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Network Traffic Prediction Based on the Wavelet Analysis and Hopfield Neural Network

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***Abstract*—Build a mathematical model is the key problem of network traffic prediction. Traditional single network flow model of is not simulate the complex characteristics of network traffic. Therefore, a network traffic prediction hybrid model based on αTrous wavelet analysis and Hopfield neural network is proposed in this paper, which can be used to predict the network traffic flow. First, network traffic is normalized and adopt αTrous wavelet transform; And then reconstruct the wavelet single, and predict through sending low frequency components into AR model and sending the high frequency component into Hopfield neural network model; Last, The predictive value are obtained by composing the components. Simulation results show that the model improves the prediction accuracy, and has the good adaptability to the network.**

***Index Terms*—Network traffic, neural network, wavelet, Hopfield.**

I. Introduction

With the rapid development of internet and the wide application of all kinds of network service, the network topology structure is gradually complicated, and the network's congestion and emergencies has more and more. Therefore, the network performance need to monitoring and prediction. Network traffic prediction is the key issues of network business management, congestion control and engineering flow. The network traffic also has certain law even in the flow mutations. According to the data of network traffic and establish the mathematical model for law to predict network traffic, which is the network traffic prediction. The network traffic prediction can prevent network congestion, and the utilization rate of the network can be effectively improved.

In essence, the network flow data is a kind of time series data, and we can carry on the model and prediction through the traditional time series processing method. But the network traffic of real environment show quite obvious multi-scale characteristic. The traditional network flow model can only deal with stationary process and special non-stationary process. So the network flow behavior is be descript that has a larger error. Therefore, the research of seeking the new method to forecast the network traffic becomes the research hot spot by the multitudinous researchers.

II. Related Work

The network traffic prediction models are divided into single forecast model and the combination forecast model according to the characteristics of the network traffic. A single forecasting model uses a mathematical model to predict network traffic, the typical representative have autoregressive model [1], the gray model [2], self similarity model [3], chaos model [4], etc. Due to many kinds of dynamic characteristics for the actual network traffic's self similarity, long related points and so on, so a single model is lack of accuracy. Combination forecast model is to predict by combination several single models, which has become the new research trend for the network traffic.

In recent years, the domestic and foreign scholars use combination predict model to fitting the network traffic according to network flow more characteristic. For example, Poisson neural network combined model [5], ARIMA and SNF combined model [6], covariant (CO) and artificial neural network (ANN) combined model [7], QPSO and BP neural network combined model [8], wavelet analysis and AR-LSSVM combined model [9], etc. Neural network has been widely used in network prediction due to the function of approximation ability and self learning ability. At present, whether a single model or combined model, are mostly used BP neural network, but the error is bigger to predict the dynamic real-time update network because it belongs to static feed forward neural network.

In addition, BP neural network is still existed slow convergence speed and the problem of easy to falling into local minimum. In order to overcome this problem, Dang Xiaochao etc. proposed a modified Elman neural network-----input multiple feedback Elman network according to network flow data obtained in the actual network measurement[10]. The model introduced chaos search mechanism in the training process of the network weights in the process, It used the Tent map to chaotic variables optimization search, which reduce the data redundancy and solve the local convergence problem. But this method has not given attention to two or more things as a result of the single model. Therefore, we need to find a more superior performance of neural network model.

Through the research, we find Hopfield neural network is meet those needs. It is a cycle of neural networks and can association memory according to the former initial data. So the dynamic process can be simple and rapidly reacted, and has adaptability to the time and space mutation. Multi-scale characteristic in the network traffic statistics characteristic is particularly important [11]-[12]. Wavelet analysis is the effective strategy to non-stationary signal processing.

Therefore, a network traffic prediction based on the wavelet analysis and Hopfield neural network is proposed in this paper. Firstly, the original data is put to wavelet transform α Trous algorithm, and normalized processing; Secondly, the single wavelet is reconstructed, and the low frequency is component into AR model and high frequency is component into Hopfield neural network modeling to

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predict; Finally, the each component is synthetic to get predicted value.

III. The Selection and Build of Submodel for Network Traffic Prediction

A. αTrous Wavelet Transform Submodule

The network traffic data is a quite discrete sequence, so the actual network flow analysis must use the discrete wavelet to decomposition and reconstruction. The existing methods with wavelet analysis of network flow decomposition and reconstruction are most using Mallat algorithm. In decomposed the original data, the signal point is reduced half after one time decomposition. Mallat algorithm has not all levels of intuitive in a certain time point, namely it has not time shift invariance. If the sequence initial value is deleted, the coefficient of transformation is also changed; it must carry on recount. So Mallat algorithm can not carry out online calculation.

Wavelet transform *α*Trous algorithm [11] is making up for the shortcomings of Mallat algorithm. In decomposed the original data, the sequence's length remain unchanged after the decomposition of each layer. Therefore, it has the time shift invariance for establishing visual contact at the same time the same scale, which can adapt to the network flow online prediction. Therefore, this paper use αTrous discrete wavelet transform as one of submodel to wavelet analysis.

The process of *α*Trous wavelet submodel decomposition and reconstruction is as follows:

Suppose the original input signal of network traffic is F(x), approximate signal is $\boldsymbol{C}_j$, detail signal is $\boldsymbol{D}_j$, $\boldsymbol{H}(k)$ is for low pass filter, $\boldsymbol{G}(k)$ is high-pass filter, and wavelet decomposition series is L.

1) The original data initialization: $C_0 = F(x)$, $H_1(k) = H(k)$, $G_1(k) = G(k)$, $j = 1$;
2) Decomposition data: $C_j[k] = C_{j-1}[k] * H_j[-k]$, $D_j[k] = D_{j-1}[k] * G_j[-k]$, * is convolution operation;
3) Sample, namely to carry on interpolation operation to filter:

$$H_{j+1}(k) = \begin{cases} H_j[\frac{k}{2}], xis\,even \\ 0, xis\,odd \end{cases}$$

$$\mathrm{G}_{j+1}(k) = \begin{cases} \mathrm{G}_j[\frac{k}{2}], xis\,even \\ 0, xis\,odd \end{cases}$$

4) j=j+1. Back to when $j \le L$; otherwise, the process is over.

The specific decomposition process is shown in Fig.1.

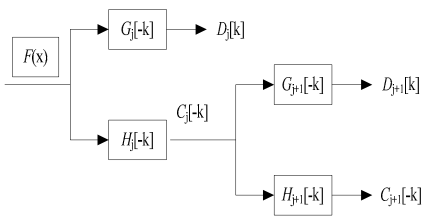

Fig. 1. The diagram of αTrous wavelet decomposition

B. Hopfield Neural Network Submodel

Hopfield network is proposed in 1982 by J. Hopfield, which is the Internet can be used associative memory. So the dynamic process can be simple and rapidly reacted, and has adaptability to the time and space mutation. Previous method mostly adopted BP neural network for network traffic prediction. BP neural network is feed forward neural network type, which can only predict according to the previous data and no coping ability to timely dynamic change. The recursive feedback of Hopfield neural network can quick react to the dynamic change of network traffic. So, we adopt Hopfield neural network in the process of training learning sub model.

The model structure of Hopfield network is as shown in Fig. 2.

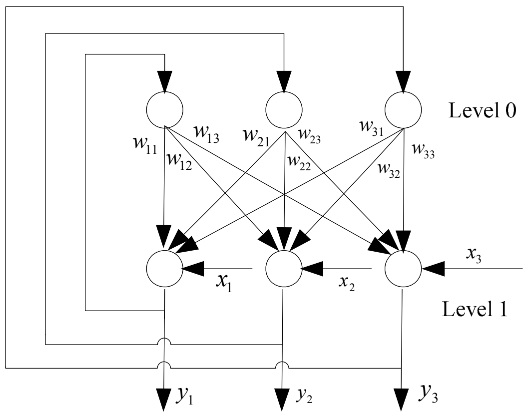

Fig. 2. The model structure of Hopfield network

Assume that the network traffic vector after wavelet transform preprocessing is $\boldsymbol{X}=\{x1,x2,\cdots xn\}$, The process for network traffic is trained and associative memory using Hopfield neural network is as follows:

1) Determine to network weight coefficient through a learning training process;
2) Memory the information of network traffic, and make the information meet that the energy is minimum in a vertex angle of n dimension cube. Make sure the network weight coefficient, input vector is put into the network, even if the vector is local data, it still be able to output completely the memory information;
3) For carrying association prediction, gives the corresponding node j (j = 1, 2,... n) to each component of $\boldsymbol{X}$ vector. The initial status of each node is y_j (0):

$$y_j(0)=x_j$$

4) Carry on calculate according to the dynamic system principle in the Hopfield network:

$$Y_j(t+1)=f[\sum w_{ij} y_j(0)-\theta_j], i,j=1,2\cdots n$$

Hereinto, f is nonlinear function, it is desirable step function.

IV. The Prediction Model and Process

The prediction model is the combination model with wavelet analysis and Hopfield network. The diagram of prediction model is as shown in Fig. 3.

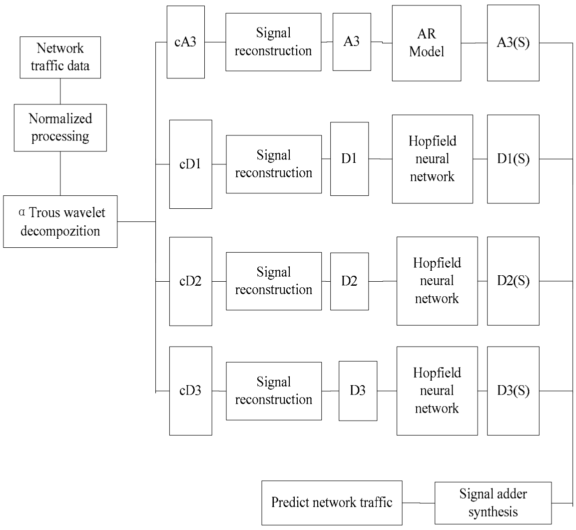

Fig. 3. The diagram of prediction model

The specific process of this model for network traffic prediction is as follows:

Step 1: The collected original data are normalization preprocessed. Suppose $\boldsymbol{X}(t)$ is stand for the network original traffic, the maximum and the minimum of network traffic is respectively for max(t) and min(t), the normalization formula is:

$$X(t)=\frac{X(t)\text{-}\min(t)}{\max(t)\text{-}\min(t)}$$

Step 2: The above normalized data are carry on αTrous wavelet transform pretreatment, and single reconstruction separate high frequency and low frequency subcomponent. In the process of wavelet transform decomposition, the forecast precision is influence by decomposition series. If series is great, the precision error can be accumulation and reduce prediction precision; if series is small, the frequency characteristics can not be separated. So this paper uses the three series, which can not only get significant nonstationary approximate component, but also can get stable approximate the details component.

Step 3: The low frequency component and high frequency component that are obtained by decomposition are input into AR model and Hopfield model to predict. The method of data predicted value adopt according to the former N time value and the later M value. Specific data classification method is as shown in Table I.

TABLE I: THE DATA CLASSIFICATION METHOD

Input value for N	Output value for M
X_1, ……X_N	X_{N+1}, ……X_{N+M}
X_2, ……X_{N+1}	X_{N+2}, ……X_{N+M+1}
……	……
X_K, ……$X_{N+K\text{-}1}$	X_{N+K}, ……$X_{N+M+K\text{-}1}$

Step 4: For low frequency information, the parameters are initialization, hereinto, N = 5, M = 1, train and test is adopt AR(5). For high frequency information, it use Hopfield neural network model to training and testing.

Step 5: The predicted value of the high frequency component and low frequency component are send into fitting apparatus to fit, and get the final network traffic prediction results.

V. THE SIMULATION EXPERIMENT RESULTS AND ANALYSIS

A. The Simulation Experiment Resuults

The experimental data are collected form January 1, 2012 to January 30, 2012. The network data traffic is count into 360.

Firstly, the original data are normalization treatment, and then carry on αTrous wavelet transform. The experimental decomposition layers are best for three. Then the low frequency and high frequency information after single reconstruction are respectively into AR model and Hopfield network. The node number input value is five. Therefore, the training data sample contains 240, and the former 216 data are the training sample, the last 24 data are the prediction sample. Finally, the final network traffic prediction results are obtained by fitting the each subsequence prediction traffic value.

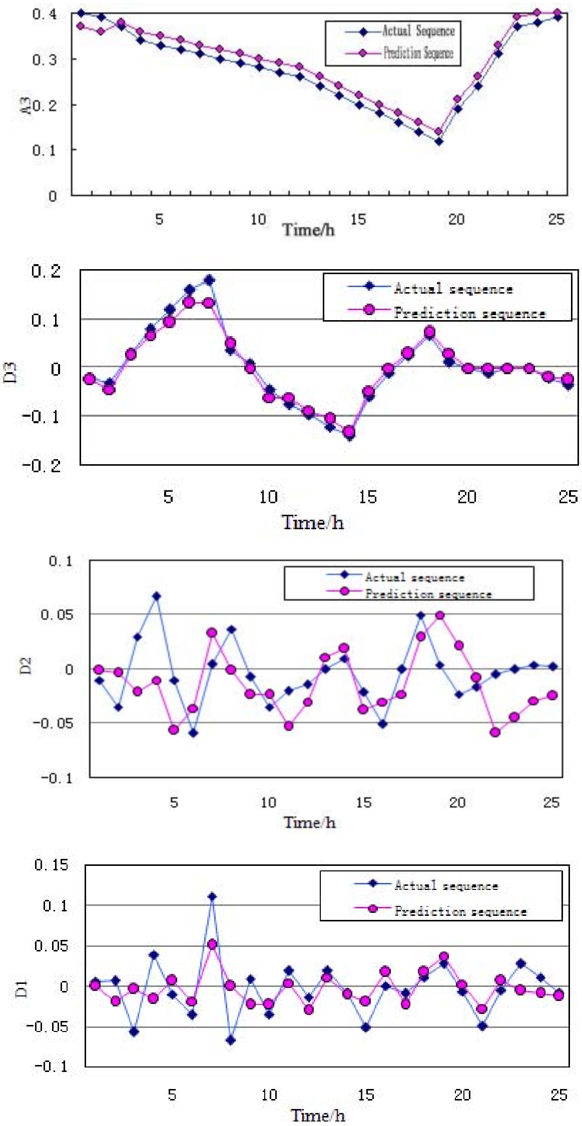

Fig. 4. The prediction results of subsequence

Fig. 4 shows the prediction results of low frequency channel and various high frequency sub channel sequence based on wavelet analysis and Hopfield neural network model. We can see form the diagram, the data traffic after normalization and the wavelet transform are decomposed into different frequency channel. These data sequence are relatively signal and smooth in frequency component than the data before decomposition. In addition, a large number of test results find that the model in this paper has higher accuracy for each sub channel, especially for the low frequency subsequence and the third layer high frequency, which results are almost same. So the final network traffic prediction results after fitting the each sub channel information forecast results is also higher.

The prediction process after training: The data traffic of the former 20 days during prediction are as the model calibration, and the data information of the later 10 days are be used to check. The 22th's data traffic are be predict according to the network data of 20th and the 21st; the 23th's data traffic are be predict according to the network data of the 21st and 22nd days; then and the like, and finally predict the network traffic of 30th day.

In order to test this model's validity and accuracy, we also carried out an experiment: the network traffic prediction is test for model based on wavelet BP neural network. Fig.5 shows the prediction result of the model of this paper, Fig.6 shows the prediction results of the model based on wavelet BP neural network.

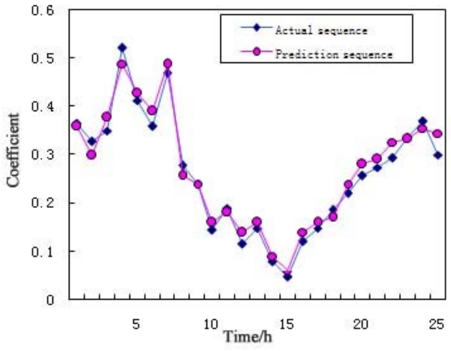

Fig. 5. The prediction results of model in this work

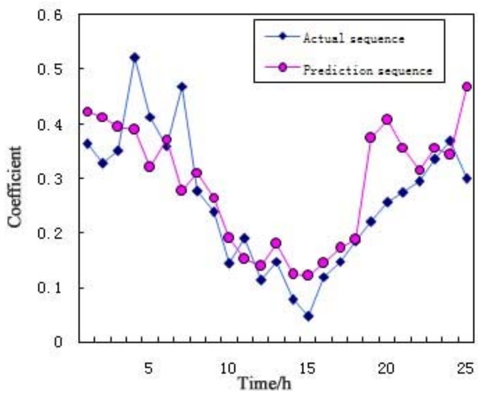

Fig. 6. The prediction results of model based on wavelet BP neural network

It can be seen from the Fig. 5, the prediction result of model in this work are basic consistent, and can better reflect the original data and dynamic rule characteristics of the network traffic. But the results of BP neural network prediction model in Fig.6 are not accuracy; some data information of the predicted value has the big deviation compared with the actual traffic, which is because the BP neural network easy to fall into local minimum.

B. Perfomance Analysis

In order to evaluate and analysis the performance of the model in this work, we adopt the root mean square error MSE as performance index:

$$MSE = \sqrt{\frac{1}{k}\sum_{i=1}^{k}(x_i - \hat{x}_i)^2}$$

Hereinto, x_i is the actual network traffic, $\hat{x}_i$ is predicted value, k is stand for the prediction test time. Here, k is corresponding to one day, which is 24 hours.

The performance test is used comparison method, the model in this work is companied with the prediction model based on wavelet BP neural network in the same experiment and data integration, and then analyzed data according to the same index. The contrast results of the experimental error for two models are as shown in Table Ⅱ.

TABLE Ⅱ: THE CONTRAST RESULTS OF EXPERIMENTAL ERROR

Test number	Prediction error of wavelet BP model	Prediction error of this work's model
1	0.0077	0.0022
2	0.0079	0.0023
3	0.0078	0.0021
4	0.0076	0.0020
5	0.0078	0.0022
6	0.0080	0.0021
7	0.0077	0.0023
8	0.0078	0.0021
9	0.0079	0.0023
10	0.0075	0.0024
mean	0.0078	0.0022

It can see from Table II that the performance of model in this work is obviously higher than the model of wavelet BP neural network traffic prediction. The prediction error is very small in this paper, and the prediction performance is very stable. Because the αTrous wavelet analysis used in this paper comprehended more characteristic and more level of network traffic, improve the reconstruction quality. Moreover, Hopfield neural network solve the problem of local minimum and slow convergence speed that exist in the BP neural network, and it has the memory function. So this prediction model is not only update to the dynamic network traffic, but also can make adjustment according to the memory, ensure the accuracy and performance is more stable.

VI. CONCLUSION

Network traffic prediction based on the wavelet analysis and Hopfield neural network is proposed in this work in the basic of the research on network traffic prediction model. First, network traffic is normalized and adopt αTrous wavelet transform; And then reconstruct the wavelet single, and predict through sending low frequency components into AR model and sending the high frequency component into Hopfield neural network model; Last, The predictive value are obtained by composing the components. Simulation results show that the model improves the prediction accuracy, and has the good adaptability to the network.

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