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Echo extraction from bottom reverberation based on chaos

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Abstract: A novel method based on chaos theory for echo extraction from reverberation is proposed. Effectiveness of this method is mainly due to a new prediction model based on radial basis function (RBF) neural networks, which uses forward and backward prediction (FBP). Principles of the model used for chaotic signal separation is explained. Performances for the chaotic signal modeling and harmonic signal extraction are analyzed using several chaotic time series as examples. The result of the model in the extraction of object echoes from real lake-bottom reverberation shows that the model can be used to extract object echoes when signal-to-reverberation-ratio is greater than 1dB.

Key words: sea bottom reverberation; object echo; signal extraction; nonlinear prediction; chaos

基于混沌理论的海底混响中目标回波提取

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摘要: 提出了基于混沌理论的混响中目标回波提取新方法。该方法主要得益于一种新的预测模型,该模型基于径向基函数神经网络,综合利用了时间序列的前向和后向预测,解释了该模型用于混沌信号分离的基本原理,用几种混沌时间序列分析了该模型用于混沌信号建模和谐波信号提取的性能。该方法用于湖试混响中目标回波提取的结果表明:该模型可以用于提取信混比不小于 1dB 的目标回波。

关键词: 海底混响;目标回波;信号提取;非线性预测;混沌

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1 INTRODUCTION

In the anti-mine sonar signal processing, strong bottom reverberation severely disturbs the feature extraction of the object echoes, and the object identification under low signal-reverberation-ratio is a difficult problem for anti-mine sonar. To extract the object echoes from reverberation is a direct method for improving the feature extraction of object echoes, but in frequency spectrum the reverberation is identical with object echoes, and linear filtering methods are hard to improve the signal-reverberationratio. The method of space filtering can combat reverberation to some degree, but for the mines laid on sea bottom far away, the improved signal-reverberation-ratio is not large enough to satisfy the demand of effective feature extraction.

Since more than ten years ago, great efforts have being made to apply the rapidly developing theory of nonlinear dynamics and signal processing methods

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based on chaos theory to medicine, economics, communication, radar, sonar, etc. The dynamical property analysis for the observed reverberations in pond-trials, lake-trials, and sea-trials[1] showed that the reverberation exhibit disjoint dynamical trajectories in four-dimensional reconstructed state space, and the close trajectories diverge or shrink by law of exponent, and that the largest Lyapunov exponent lies between 0 and 0.3. It implies that the necessary condition of the reverberation having chaos properties is satisfied, and, therefore, the received signals of active sonar may be modeled by low dimensional dynamical methods and can be processed by methods based on chaos theory.

In the case of unknown dynamical equations of the chaos system, the methods of signal separation based on chaos theory can be divided into two kinds. One is the methods of blind signal separation without any priori knowledge available, for example locally geometrical projection methods[2], and the other is the methods using some available information, which may be a long enough clean time series having the same dynamics as observations. One of the latter is scaled probabilistic cleaning methods[3], in which the probabilistic characteristics of the orbits in reconstructed state space come from a clean chaotic signal. In order to gain correct probabilistic characteristics, the length of the clean chaotic signal must be long enough, and this method is very time-consuming and needs large memories while working.

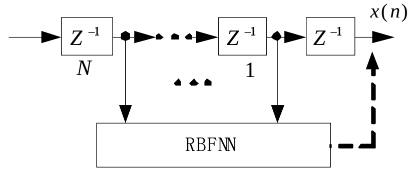
Sea bottom reverberation is the summation of backward scatter of sound projected onto sea bottom. Within some distance, the angles of incidence of sound rays at sea bottom are almost equal and the sound scatter characteristics of the sea bottom are identical. The reverberation within some distance segment can be modeled by low dimensional dynamical methods and the built model can be used to predict the reverberation in succeeding signals and combat it. If the sound scattering characteristics of the sea bottom ahead are consistent with those of modeled areas, the dynamical characteristics and evolving rules would be close and the prediction error should be small. On the contrary, if the sound scattering characteristics ahead distinctly differ from those of modeled areas or there is a big stone or a man-made object, the changes of the dynamical characteristics and evolving rules would result in greater prediction errors. If the modeling precision is high enough, the object echoes buried in sea bottom reverberation could be partly separated.

In this paper, a new model based on RBF neural networks for chaotic time series is proposed and is applied to partly separating the object echoes buried in sea bottom reverberation.

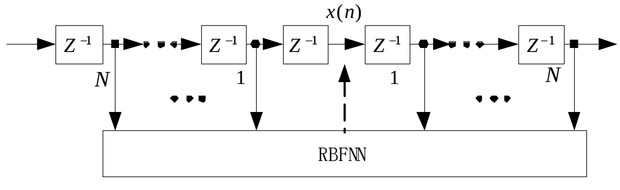
2 FBP MODELS AND ITS FUNDAMENTAL OF SIGNAL SEPARATION

2.1 FBP models based on RBF neural networks

Henry Leung[4,5] used only the N data before time n for modeling the time series y(n), and this kind of model is called forward prediction (FP) models. But, in the case of long data available, the data after time n can also be used to build the prediction model. It is similar to smoothing in linear filtering and the simultaneous use of the 2N data before and after time n may provide more accurate description for the dynamical system. The structures of the FP model and the FBP model based on RBF neural networks are showed in figure 1.



(a) Forward prediction model



(b) Forward and backward united prediction model

Fig.1 Two types of prediction models

In order to measure the prediction effectiveness of a model for the chaotic time series, the normalized in-sample prediction error Δ_f and the normalized out-of-sample prediction error Δ_p are respectively defined by

$$\Delta_f=\lg\frac{\frac{1}{N_L}\sum_{n=1}^{N_L}[\hat{f}_k(X(n))-Y_k(n)]^2}{\mathrm{Var}\{Y_k(n);n=1,2,\cdots,N_L\}}, \qquad (1)$$

$$\Delta_p=\lg\frac{\frac{1}{N_T}\sum_{n=1}^{N_T}[\hat{f}(X(n))-Y_k(n)]^2}{\mathrm{Var}\{Y_k(n);n=1,2,\cdots,N_T\}}, \qquad (2)$$

where $\mathrm{Var}(Y_k(n))$ denotes the variance of the time series $\{Y_k(n)\}$.

2.2 Fundamental of signal separation

If the nonlinear dynamics of the system is known, that is to say, the evolving equation $x(n+1)=F(X(n))$ is given, the chaotic time series satisfying the nonlinear dynamics can be estimated, and the signal of interest, for example, harmonic signals, could be extracted by subtraction. If the nonlinear dynamics is unknown but a long enough clean time series satisfying the same dynamics is available, the prediction model of the system $x(n+1)=\hat{F}(X(n))$ could be established by any modeling method based on chaos theory and is used to separate the chaotic time series from other signals.

In spite of many proposed prediction models for chaotic time series, the prediction model applied to signal separation is lacking, one of which is the forward prediction model based on RBF neural networks. With the long enough clean time series satisfying the same dynamics, it is supposed that $x(n+1)=\hat{F}(X(n))$ is the estimated prediction model based on phase space reconstruction. If the signal of interest $s(n)$ added to the chaotic time series $c(n)$ is very weak, the attractor in reconstructed phase space do not change greatly with the little disturbance. After the observed time series $x(n)$ is predicted with the built prediction model, the predicted time series $c(n)$ will satisfy the dynamics more closely. The error $e(n)=\hat{x}(n)-x(n)$ is composed of two components: one is the prediction error $e'(n)$, which comes from the prediction model having limited precision.

$$e'(n)=c(n)-\hat{x}(n) \qquad (3)$$

If the precision of the prediction model is high enough, the error should be very small; the other is the added signal $x(n)$, which is often much concerned with in engineering application.

$$\begin{aligned} s(n)&=e(n)-e'(n)\\ &=e(n)-(c(n)-\hat{x}(n)) \end{aligned} \qquad (4)$$

From the point view of signal separation, the prediction error $e(n)$ of the model for the observed time series is the estimation for the signal $s(n)$ in fact. If the prediction error $e'(n)=0$, we have $\hat{s}(n)=e(n)=s(n)$.

However, when the attractor is disturbed greatly, the prediction precision of the model for the chaotic time series will decrease, which leads to the severe distortion of the signal of interest. Li Yue, et al.[6] proposed a method used to detect weak harmonic signals in chaotic signals by RBF neural networks. Although the weak harmonic signals can be detected accurately, the separated harmonic signals do not agree with the original added signals both in amplitude and phase.

For a nonlinear dynamical system, the orbits will converge on the chaotic attractor from any point in the given range after several iterations of the evolving equations. For a chaotic time series containing other signals, the orbits in the reconstructed state space go away from the chaotic attractor more or less, and the orbits predicted by the united model $\hat{F}(X)$ will approach the attractor a bit. Suppose the estimated signal after the first prediction is denoted by $\hat{x}_1(n)$. One proceeds to predict the signal $\hat{x}_1(n)$ using the model $\hat{F}(X)$ and gets the second estimated signal $\hat{x}_2(n)$. By this rule, after L iterations, one gets the L th estimated signal $\hat{x}_L(n)$, which is almost compatible with the approximated dynamics, and the prediction error $e'(n)$ is very small. According to formula (2), the prediction error after the L th iteration $e_L(n)=x(n)-\hat{x}_L(n)$, and is the more accurate estimation for the added signal $s(n)$.

Therefore, if the forward and backward united prediction model, which has higher modeling precision, is used to predict the observed time series several times, the chaotic time series could be separated from the added signal in some degree.

And in order to measure the separation effectiveness of a model, the signal-noise-ratio (SNR) is defined by

$$SNR=\frac{\frac{1}{T}\sum_{i=1}^{T}s^2(n)}{\frac{1}{T}\sum_{i=1}^{T}(e(n)-s(n))^2}=\frac{\frac{1}{T}\sum_{i=1}^{T}s^2(n)}{\frac{1}{T}\sum_{i=1}^{T}e'^2(n)}, \quad (5)$$

where T is the length of the signal. The less the prediction error is, the higher the SNR of the separated signal of interest is.

3 SIMULATION EXPERIMENTS

3.1 Modeling experiments of chaotic time series

The simulation experiments below show the validity of the proposed model. Two representative maps and two representative flows are selected to compare the performance of the forward prediction model and the forward and backward united prediction model. The two maps are Henon and Logistics map, and the two flows are Lorenz and Rossler.

According to the equations of the four chaotic systems, sufficiently long chaotic time series are produced by computer and two sections of 512 samples of the four chaotic systems are respectively selected as training sets and testing sets for prediction models based on RBF neural networks. For the forward prediction model, the number of input nodes of the RBF neural networks is equal to the embedding dimension and, for the forward and backward united prediction model, the number of input nodes has to be doubled because the two states of the system before and after time t are used. The number of output nodes of the RBF neural networks for the two prediction models is 1 and the number of hidden nodes depends on the number of the input nodes and the size of the training sets. The embedding dimension and the time delay can be referred to the false neighbor method and the mutual information method.

Table 1 shows the normalized in-sample error and out-of-sample error of the two models for four types of chaotic time series. In table 1, we can see that the two types of errors of the forward and backward united prediction model for Henon, Lorenz, and Rossler systems are less than those of the forward prediction model, and, for Logistic systems, the two types of errors of the forward and backward united prediction model are a bit greater than those of the forward prediction model. This mainly results from the bad time-reversibility of Losgistic chaotic system. It implies that the proposed prediction model has better prediction performance than the forward prediction model for the chaotic systems with good time-reversibility.

3.2 Experiments of harmonic signal extraction from chaotic time series

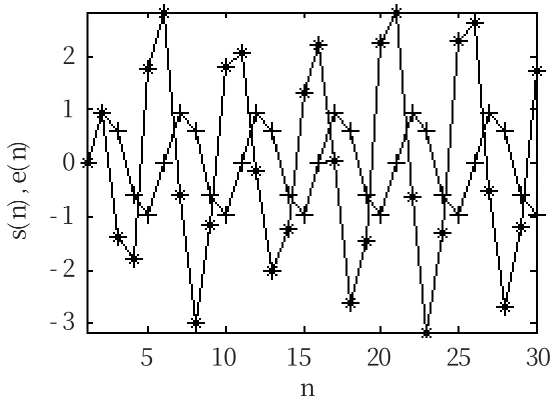
To take example for Lorenz, we compared the performance of the improved model with that of the forward model in harmonic signal extraction. We integrated the differential equations of Lorenz using the fourth-order Runge-Kutta method and the time series x(t) is used as the chaotic background.

We take 800 samples of the Lorenz time series as the training data for RBF neural networks. By the false nearest neighbor method, the embedding dimension d should be 4, and by the mutual information method, the embedding time delay τ should be 5. However, from the point view of actual predic-

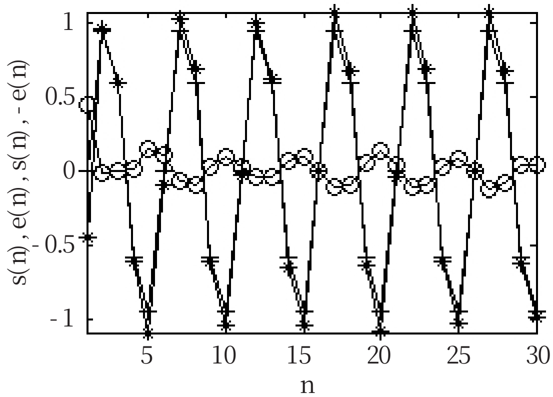
Table 1 Two types of normalized error of two prediction models for 4 chaotic time series

Prediction Models	Normalized in-sample Error (Δ_f)				Normalized out-of-sample Error (Δ_p)			
	Henon	Logistic	Lorenz	Rossler	Henon	Logistic	Lorenz	Rossler
FP Models	-5.77	-7.72	-5.15	-5.39	-5.78	-7.70	-4.74	-5.21
FBP Models	-6.30	-6.52	-6.76	-7.49	-6.20	-6.16	-6.22	-7.48

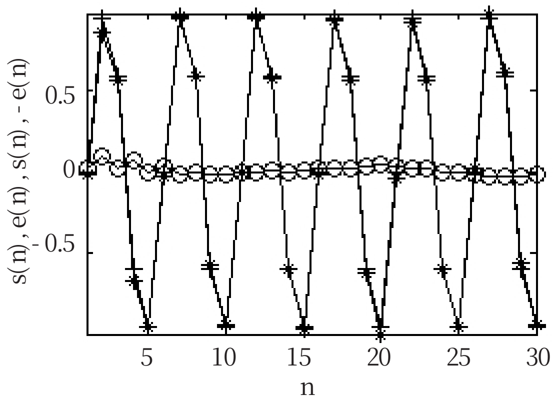
tion effectiveness, the prediction precision is highest when the time delay is 1. RBF neural networks are trained to build the dynamical model of the Lorenz system. In another section of 500 samples of the Lorenz time series we add a harmonic signal with magnitude 1 and normalized frequency 0.2, and the signal-noise-ratio is about -26.30 dB. When we take d=4, τ=2, part of the extracted harmonic signal by the forward model is shown in figure 2(a). In figure 2 and figures below, the symbol '+' denotes the added harmonic signal s(n), the symbol '*' the prediction error e(n), namely, the estimation of the model for the added harmonic signal s(n), and the symbol 'o' the out-of-sample error e(n), namely, s(n)-e(n). In this figure, we can see the severe distortion of the extracted harmonic signal in amplitude and phase compared with the added harmonic signal. Part of the extracted signal by the forward and backward united model is shown in figure 2(b). We can see the good superposition of the extracted signal and the added signal. The signal-noise-ratio of the extracted signal SNR=17.52dB. Thus it can be seen that the performance of the harmonic signal extraction has been improved greatly. All parameters of the united model are taken as above, and after 6 iterations part of the extracted harmonic signal is shown in figure 2(c). It can be seen that the out-of-sample prediction error for the chaotic time series decreases a little more and the signal-noise-ratio of the extracted harmonic signal SNR=30.42dB. It shows that iterations of the prediction model may help to lower the out-of-sample prediction error, which is compatible with the theory above. But too many iterations would make the prediction go contrary.



(a) The result of forward prediction model used for signal separation



(b) The result of forward and backward united prediction model used for signal separation



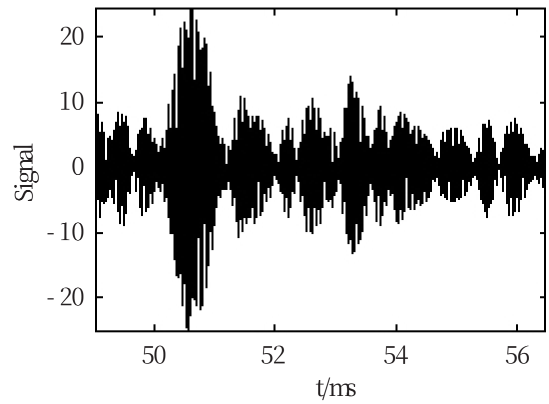
(c) The result of forward and backward united prediction model used for signal separation after several iterations

Fig.2 Harmonic signal extraction from Lorenz time series

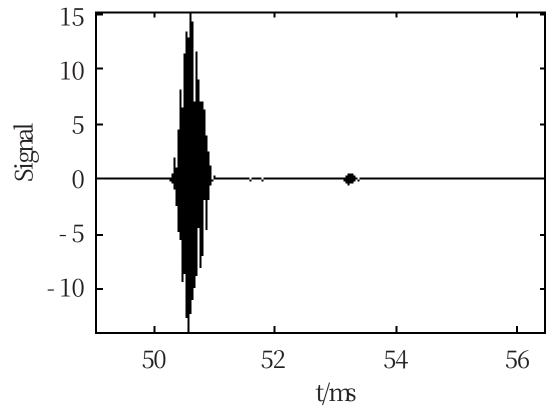
4 OBJECT ECHO SEPARATION FROM SEA BOTTOM REVERBERATION

4.1 Data

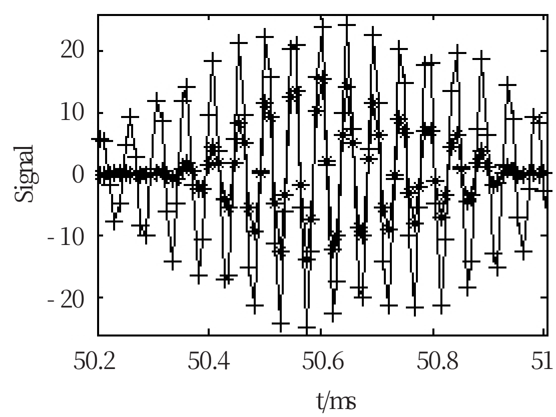
The reverberation was sampled in a lake-trial. The middle frequency of the transmitted CW pulses is 20kHz and the pulse width is 0.2ms. The sample frequency is 108kHz. The object is a oxygen bottle, which lies on the lake bottom with depth 5.56m and distance 34m and is located in the normal direction of the receiving array. The received data are processed by band filtering and power normalization and 31 formed beams rang from -15° to 15°.



(a) The part of beam signal containing an object return



(b) The extracted object echo



(c) The details of the waveforms before and after the extraction of the object echo

Fig.3 The extraction of an object echo from reverberation

The normal direction of the receiving array is 0°.

4.2 Object echo separation

Because the receiving array has beam width of 5° at 20kHz, the beam data in directions deviating from the object also contain object echoes with lower signal-reverberation-ratio. Part of the beam data in direction of -6° is shown in figure 3(a), and an object echo with the signal-reverberation-ratio about 1dB ranges from 50ms to 51ms. We take the number of input nodes of RBF neural networks N=4, the size of training data N_L=800, the size of pre-dicting data N_L=800, and the embedding time delay τ=1. The error time series of the FBP model based on RBF neural networks after 3 iterations is shown in figure 3(b). We can see that the object echo is partly extracted from the reverberation with the gain in the signal-reverberation-ratio of 60dB. The details of the waves before and after extraction are shown in figure 3(c), where the symbol '+' denotes the wave before extraction and the symbol '*' the wave of the object echo after extraction. The processing results for many lake-trail data show that the proposed method has good extraction performance for object echoes with signal-reverberation-ratio above 1dB.

5 CONCLUSIONS

In this paper a new prediction model based on RBF neural networks, which unites the forward and backward maps, is proposed, and the fundamental of the model used for chaotic signal separation is explained. With the example of four typical chaotic systems, the performance of the proposed model used for modeling chaotic time series and harmonic signal extraction are analyzed, and the results show that the proposed model has better prediction performance than the FP model for chaotic time series with good time-reversibility, and the proposed model and its iteration can be used to extract the harmonic signal from the chaotic time series. The result of the model for the real lake-trail data shows that it has good extraction performance for the object echoes with the signal-reverberation-ratio above 1dB.

References

[1] CAI Zhiming, ZHEN Zhaoning, YANG Shi'e. Chaos characteristic analysis of underwater reverberation[J]. Acta Acustica, 2002, 27(6): 497-501.

[2] WANG Fuping, GUO Jingbo, WAN Zhanji, XIAO Da chuan. Harmonic signal extraction from strong chaotic

interference[J]. Acta Physic Sinica, 2001, 50(6): 1019-1023.

[3] JIANG Keyu, CAI Zhiming. Optimization of scaled probabilistic cleaning methods. Acta Physic Sinica, 2005, 54(10): 4596-4601.

[4] Henry Leung. Signal detection using the radial basis function coupled map lattice[J]. IEEE Transaction on Neural Networks, 2000, 11(5): 1133-1151.

[5] Henry Leung. Detection of small objects in clutter using a GA-RBF neural network[J]. IEEE Transaction on Aerospace and Electronic Systems, 2002, 38(1): 98-118.

[6] LI Yue, YANG Baojun, Shi Yaowu. Chaos-based weak sinusoidal signal detection approach under colored noise background[J]. Acta Physica Sinica, 2003, 52(3): 526-530.

简 讯

中国声学学会水声分会2006年度工作总结和2007年度活动计划

一、2006年度工作总结

2006年度水声分会的工作主要包括三方面的内容:

1.2006年7月4日-8日,分会与中国造船工程学会仪器仪表学会、水中兵器学会、电子技术学会在湛江联合主办了水下声系统学术会议,会议共收到论文46篇,会上交流论文21篇。

2.参加2006年全国声学学会学术交流会。

3.召开水声分会工作会议。2006年10月18日,水声分会借全国声学学会学术会议召开之际,在厦门召开了水声分会委员会议,这是2005年水声分会换届后的首次委员工作会议,共22位委员参加了会议。

会上,分会领导进行了分工。分会主任孙超负责全面工作,副主任顾亚平、李琪分管学术工作,张春华、朱焕培分管组织工作,梁捷、俞德飞分管科普、外事工作。

孙超主任介绍了新一届水声分会的工作设想,准备于2007年、2009年组织2次全国水声学术会议,2008年开一些小规模的专题研讨会,并要求各位委员积极发挥水声学方面的交流和桥梁作用。

张春华副主任提议水声学的学术交流可尝试通过声学学会网站进行专题交流,从而不受时间、地点的制约。

会上,委员们为学会的工作献计献策,最后确定明年的水声学术会议于9、10月份在郑州召开。

二、2007年度活动计划

序号	活动名称	主要内容	时间	地点	人数	联系人	电话
1	全国水声学术会议	交流学术论文	9、10月	郑州	60	丁玉薇 杨益新 王竹湘	021-64174105 029-88460373 0571-56782271
2	水声分会工作会议	讨论2008年工作内容	同上	同上	30	同上	同上

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