows. The proposed new ESNs using complex network are described in Sect. 2. In Sect. 3, simulation experiments are carried out to evaluate the performance of the proposed new ESNs. Finally, our work is discussed and concluded in Sect. 4.

2 New ESN based on complex networks

ESN is a new kind of artificial neural network, where a sparsely connected RNN has most of its weights fixed to the randomly chosen values [25]. The only trainable weights are those on links connected to the outputs. ESN leads to a fast, simple and constructive algorithm for supervised training of RNNs. In general, the classical ESN consists of three parts as illustrated with Fig. 1: the left part is input, the mid part is a large DR, and the right part is output. More information about the training and exploring methods can be found in Ref. [22].

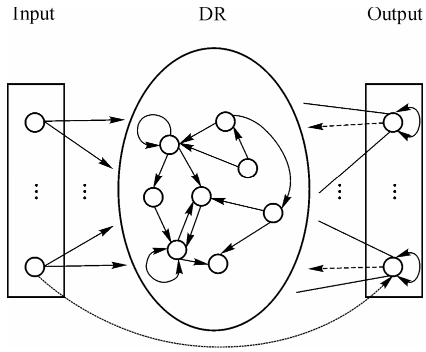
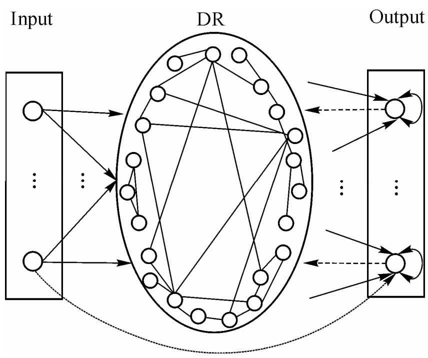


Fig. 1 System architecture of ESN

The proposed new ESNs (SWESN, SFESN and MESN) are able to imitate more actual learning mechanisms of the biological brain by introducing various complexities to the DR. Although the new ESNs are more complicated than the classical ESN, they have the same structure. It is clear from Fig. 2 that the new ESNs also consist of three parts. The only difference lies in the architecture of DR. Supposing that there are N neural units in the DR to be constructed, then the construction of this DR can be considered as how to generate the connections among these units. In Ref. [22] Jaeger et al. chose a randomly connected way. The methods to generate the new DRs are described as follows:



(a) SWESN