Network Traffic Model with Multi-fractal Discrete Wavelet Transform in Power Telecommunication Access Networks

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Abstract. With the development of communication networks, a lot of new applications emerge in the power telecommunication access networks, which have many new features and properties of the network traffic. These features are important for modeling the network traffic in the network-level. This paper propose a new feature extraction and network traffic model method. Firstly, we analyze the features of network traffic in time-frequency domain. Then, we use discrete wavelet transform to exploit the features of network traffic in the time domain and frequency domain. We run multi-fractal discrete wavelet transform (MDWT) for network traffic to decompose them into different frequency component and train an artificial neural network to predict the low- and high-frequency components of network traffic, and use them to reconstruct the network traffic. Finally, in order to validate our network traffic model, we conduct the network traffic prediction on the actual data. Simulation results show that our approach is feasible.

Keywords: Network traffic · Multi-fractal · Discrete wavelet transform · Power telecommunication access networks

1 Introduction

With development of the communication network, there are many new applications appeared in power telecommunication access networks and the network architecture has become more complexity in the recent years, so there are more features has appeared in the telecommunication networks, which leads to a huge challenge for the network management [1, 2]. There are many researches show that flow traffic in the network has important statistical characteristics, such as correlation and self-similarity,

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as well as in the power telecommunication access networks [3, 4]. The complex behavioral characteristics of network traffic are usually manifested in bursts on time domain and frequency domain.

In order to increase the performance of the network, it is important for network managements to obtain the accurately model to demonstrate the features of network traffic. Accurate traffic prediction models can influence the planning and optimization of the network. The end-to-end traffic in the network shows the data transmission in the network-level behaviors, this is very significant for the network planning, network management and service quality improvement which provided by the operators and service providers. So the end-to-end network traffic has attracted much attention of researchers and operators around the world [5]. The network traffic in the network are changed over time and there are many features for different types of applications and network devices.

Flow traffic model in the network is very hard. However, the flow traffic in the network has multi-scale features, so we can learn more information about network traffic and construct an approximate model for the end-to-end traffic in the network through feature analysis and feature extraction. The back propagation (BP) neural networks and multi-population quantum genetic algorithm are used to improve the prediction precision of network traffic. Since the neural network has a long convergence time, so the multi-population quantum genetic algorithm is proposed to adjust the initial weights and thresholds of the BP neural network to decrease the convergence time [6]. The dynamic programming (DP) based time-normalization algorithm is proposed to detect anomaly traffic in the network [7]. The spatio-temporal correlation of normal traffic and the sparse nature of anomalies are used to detect the anomalous traffic in the network with lacking of sufficient flow-level measurements [8].

The feature analysis is used to detect the anomalous traffic in the network [9]. Moreover, the model-based network event detection framework is built by analyzing and extracting the feature of network traffic [10]. The continuous wavelet transforms based on multi-scale analysis are performed to detect the anomalous in the high-speed backbone networks [11]. The combination of unsupervised feature extractor and anomaly detector to construct an anomaly detection model for high-dimensional spaces [12]. Additionally, from the network-wide traffic perspective, the anomalous of the network traffic can be correctly detected via signal transformations [13]. The manifold similarity index and manifold learning technology are used to study the spatial-temporal characteristics of highway traffic flow [14]. The time-frequency analysis of end-to-end traffic is used to localize traffic features of time-frequency properties and reconstruct network traffic in large-scale communication networks [15]. There are many methods to extract the network traffic and use them to model the network traffic, however, the prediction errors of these proposed methods are large.

This paper proposed a new scheme MDWT to accurately and effectively predict the network traffic in the network. Network traffic modeling and predicting of network traffic is very hard due to the network traffic has highly fluctuation over the time. In this paper, we analyze the features of the network traffic in the time-frequency domain. Then, we use the discrete wavelet transform to exploit the features of the network traffic in the time domain and frequency domain. Then, we run MDWT for network traffic to decompose the network traffic and train an artificial neural network to predict the low- and high-frequency component, and use them to reconstruct the network traffic. Simulation results show that our approach is effective and promising.

The architecture of this paper as follow. In Sect. 2, we describe the scheme proposed and analysis the features of the network traffic, and propose the algorithm MDWT. In Sect. 3, we do some simulations and compere the performance of different methods for modeling the network traffic. In Sect. 4, we make a conclusion about our work in this paper.

2 Problem Statement

Flow is also defined as a sequence of packets which are sent from origin nodes to destination nodes. We usually call the origin node and the destination node as an origin-destination (OD) pair. In the power telecommunication access networks, the flows of OD pairs have the characteristics such as correlations, self-similarity and time-varying. The traffic of flows changes over the time, therefore, it is very difficult to use mathematical models to depict the network traffic of flows in the network. The network traffic changes over time, then we represent the network traffic in the power telecommunication access network at time t as $x(t)$ where $t = 1, 2, 3, \ldots$. Since the traffic in the network has the correlations on the frequency-domain and time-domain, respectively, so we characterize the time-frequent features of the network traffic. Due to the complex of the flow traffic, we extract the some features firstly from the network traffic. In the signal process domain, wavelet transform is often used to analyze the multi-scale feature of signals. Then, we use the wavelet method to process the flow traffic in the network.

Discrete wavelet transform (DWT) is a mathematical transformation of the one-dimensional discrete signal $x(t)$, it decomposes the signals into the some orthogonal one-dimensional signals. For the network traffic which has the time-frequent features, so we decompose it into two orthogonal one-dimensional signals to decompose the signals, namely time-domain and frequency-domain. In DWT, signals are usually decomposed into the smooth signal after time shifting $\phi(t)$ in the time-domain and the detail signals of the scale changing $\theta(t)$ in the frequency-domain. As we know that the network traffic at different slots have then correlations and self-similarity. Then, the smooth signals $\phi(t)$ the time-domain are low-pass signals and the detail signals at frequency-domain $\theta(t)$ are high-pass signals. So, signals can be written with the basic function as

$$\phi_{l,k}(t) = 2^{-l/2}\phi_0(2^{-l}t - k),\ k \in Z \tag{1}$$

$$\theta_{l,k}(t) = 2^{-l/2}\theta_0(2^{-l}t - k),\ k \in Z \tag{2}$$

where θ_0 and ϕ_0 are the basic function bases which are orthogonal with each other, l is the scale coefficient, and k is the index of basic orthogonal basis.

The network traffic $x(t)$ can be reconstructed with basic orthogonal basis as

$$x(t) = \sum_{k} c(k)\phi_{l,k}(t) + \sum_{k}\sum_{l=0}^{L} d(k)\theta_{l,k}(t) \tag{3}$$

where l is the level coefficient, $c(k)$ and $d(k)$ are the scaling and translation coefficient, respectively. k is the index of basic orthogonal basis. Then, we can obtain the scale coefficient and wavelet coefficient of wavelet transform with iteration method:

$$c^{l}(k) = 2^{-1/2}(c^{l+1}(2k) + c^{l+1}(2k+1)) \tag{4}$$

$$d^{l}(k) = 2^{-1/2}(c^{l+1}(2k) - c^{l+1}(2k+1)) \tag{5}$$

where $c^{l}(t)$ donates the scale coefficient, and $d^{l}(t)$ donates the wavelet coefficient. Then, from the Eq. (3), we can obtain the scale coefficient

$$c^{l+1}(2k) = 2^{-1/2}(c^{l}(k) + d^{l}(k)) \tag{6}$$

$$c^{l+1}(2k+1) = 2^{-1/2}(c^{l}(k) - d^{l}(k)) \tag{7}$$

The flow traffic from origin node i to destination node j can be expressed as $x_{ij}(t) = \{x_{ij}(1), x_{ij}(2), \ldots\}$, where t is the measured slot. So, the network traffic can be represented as a waveform transform with limited duration and frequency

$$x_{ij}(t) = \sum_{k=-\infty}^{\infty} c_{ij}^{l}(k)2^{-L/2}\phi(\frac{t}{2^{L}} - k) + \sum_{k=-\infty}^{\infty}\sum_{l=1}^{L} d_{ij}^{l}(k)2^{-l/2}\theta(\frac{t}{2^{l}} - k) \tag{8}$$

where ϕ(t) and $\theta(t)$ are basic orthogonal basis of smooth signals and detail signals.

$$x_{ij}^{low}(t) = \sum_{k=-\infty}^{\infty} c_{ij}(k)2^{-1/2}\phi(\frac{t}{2} - k) \tag{9}$$

$$x_{ij}^{high}(t) = \sum_{k=-\infty}^{\infty} d_{ij}(k)2^{-1/2}\theta(\frac{t}{2} - k) \tag{10}$$

then, we use $x_{ij}^{low}(t)$ and $x_{ij}^{high}(t)$ to express the low frequency components and high frequency components, respectively.

The network traffic in the network-level can be collected by sampling the end-to-end flow, and the collected network traffic in the network-level is actually a time series signal $x_{ij}(t)$, so the multi-fractal analysis of the network traffic becomes into analyze the network traffic sampling sequence.

$$x_{ij}(t) = \{x_{ij}(1), x_{ij}(2), \ldots\} \tag{11}$$

where $x_{ij}(t)$ is the network traffic from origin node i to destination node j at time slot t. From Eq. (9), we use the Haar wavelet as the origin signals, so the $\phi(t)$ and $\theta(t)$ can be expressed as

$$\phi(t) = \begin{cases} 1, & 0 \le t \le 1 \\ 0, & otherwise \end{cases} \tag{12}$$

$$\theta(t) = \begin{cases} 1, & 0 \le t \le 1/2 \\ -1, & 1/2 \le t \le 1 \\ 0, & otherwise \end{cases} \tag{13}$$

The network traffic $x_{ij}(t)$ exhibits different scale features on each orthogonal basis. Then we use the Haar wavelet to execute the wavelet transform on the network traffic $x_{ij}(t)$ to find the scale coefficient $\{c^l(k)\}$ and wavelet coefficient $\{d^l(k)\}$, respectively. Then we use the network traffic $x_{ij}(t)$ as the input and use the as the $\{c^l(k)\}$ and $\{d^l(k)\}$ as the output to train an artificial neural networks to obtain the model which predict the coefficient of $x_{ij}^{low}(t)$ and $x_{ij}^{high}(t)$. Then, we reconstruct the network traffic as follow:

$$\hat{x}_{ij}(t) = x_{ij}^{low}(t) + x_{ij}^{high}(t) \tag{14}$$

With low- and high-frequency components which are predicted by artificial neural network, we con model the network traffic in the network. This model can accurately predict network traffic, and help operators to manage the network. Now we show the process of our algorithm as follows:

Step 1: Obtain the discrete network traffic $x(t)$ as the initial traffic data set.
Step 2: Based on Eqs. (3)–(7), carry the wavelet transform with Haar wavelet to obtain the scale coefficients $\{c^l(k)\}$ and wavelet coefficient $\{d^l(k)\}$.
Step 3: By Eqs. (11)–(13), make the scale coefficients and wavelet coefficient as the output and make the measured network traffic $\{x_{ij}(t)\}$ as input to train an artificial neural networks which used predict scale coefficients and wavelet coefficient.
Step 4: Use the prediction result of the scale coefficients and wavelet coefficient in step 3 to calculate the low frequency components $x_{ij}^{low}(t)$ and high frequency components $x_{ij}^{high}(t)$.
Step 5: According to Eq. (14), we reconstruct the network traffic $\hat{x}_{ij}(t)$.
Step 6: Save the results to file and exit.

3 Simulation Results and Analysis

In this section, we make some simulations to verify the performance of the algorithm MDWT proposed in this paper. Then, we use the actual data in the simulations to compare the performance of our algorithms. The actual data is collected from the Abilene backbone network in the United States validate MDWT. Then, we make a comparison about the performance with other methods that principal component analysis (PCA), WABR [15] which have been widely studied for the network traffic modeling. The network traffic prediction results of MDWT method has been discussed in the following. Then, we talk about the relative errors of the network traffic prediction of different methods. Finally, we discuss the prediction errors of them. In the simulation, the front 500 points data are used to train the model we proposed and the last 1500 points are used to compare the prediction errors of the network traffic for different methods.

Figure 1 curves the actual traffic and prediction results network traffic of network traffic flows 67 and 107, where the flows 67 and 107 are randomly selected from the 144 ODs in the Abilene backbone network, as well as the network traffic of other ODs has the similar trend in our simulations. Then, we make a discussion about prediction results of the OD 67 and 107 as an examples here. The end-to-end traffic of flows in the network-level can reflect the data transmission of the network. Figure 1(a) indicates that the actual network traffic has the time-varying nature, and the prediction results is similar with the actual traffic in the network, this means that the model proposed in this paper can extract the network features accurately of OD 67. Likewise the flows 107, the prediction results of flow 107 is closed with the actual network traffic and it also show our method is feasible. From Fig. 1, we very clearly know that the network traffic in each slot has the vary-time nature and the vary-time nature of network traffic of OD 67 is much larger than the network traffic of flow 107, however, our algorithms can also capture the network traffic with the high accuracy.

Then, we talk about the prediction errors of our algorithm and other methods. Since the end-to-end traffic in the network changes over time, it is very hard and meaningless to compare the absolute errors of the network traffic. Inspired by the existing researches, we compare the relative errors of different methods over the time. In order to reduce the randomness of the prediction process, we run many times to calculate the average relative errors here. The relative errors of the prediction traffic can be expressed as:

$$re_i(t) = \frac{1}{N}\sum_{n=1}^{N}\frac{|\hat{y}_i(t) - y_i(t)|}{y_i(t)} \tag{15}$$

where N is the running times, we set it as 300 here, and $y_i(t)$ is the network traffic of end-to-end flow i at time t, $\hat{y}_i(t)$ is the prediction result of network traffic of flow i at time slot t.

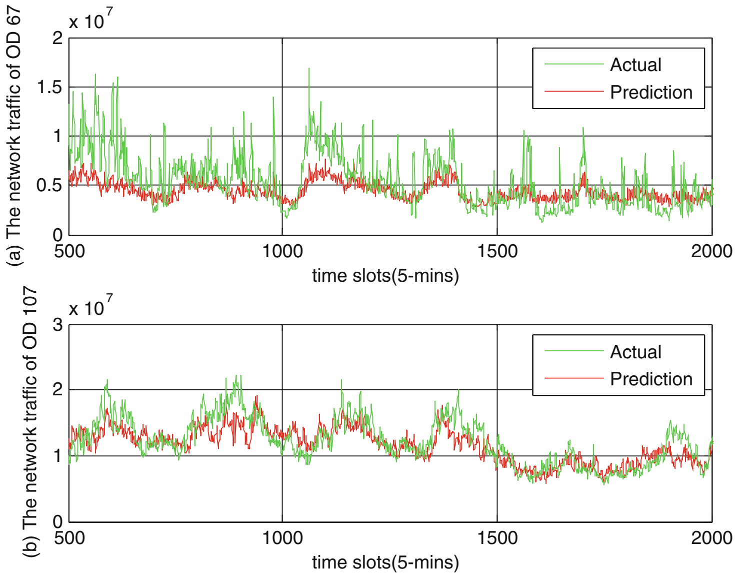

Fig. 1. Prediction results of network traffic of OD 67 and 107.

Figure 2 exploits the average relative errors of the network traffic prediction results of OD 67 and 107 for different methods. From Fig. 2(a), we know that the network traffic prediction results of OD 67 hold lowest relative errors for MDWT, while the relative errors basic of the prediction results for PCA is the largest of them, this shows that the traffic prediction performance of MDWT is well. Importantly, the fluctuation of the relative errors over time is more stable for the MDWT than PCA and WBAR, and the average relative errors of MDWT is the lowest of them. Thus, the MDWT can more accurately and effectively model the features of end-to-end traffic in the network. With the model MDWT, we can predict the network traffic more accurately than previous methods in the network.

In the following, we use the Root Mean Square Error (RMSE) to further compare the performance for above three algorithms. The RMSE are given as follows:

$$RMSE = \sqrt{\frac{1}{K}\sum_{k=1}^{K}\left(re_i(t)\right)^2} \tag{16}$$

where K is the length of the sampling windows. $re_i(t)$ is the relative errors of the flow i at time slot t. The RMSE can more clearly shows the accuracy and the stability of the model.

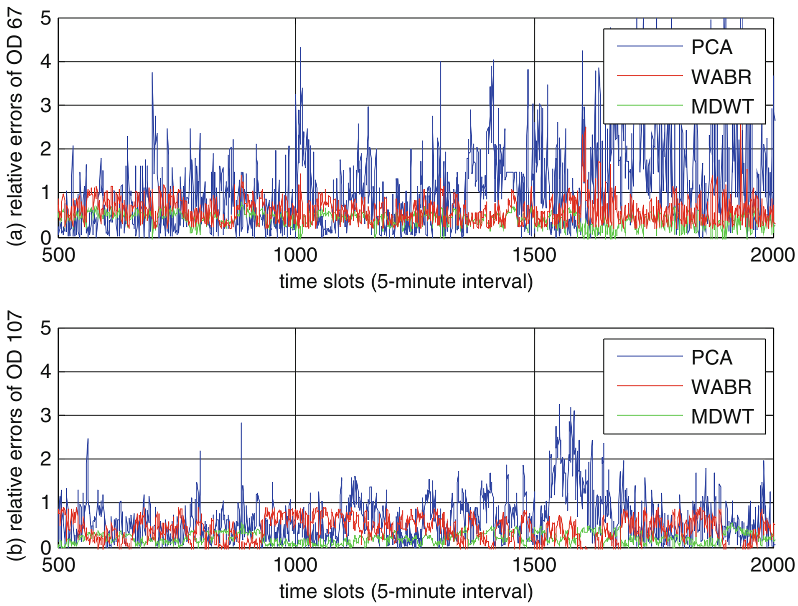

Fig. 2. The average relative errors for network traffic of OD 67 and 107.

Figure 3 exhibits the RMSE of relative errors of prediction results of end-to-end network traffic of OD 67 and 107 for different models. Figure 3(a) shows the RMSE of relative errors f prediction results for OD 67, when the average relative errors is about 0.5, the probability of MDWT, WABR and PCA are 95%, 30% and 5%, respectively. This shows that the relative errors of prediction results of MDWT is smallest of the three methods. The CDF curve of the MDWT is very steep, it means the network traffic prediction results of MDWT is more accurate than PCA and WABR, and the performance of network traffic prediction of the MDWT is stable. Similarly, for network traffic of OD 107, the green curve shows that MDWT can more accurately model the network-level network traffic. When the average relative errors is about 0.3, the probability of MDWT, WABR and PCA are 95%, 10% and 5%, respectively. This also shows that the relative errors of prediction results of MDWT is smallest of the three methods. Then, from Fig. 3, we know that the proposed method MDWT can accurately model the network traffic and keep better modeling performance for network traffic than the previous method PCA and WABR.

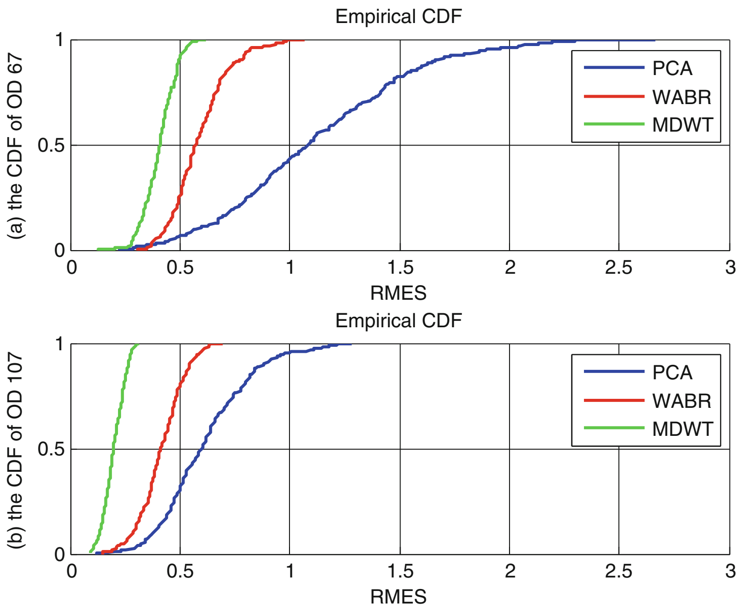

Fig. 3. The REMS of network traffic of OD 67 and 107. (Color figure online)

4 Conclusions

This paper studies the network traffic modeling and prediction in the power telecommunication access networks. Because network traffic fluctuates greatly over time, so it is very hard to model the network traffic. This paper propose a method to model and predict the network traffic. Firstly, we analyze the time-frequency features of the network traffic in the time-frequency domain. Then, we use the discrete wavelet transform to exploit the features of the network traffic in the time domain and frequency domain. Then, we run MDWT for the network traffic to decompose the network traffic and train an artificial neural network to predict the low-frequency component and high-frequency component. Finally, we do some simulations to verify our network traffic model and predict the network traffic. Simulation results show that our approach is effective and promising.

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