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Retraction

Retracted: Research on Nonlinear Time Series Processing Method for Automatic Building Construction Management

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This article has been retracted by Hindawi, as publisher, following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of systematic manipulation of the publication and peer-review process. We cannot, therefore, vouch for the reliability or integrity of this article.

Please note that this notice is intended solely to alert readers that the peer-review process of this article has been compromised.

Wiley and Hindawi regret that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

[1] Y. Liu, "Research on Nonlinear Time Series Processing Method for Automatic Building Construction Management," *Journal of Control Science and Engineering*, vol. 2022, Article ID 7025223, 6 pages, 2022.

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Research Article

Research on Nonlinear Time Series Processing Method for Automatic Building Construction Management

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Aiming at the nonlinear time series of automatic building construction management, a neural network prediction model is proposed to analyze and process the nonlinear sequence of deformation monitoring number cutter. The specific content of this method is as follows: for the noise problems existing in deformation monitoring data, a wavelet is used to denoise the preprocessing; for the BP network and RBF network commonly used in neural networks, the performance of the two networks is compared and demonstrated by MATLAB program, which proves that RBF neural network can significantly improve the accuracy of deformation prediction. By comparing the results, the maximum relative error of BP network prediction is 18.59%, while the maximum relative error of RBF network prediction is 29.16%, and the average relative error of 13P network prediction is 7.02%, while the average relative error of RBF network prediction value is 10.5%. The comprehensive error of network prediction is 6.1%, RBF network prediction is 8.52%, the standard deviation RMSE of BP network prediction error is 15.347, and that of RBF network prediction error is 21.401, and it shows that the prediction accuracy of BP network is higher than that of RBF network.

1. Introduction

With the development of the economy, science, and technology, all kinds of scientific predictions, especially predictions based on data analysis, will be more widely used and further promote the research of prediction methods. Time series refers to the observation data formed at different times by a variable or multiple variables in the system recorded in time sequence, and the changes of the series reflect the movement law W of the system. In real production and life, time series can be seen everywhere, for example, measurement data of sensor equipment, product sales records, stock index, and coal mine gas content can all be regarded as time series by W [1]. The intrinsic connection between the adjacent data of time series is an essential feature of time series [2]. Prediction based on time series is to establish a mathematical model reflecting the dynamic relationship contained in the time series according to the observed values of the system, and it is an important part of the prediction method system to reveal the movement law of the system or the internal relationship and movement law between a phenomenon and other phenomena and to predict its future change and development law and trend. In view of this research problem, Monsen et al. proposed a generalized exponential autoregression model and conducted relevant application studies based on this model [3,4]. On the basis of the above model, Shi et al proposed a general form of nonlinear model, namely, the state-dependent model. In the past two decades, studies on the combination of this model and the RB Qiusheng meridian network have also been developed and applied to relevant engineering fields [5]. Ren et al. proposed the functional cocientar model, which is also a special case of the state-dependent model [6]. On the basis of current research, a neural network prediction model was proposed to analyze and process nonlinear sequences in deformation monitoring number guillotine [7]. The specific content of the method is as follows: for the noise problems existing in the deformation monitoring data, a wavelet is used to denoise the preprocessing; for the BP network and RBF network commonly used in neural networks, by designing MATLAB programs, the performance of the two networks is compared and demonstrated, which proves that

RBF neural network can significantly improve the accuracy of deformation prediction [8]. By comparison, the maximum relative error of BP network prediction is 18.59%, while the maximum relative error of RBF network prediction is 29.16%, the average relative error of 13P network prediction is 7.02%, the average relative error of RBF network prediction value is 10.1 5%, the comprehensive error of B1 network prediction is 6.1%, the comprehensive error of RBF network prediction is 8.52%, the standard deviation RMSE of BP network prediction error is 15.347, and the standard deviation RMSE of RBF network prediction error is 21.401, and it shows that the prediction accuracy of BP network is higher than that of the RBF network.

2. Methods

2.1. Time Series Are Preprocessed by Wavelet

(1) Definition of wavelet transform

According to the definition of wavelet transform, wavelet (basic wavelet or mother wavelet) is a function or signal $\psi(t)$ in the space of square-integrable function $L^2(R)$ as shown in

$$C_\psi = \int_0^\infty \frac{|\psi(\omega)|^2}{\omega} d\omega < \infty. \tag{1}$$

Sometimes, $\psi(t)$ is also called the wavelet function, or mother wavelet, formula (1) is called the admissibility condition, and the wavelet function $\psi(t)$ satisfying formula (1) is also called the admissibility wavelet.

Formula (2) is obtained from the expansion and translation transformation of function ψ.

$$\psi_{ab}(t) = \frac{1}{\sqrt{|a|}} \psi\left(\frac{t-b}{a}\right), \tag{2}$$

where a is the expansion factor and b is the translation factor, if different parameters a and b are selected, the wavelet transform of any function $f \in L^2(R)$ can be expressed as follows:

$$\begin{aligned} w_f(a,b) &= \langle f, \psi_{a,b} \rangle \\ &= |a|^{-\frac{1}{2}} \int R\psi\left(\frac{t-b}{a}\right) f(t) dt, \end{aligned} \tag{3}$$

where $\langle .... \rangle$ represents the inner product and $\overline{\psi}$ is the conjugate of ψ.

(2) Principle and steps of nonlinear wavelet transform threshold denoising method

The deformation analysis data collected by deformation monitoring, namely, the time series of a deformation observation quantity (such as displacement) can be regarded as a signal of displacement changes in time or space, and this kind of signal is affected by all kinds of complex external factors (such as wind, temperature, and atmospheric refraction) so that the deformation signal collected has a certain amount of error, the error is a strong noise, while the deformation signal of the deformed body is a weak signal, which affects our further prediction of the deformation shape change trend [9]. Therefore, it is necessary to extract useful information from deformation signals before further analysis of deformation data. "321(nonlinear wavelet threshold value), also known as "wavelet shrinkage," and this method is mainly used for the mixed-signal with white noise (useful signal, white noise) in the wavelet transform domain with different energy concentration amplitude of different characteristics. Wavelet is used to decompose the observation sequence, the wavelet coefficient below the wavelet threshold becomes zero, the processed sequence is reconstructed, the signal is separated from the noise, and the noise in the signal is suppressed effectively. Given a threshold δ, all values of wavelet coefficients with absolute values less than δ in the wavelet transform coefficients are replaced by 0 regions, which is called noise. The wavelet coefficients with absolute values greater than δ are re-evaluated and reconstructed into new denoised signals. Therefore, the selection of threshold is directly related to the denoising effect. There are two methods to determine the threshold: the fixed threshold method, wavelet decomposition, and reconstruction method to determine the threshold.

(3) Improved denoising algorithm by a threshold method

There are some shortcomings in the application of soft threshold and hard threshold in denoising. Based on this, an improved algorithm is proposed as follows.

$$\begin{aligned} \widehat{w}_{j,k} &= \left\{ \frac{sign\left(w_{j,k}\right)\left(\left|w_{j,k}\right| - a\lambda_j\right)}{0} \cdots \left|w_{j,k}\right| \right. \\ &\left. \geq \lambda_j, \left|w_{j,k}\right| < \lambda_j, a = \frac{\lambda_j}{\left|w_{j,k}\right|} \right\}, \end{aligned} \tag{4}$$

where λ_j is the threshold selected by the wavelet coefficient and $\lambda = \sigma\sqrt{2\log(N)}$ and σ_j are the standard variance of noise at j layer.

(4) Denoising effect index

The trivial root of the variance among the original signal and the denoised estimated signal is called the equipartition error as follows:

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_n [f(n) - \widehat{f}(n)]^2}, \tag{5}$$

where $f(n)$ is the original signal and $\widehat{f}(n)$ is the estimated signal after wavelet filtering; the smaller the root mean square error, the better the filtering effect. The deviation between the original signal and the denoised estimated signal is

$$\mathrm{BLAS} = \frac{1}{n}\sum_{n}\left[f(n) - \hat{f}(n)\right]^2. \tag{6}$$

Generally speaking, the better the fitting degree of the estimated signal after denoising is with the original signal, the better the denoising effect is, that is to say, the closer the deviation is to 0, the better. SNR is a traditional method of noise measurement, as follows:

$$\begin{aligned} \mathrm{SNR} &= 10 \times \log_{10}\left(\frac{\mathrm{power}_{\mathrm{signal}}}{\mathrm{power}_{\mathrm{noise}}}\right), \\ \mathrm{power}_{\mathrm{signal}} &= \frac{1}{n}\sum_{n} f^2(n), \mathrm{power}_{\mathrm{noise}} \\ &= \frac{1}{n}\sum_{n}\left[f(n) - \hat{f}(n)\right]^2 = \mathrm{RMSE}^2. \end{aligned} \tag{7}$$

where $\mathrm{power}_{\mathrm{signal}}$ is the power of the real signal and $\mathrm{power}_{\mathrm{noise}}$ is the power of the noise. The optimal wavelet tree after wavelet packet decomposition adopts the entropy criterion [10]. It can be clearly seen from Figure 1 that the image effect after denoising by wavelet packet is better, and the image is smoother. Generally speaking, the smoothness of the restored signal is good, indicating that the restored signal is less disturbed by noise, the denoising effect is better, and the filtering method is good. Considering the above evaluation indexes of denoising method comprehensively, the evaluation criteria of wavelet filtering denoising performance are as follows: the wavelet denoising experiment for the same group of data shows that the performance of the wavelet filtering method is relatively good if the recovered signal obtained by a wavelet filtering method has a small root mean square error, a relatively high signal-to-noise ratio, a large signal-to-noise ratio gain, and a good smoothness of the recovered signal.

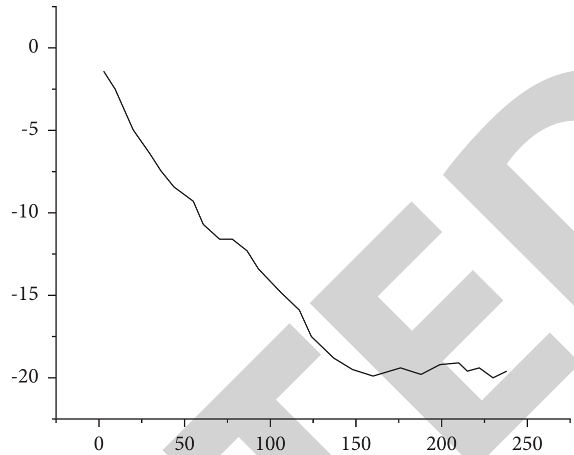

Figure 1: Wavelet packet denoising diagram.

2.2. Chaos and Basic Methods of Time Series. The trajectory produced by a chaotic system, after a certain period of change, will eventually behave in a regular way, producing a regular and tangible trajectory, and such trajectory, when transformed into time-related sequence after similar pull-up and folding, presents chaotic and complex features [11]. Since the driving factors of chaotic system are mutually affecting, the data points successively generated in time are related. The prediction method of chaotic Kitagawa taro series can establish a book model and then make prediction according to the objective law calculated by the number eight sequence itself, so as to avoid the artificial observation of prediction and improve the accuracy and reliability of prediction. At present, prechaotic time series prediction methods are often used:

(1) Local method

The local method takes the last point in the space as the central point and several track points closest to the central point as the relevant points and makes fitting to these relevant points to estimate the direction of the next point in the trajectory and finally to separate the predicted value from the industrial standard of the predicted trajectory point. The different order of mountain fitting function can be called zero-order local method, first-order local method, and so on. In this method, the number of participating points is more important, which directly affects the prediction accuracy.

(2) Weighted local area method

The weighted local method is the basis of the local method t, which considers the influence of the distance between the center point and the reference point on the prediction accuracy. The space distance of the center point is introduced into the fitting function as a parameter to fit the relevant points, estimate the trajectory, and separate the predicted value from the predicted trajectory points. The prediction accuracy of this method is higher than that of the first two methods.

(3) Neural network method

Due to the existence of definite regularity in chaotic time sequence, which is generated from nonlinearity, it shows the correlation of time sequence in time delay state space, makes the system seem to have some kind of memory, and at the same time difficult to express in ordinary analytical terms; therefore, we can find out the internal law of chaotic time series by learning the powerful nonlinear mapping ability of the neural network and then make a prediction.

2.3. Neural Network Prediction in Deformation Analysis. Neural network is essentially a nonlinear mathematical transformation system, with self-organization and self-learning ability, by learning a given data sample, and it automatically approximates the fitting function that can best approximate the rule of sample data; there is no need to establish any mathematical and physical model and manual intervention, through "black box operation," and it can build prediction model automatically and map arbitrary highly nonlinear input-output relation accurately and has fault tolerance and self-adaptability. Assume that the prediction target of the system is $Y = \{y(1), y(2), \ldots, y(n)\}$ and the observation series $X_i = \{x_i(1), x_i(2), \ldots, x_i(n)\}$ is the input time series of the network, $i = 1, 2, \ldots, m$ and m are input dimensions, and the mapping between input and output is expressed as follows:

$$x(t+T) = F(x(t)). \tag{8}$$

The predicted target Y and the predicted value $x(t+T)$ were used to correct the error back transmission threshold and then the most consistent model was established. Specific steps of chaotic time sequence prediction:

(1) Establish the neural network and calculate the embedding dimension according to the chaotic time sequence and take the embedding dimension as the network input number.

(2) In the learning stage, learning rules of neural network are selected based on whether there is a teacher learning mode.

(3) In the prediction stage, all known observation values are taken as input, and the output obtained through training is the predicted value. In the following content, Lyapunov index commonly used in chaos prediction will be used for prediction first, and then RPF and BP networks will be used for prediction and comparative analysis of data.

3. Results and Analysis

There is a deformation monitoring point on the bank of a certain river bank, long-term observation of the deformation point on the bank of this river has obtained a large number of settlement observation values, the deformation signal obtained from the observed data is shown in Figure 2, and the signal curve in Figure 2 shows that the signal is disturbed by noise. Daubechies wavelet with compactly supported orthogonal wavelet basis is used for denoising. According to the three-layer detail signal, the threshold value is determined and reconstructed after threshold processing.

Both RBF neural network and BP neural network can approximate any nonlinear continuous mapping with arbitrary precision. However, there are differences in the following aspects: RBF neural network is three-layer static. BP neural network can be two-layer or multilayer. In mathematics, the BP network is the probability approximation of the input and output functions, while RBF is the approximation of the judgment boundary surface. In the BP network, the input of each neuron is a combination of the output of the previous layer, so the judged boundary surface is a combination of straight lines. Since RBF uses radial basis functions and is circular or elliptical, the two networks can be used separately with a certain degree of understanding of the shape of the boundary surface. BP network is weight learning to minimize the error of the output layer. Each neuron has the

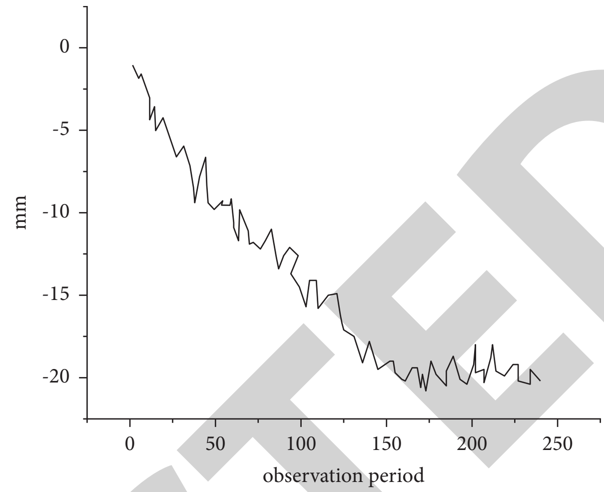

Figure 2: Deformation signal.

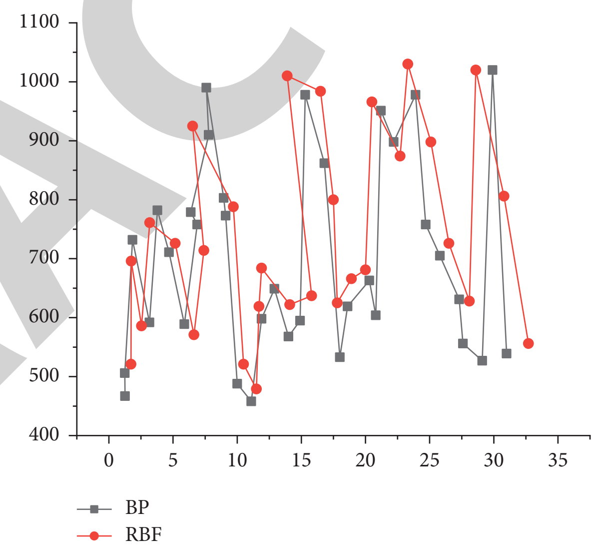

Figure 3: BP network prediction and RBF network prediction.

same input and output characteristics, but the role of each neuron in the middle layer is not so clear [12].

RBF is based on the nonlinear projection of pattern recognition problems to higher dimensions, so that it is easy to separate. Each neuron in the middle layer has different input and output characteristics, so their respective roles are clear. RBF is a fast learner. Because many RBF learning algorithms can be divided into two sections, each can be fast, while the BP network must learn all weights at the same time. Moreover, because the BP network is a multilayer structure, if the weight of the front layer is uncertain, the weight of the back layer is also uncertain, so there is a great difference in learning time. In the following, we will use an example about BP network and RBF on the same problem to predict the situation, and we will achieve it through MATLAB programming. We write the following code to compare the BP network and RBF network. The results are shown in Figure 3.

From the comparison in Figure 3, we find that the predicted value of the RBF network is more consistent with

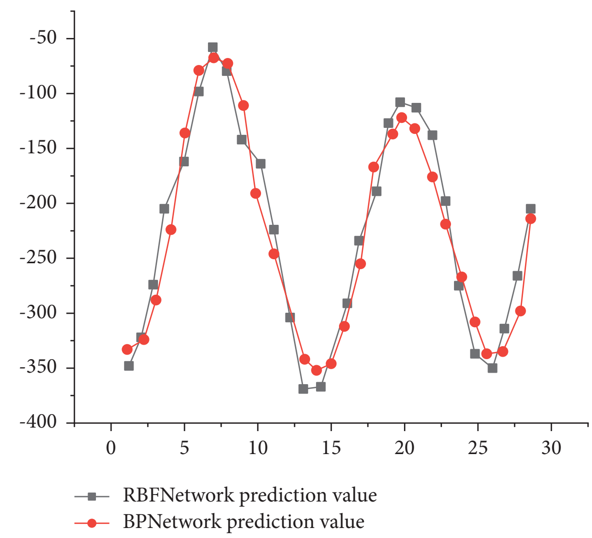

Figure 4: Comparison of RBF network predicted value and BP network predicted value.

the measured value, which is closer to the measured data than that of the BP network.

The trained network is used to predict chaotic time sequence, and the prediction results are shown in Figure 4.

The maximum relative error of BP network prediction is 18.59%, while the maximum relative error of RBF network prediction is 29.16%, and the average relative error of 13P network prediction is 7.02%, the average relative error of RBF network prediction value is 10.5%, B1), the comprehensive error of network prediction is 6.1%, RBF network prediction is 8.52%, the standard deviation RMSE of BP network prediction error is 15.347, and that of RBF network prediction error is 21.401; from the error comparison of the above parties, the prediction accuracy of BP network of chaotic time sequence is higher than that of the RBF network.

4. Conclusions

A neural network prediction model is proposed to analyze and process nonlinear sequences in deformation monitoring number guillotine. The specific content of this method is as follows: for the noise problems existing in deformation monitoring data, wavelet is used to denoise the preprocessing, for BP network and RBF network commonly used in neural networks; the performance of the two networks is compared and demonstrated by MATLAB program, which proves that RBF neural network can significantly improve the accuracy of deformation prediction. By comparing the results, the maximum relative error of BP network prediction is 18.59%, while the maximum relative error of RBF network prediction is 29.16%, and the average relative error of 13P network prediction is 7.02%, the average relative error of RBF network prediction value is 10.5%, B1), the comprehensive error of network prediction is 6.1%, RBF network prediction is 8.52%, the standard deviation RMSE of BP network prediction error is 15.347, and that of RBF network prediction error is 21.401; it shows that the prediction accuracy of BP network is higher than that of the RBF network. The neural network has the advantages of distributed storage, parallel processing, self-learning, self-organization, and nonlinear mapping, etc, and it needs to be further studied when combined with other technologies to solve more complicated deformation monitoring data. How to quantitatively solve the development orbit and prediction period of a chaotic system is not given. The problem of overfitting still exists after denoising is to be further studied.

Data Availability

The data used to support the findings of this study are available from the author upon request.

Conflicts of Interest

The author declares no conflicts of interest.

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