Applied Mathematics & Information Sciences
An International Journal

Target detecting in sea clutter with echo state network

Zhan Xu and Jianwei Wan

College of Electronic Science and Engineering, National University of Defense Technology, Changsha, 410073, China

Received: March 3, 2012; Revised May. 15, 2012; Accepted May. 22, 2012
Published online: 1 Sep. 2012

Abstract: This paper use echo state network (ESN), feedforward echo state network (FE-ESN) and tapped delay line with inputs (TDL-I) to predict the sea clutter time series and detect target embedded in sea clutter. The performance of predicting and detecting using these methods is compared. A set of time series from IPIX radar data is tested. Numerical experiments reveal that FE-ESN and TDL-I show high prediction precision and good detection effect as same as ESN. Furthermore, FE-ESN and TDL-I have simplication architecture.

Keywords: Echo state network, Feedforward echo state network, Tapped delay line with inputs.

1. Introduction

Neural networks have a wide range application, including pattern recognition, automatic control, signal processing, aid decision making, artificial intelligence, etc [1–3]. Echo state network (ESN) is a novel recurrent neural network (RNN) architecture which was introduced by Herbert Jaeger for time series prediction [4–6]. The kernel part of ESN is a single reservoir with tens or hundreds of neurons that are randomly and sparsely interconnected. The degree of the sparseness is from 2% to 20%. The reservoir is fixed, that is to say, the reservoir itself is not changed once the network is setup. During the training process of ESN, only the output connections are changed through offline linear regression or online methods. ESN has dynamic characteristic and short-time memory function. The stability of ESN is better than the traditional networks, and can be successfully applied in chaotic and nonlinear dynamic systems modeling, identification and control [6–8]. Feedforward echo state network (DESN) and tapped delay line with inputs (TDL-I) are presented by Michal Cernansky for modeling several time series [9]. We apply ESN, FE-ESN and TDL-I to predict the sea clutter time series and detect target. The great mean squared error (MSE) differences between real-life sea clutter data and prediction value are available for detecting target.

2. Echo State Network Model

The general structure of an ESN with an N-neuron reservoir is shown in Fig. 4. The number of input layer nodes is K, and the number of output layer nodes is L. The update of the reservoir state is expressed by

$$x(n) = f(W^{in}u(n)+Wx(n-1)+W^{b}d(n-1)+\gamma(n)) \quad (1)$$

where f is a sigmoidal activation function, $x(n)$ is the internal state of the reservoir at time step n, $u(n)$ is the input vector at time step n, $d(n-1)$ is the teacher signal (real-life data or test sample) at the previous time step, and $\gamma(n)$ is the current artificial noise vector inserted into the state update equation to ensure stability of the network. In general, the range for $\gamma(n)$ is from 0.0001 to 0.01. The input weight W^{in} is an $N \times K$ matrix which reflects the connection from input nodes to the reservoir. The entries of this matrix are selected at random. The recurrent weight W is an $N \times N$ matrix which reflects the interconnection in the reservoir. This matrix is a sparse and random matrix. To ensure echo characteristic in ESN, the spectral radius $\rho(W)$ must be less than 1. The feedback weight W^b is an $N \times L$ matrix which reflects the connection from output nodes to the reservoir. The output of ESN is typically given by

$$y(n) = f^{out}(W^{out}x(n)) \quad (2)$$

where f^{out} can be either linear or sigmodal, depending on the task of interest, the output weight W^{out} is an $L \times (K+$

* Corresponding author: e-mail: xuzhan121@163.com

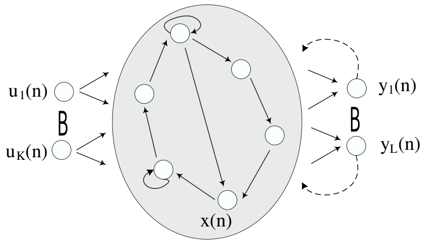


Figure 1 The basic structure of ESN, with K input node and L output node

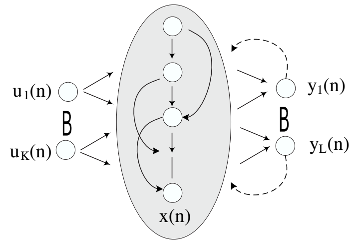


Figure 2 The structure of FE-ESN.

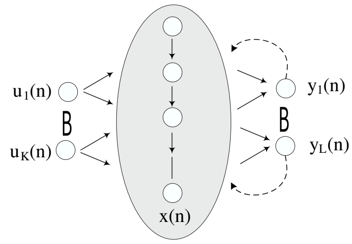


Figure 3 The structure of TDL-I.

N) matrix which reflects the connection from the reservoir to output nodes. The output weight is determined through either online or offline training. In this paper, we use the offline pseudoinverse method for updating output weight.

3. Simplification Echo State Network Model

FE-ESN is a simplification architecture of ESN. The hidden units connect in a feedforward manner. Units in a reservoir can be indexed and their activities depend only on activities of units with smaller indices. The activities do not cycle. That is to say, the activity of the first unit does not depend on activity of the last unit. Nodes represent units and edges represent connections. FE-ESN is shown in the Fig. 5(a). All connections are still recurrent ones because units are fed by activities from previous time steps. The training process of FE-ESN is same to that of regular ESN. The only difference is how a recuurent weight matrix is generated. Recurrent weight matrix is rescaled to the required spectral radius and the matrix is then made lower triangular by keeping only elements below diagonal. To force the ESN to keep longer history of inputs in activities, $w_{i,i-1}$ which stands for the weight of unit i connected with the previous one $i-1$ is chosen constant value. In this paper, we choose the value of spectral radius λ.

Tapped delay line with inputs (TDL-I) is a further simplification architecture of ESN. The reservoir of units organized into a tapped delay line. TDL-I is shown in the Fig. 5(b). Units in a reservoir can be indexed and their activities depend only on activity of unit with last index. The only nonzeros are $w_{i,i-1}$ in recurrent weight matrix. TDL-I uses hidden units with nonlinear activation function and was constructed in very simple nonlinear combination of inputs. All connections are set to 1.0. It supposes that the process being modeled can be handled with autoregressive model.

4. Data Description

In this study, the McMaster IPIX datasets are used to be training time series for testing the performances of ESN in detecting target. The McMaster IPIX radar is an instrumentation-quality X-band radar system. The radar data were collected in November 1993 from Osborne Head Gunnery Range (OHGR) at Dartmouth, Nova Scotia, Canada. Fourteen sea clutter measurement datasets were obtained from a website maintained by Professor Simon Haykin: http://soma.ece.mcmaster.ca/ipix/dartmouth/datasets.html. The operating frequency of IPIX radar is 9.39GHz, so the wavelength is about 3cm. The wave height of the ocean varies from 0.8m to 3.8m, but the peak height even arrives at 5.5m. The wind conditions vary from 0 to 60km/hr generally, but the gusts reach to 90km/hr. The grazing angle varies from less than 1° to a few degrees. We consider amplitude data of two polarizations, HH (horizontal transmission, horizontal reception) and VV (vertical transmission, vertical reception). Each dataset contains fourteen spatial range bins, and each range bin has 2^{17} samples and the sampling frequency is 1000Hz. The target is a small spherical block of styrofoam wrapped with wire mesh. A few of the range bins hit a target, and the range bin where the target is strongest is labeled as the primary target bin. Due to the target moves around, the bins close to the primary target bin may also hit the target. They are labeled as the secondary target bins.

5. Experiments

We study the performance of ESN, FE-ESN and TDL-I with the McMaster IPIX radar sea clutter data. The number of neurons in dynamic reservoir is 30. The non-zero entries of W^{in} and W^{b} are uniformly distributed random variables within the range [-0.5,0.5] and [-4,4], respectively.

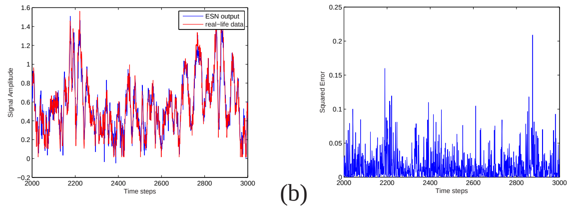
(a) (b)


Figure 4 (a)Prediction of ESN, (b)Squared error of ESN.

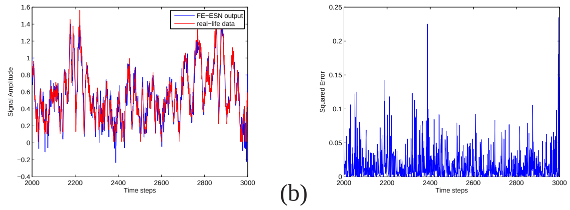
(a) (b)


Figure 5 (a)Prediction of FE-ESN, (b)Squared error of FE-ESN.

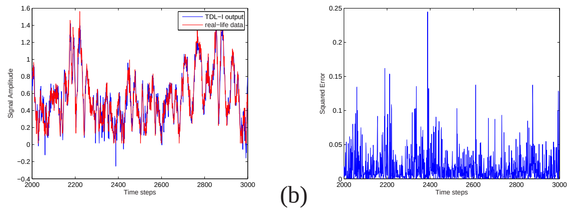
(a) (b)


Figure 6 (a)Prediction of TDL-I, (b)Squared error of TDL-I.

The entries of the recurrent sparse weight W are randomly created and was rescaled to spectral radius $\rho(W)$=0.7. The entries of the artificial noise which inserted into the state updated equation are random number within the range [-0.0005,0.0005].

The typical prediction curves of amplitude versus time steps for the range bin of sea clutter without target are shown in Fig. 4(a), Fig. 5(a) and Fig. 6(a). Red line denotes the amplitude of the real-life sea clutter data, and blue line denotes the prediction curve of ESN, FE-ESN and TDL-I. The squared errors between real-life data and prediction values are also presented in Fig. 4(b), Fig. 5(b) and Fig. 6(b). From these figures, we can deduce that the prediction results using ESN, FE-ESN and TDL-I are all in good agreement with the real-life sea clutter data without target. The squared errors of three methods all belong to small ranges. The results indicate although FE-ESN and TDL-I simplify architecture of reservoir, they still have high accuracy for predicting sea clutter time series.

Since the ultimate goal of sea clutter study is to improve the performance of target detection within clutters. We use ESN, FE-ESN and TDL-I to detect target embedded in sea clutter. MSEs for the fourteen range bins data are shown in Fig. 7. The MSEs results are presented in Table 1. It is not difficult to see that MSEs for the data with the primary target using above three methods are much larger than that without the target. The MSEs without target of three methods are very small compared to that with target. Using the great mean squared error differences between real-life sea clutter data and prediction values, we can detect target in sea clutter. In addition, FE-ESN and TDL-I not only have the simplicity architecture, but also have good detecting effect as same as ESN. It turns out that this is a generic feature for all the measurement data.

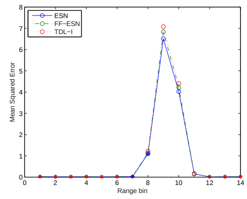


Figure 7 The mean squared errors for the 14 range bins.

Table 1 Prediction results of MSEs for the 14 range bins

n	ESN	$FE-ESN$	$TDL-I$
1	0.0246	0.0281	0.0295
2	0.0177	0.0214	0.0226
3	0.0196	0.0235	0.0249
4	0.0222	0.0258	0.0274
5	0.0166	0.0203	0.0214
6	0.0217	0.0258	0.0270
7	0.0285	0.0336	0.0346
8	1.1002	1.1435	1.2252
9	6.5115	6.8334	7.0786
10	4.0233	4.2203	4.4028
11	0.1507	0.1505	0.1717
12	0.0165	0.0200	0.0212
13	0.0198	0.0233	0.0246
14	0.0219	0.0255	0.0265

6. Conclusion

We apply ESN, FE-ESN and TDL-I for predicting sea clutter time series. MSEs differences between real-life sea clutter data and prediction value are available for detecting target. The experiments demonstrate that beside simplicity architecture FE-ESN and TDL-I have high prediction precision for sea clutter data, and also have good effect for detecting target.

Acknowledgement

The authors acknowledge the financial support of National Natural Science Foundation of China, project No. 11101430.

The author is grateful to the anonymous referee for a careful checking of the details and for helpful comments that improved this paper.

References

[1] R. Rajagopal, IEEE Transactions on Signal Processing, **59**, 373 (2011).
[2] J. Bao, L.J. Zhou and Y. Yan, Appl. Math. Inf. Sci. **6** 317 (2012).
[3] N. Zhang, Appl. Math. Inf. Sci. **6** 129 (2012)
[4] H. Jaeger, GMD-Forschungszentrum Informationstechnik **148**, 43 (2001).
[5] H. Jaeger, Advances in neural information processing systems **8**, 593 (2003).
[6] H. Jaeger and H. Haas, Science **304**, 78 (2004).
[7] K. Ishii, T. Zant, V. Becanovic and P. Ploger, In Proc. OCEANS'04, 1205 (2004).
[8] P.G. Ploger, A. Arghir, T. Gunther and R. Hosseiny, In Proc. RoboCup, 157 (2003).
[9] M. Cernansky and P. Tino, Proceeding ICANN '08 Proceedings of the 18th international conference on Artificial Neural Networks, 778 (2008).

Zhan Xu received the B.S. degrees in electrical science and technology from College of Electronic Science and Engineering, National University of Defense Technology in Changsha, Hunan, 2002. He is now a doctoral student. His research interests include target detection, sea clutter, neural network, and radar signal processing.

Jianwei Wan is a full professor of National University of Defense Technology, Republic of China. He received his Ph.D. degree in 2000. His research interests include radar signal processing, communications technology and hyperspectral imaging.