A Prediction Algorithm for Real-Time Video Traffic Based on Wavelet Packet

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Abstract. Long-term prediction is a key problem in real-time video traffic applications. Most of real-time video traffic belong to VBR traffic and has specific properties such as time variation, non-linearity and long range dependence. In this paper, feature extraction method of real-time video traffic based on multi-scale wavelet packet decomposition is proposed. On this basis, LMS algorithm is adopted to predict wavelet coefficients. Through reverse wavelet transforms of the predicted wavelet coefficients, the long-term prediction of real-time video traffic is realized. Numerical and simulation results show that this long-term prediction algorithm can accurately track the variation trend of video signal and obtain an excellent prediction result.

Keywords: real-time video traffic, wavelet packet, multi-scale decomposition, long-term prediction, LMS.

1 Introduction

In recent years, the proportion of video traffic transmission in network is gradually increased. Prediction of video traffic in coming period will do much help to improve the quality of video transmission [1-3]. Therefore, study of real-time video traffic prediction algorithm has important significance considering the requirements of efficient bandwidth allocation. Traditional bandwidth analysis method for pre-encoded video is not suitable for the analysis of real-time video traffic because signal encoding method can not be obtained in advance.

Self-similarity and long-range dependence are essential to accurately traffic prediction [4]. Related studies have shown that the broadband network traffic and video traffic both have nature of long-range dependence and self-similarity in addition to short-range dependence [5, 6]. Some traffic prediction algorithms have been proposed [7, 8], most of which belongs to short-term prediction (1 to 10 frames), such as ARX and ARMA etc. Long-term prediction is one of the most difficult problems in the area of video traffic prediction. In this paper, we proposed an optimal multi-scale decomposition method of real-time video traffic and realize a long-term prediction of decomposed video traffic based on LMS algorithm.

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2 Optimal Multi-scale Decomposition of Real Time Video Traffic

Multi-scale decomposition of signal comes from the wavelet theory [9], and wavelet packet decomposition is based on wavelet decomposition. Combined with a rigorous mathematical theory and numerical calculations, wavelet packet decomposition can be used to conduct multi-level signal decomposition in different frequency bands.

2.1 Analysis of Video Traffic Wavelet Packet Decomposition

Prediction commonly use linear time series analysis and nonlinear time series analysis method. The former assumes that the sequence is a linear correlation structure, the latter assumes that the series has chaos characteristic. For signals with long-range dependence, wavelet decomposition is an important method to change its long-range dependence. In this paper, we adopt α/β traffic model to describe the video traffic [10]. Alpha components of traffic is highly non-Gaussian and entirely responsible for the bursty behavior, β component is a aggregation of low-rate traffics, and has a long-range dependence, its marginal distribution can be well approximated with a Gaussian distribution, so β traffic can be expressed using a fractal Gaussian approximation. An aggregate traffic can be decomposed into[10]:

$$Total_{traffic} = \alpha_{traffic} + \beta_{traffic} \tag{1}$$

Literature [11] mentioned that for a video traffic expressed with α/β traffic model, if β traffic obey fractal Gaussian distribution and α traffic obey the Gaussian distribution, wavelet transform coefficients is short-range dependence in the same scale after wavelet transform. Thus, if we predict wavelet transform coefficients with short-range dependence using traditional series prediction method, we will be able to predict both the variation trend of video traffic and the bursty behavior of video traffic.

2.2 Optimal Wavelet Packet Decomposition of Video Traffic

The quality of signal decomposition and time-frequency analysis is heavily dependent on the choice of the fundamental function, so it is necessary to solve two problems, one is how to evaluate the pros and cons of a basis, the second is how to find the optimal basis in a wavelet library quickly. According to the selection principle of optimal basis [12], the cost function of video signals is defined as the Shannon entropy of wavelet packet coefficient sequence $u = \{u_j\}$, which is generated by decomposition of video signal $x(t)$ using an orthogonal wavelet basis.

Definition 1: set sequence $u = \{u_j\}$, $P_j = |u_j|^2 / |u|^2$, if $P = 0$, $P_j \log P_j = 0$, shannon entropy of u is defined as:

$$M(u) = -\sum_j p_j \log p_j \tag{2}$$

The cost function should have additivity, namely $M(0) = 0$, $M(\{u_j\}) = \sum_j M(u_j)$, and values of $M(u)$ should reflect the concentration of the coefficient.

Definition 2: let $M(u)$ be the cost function, $u = \{u_j\}$ is a vector in space V, B is an orthogonal basis selected from the library, B_u is expansion coefficients of u with basis B. $\forall$ u $\in V$, if $M(B_u)$ is the smallest, then B is the optimal basis.

This orthogonal basis library is a binary tree structure if it meet the following conditions. First, subset of basis vectors is equivalent to a interval of non-negative integer set N, namely $I_{n,k} = \left[2^k n, 2^k(n+1)\right]$, where $k \in Z$, $n \in N$. Second, each basis in the library corresponds to a disjoint covering composed of $I_{n,k}$ in N. Thirdly, if $V_{n,k}$ is equivalent to $I_{n,k}$, then $V_{n,k+1} = V_{2n,k} \oplus V_{2n+1,k}$. If the library is a tree, optimal basis can be found by induction of k. Let $B_{n,k}$ be a basis of corresponding vector $I_{n,k}$, $A_{n,k}$ is the optimal basis of u subject to B_n. To $k = 0$, there exists a single basis, namely $I_{n,0}$, to be the optimal one, and formula $A_{n,0} = B_{n,0}$ holds for all $n \geq 0$. Let $k \geq 0$, $n \geq 0$, $V = I_{0,k}$, we can use the following formula to generate u's optimal orthogonal basis related with cost function M.

$$A_{n,k+1} = \begin{cases} B_{n,k+1} & \text{if } M(B_{n,k+1}(u)) < M(A_{2n,k}(u)) + M(A_{2n+1,k}(u)) \\ A_{2n,k} \oplus A_{2n+1,k} & \text{otherwise} \end{cases} \tag{3}$$

As to real-time video traffic sequence, using the bottom-up search algorithm, we can find a wavelet packet sequence which makes the cost function minimum, and then we can find the optimal basis. This algorithm is shown as follows:

- Step 1: calculate each node's cost function $M(u)$ in every step of the wavelet packet decomposition;
- Step 2: mark all nodes from the lowest layer, take their cost value as an initial value and calculate the sum of pair wise, then compare with parent node' value in upper layer;
- Step 3: if cost value of parent node is lower than that of child node, parent node should be marked. Otherwise, calculate the sum of two child nodes' cost function value and replace the cost value of parent node, and so forth, until the top level;
- Step 4: check and record all the marked nodes. When the upper node is marked, the mark of corresponding child nodes is deleted, after $o(N \log N)$ operations, all marked nodes of top level is selected, these marked nodes compose of non-overlapping coverage in $L^2(R)$ space, then coefficients are extracted from the optimal basis and output.

3 Video Traffic Prediction Based on Wavelet Packet

As mentioned above, frequency division of real-time video signal can be determined if we can find the optimal orthogonal wavelet packet basis in $L^2(R)$. This section gives video traffic prediction algorithm based on optimal wavelet packet decomposition.

LMS algorithm is a linear filtering method; it uses a linear combination of historical data to predict. This algorithm is more adaptive, simple and effective, does not need to know the autocorrelation structure of time series and able to achieve satisfactory online prediction results of real-time signal [13]. Real-time prediction accuracy of the LMS algorithm is close to the long memory model prediction accuracy when the signal has lower Hurst parameter and do not show very long correlation [14].

For prediction problem in the wavelet domain, LMS algorithm can be described as follows : there exists two sets of variables $d(i)$ and $p(i)$, where $d(i)$ is a known set of wavelet coefficients, $p(i)$ is a set of wavelet coefficients need to be predicted, namely, $p(i)$ is a function with an input set $\{d(i),\ d(i-1),\ \cdots,\ d(i-M+1)\}$. Assume that this function is linear and we have:

$$p(n+k)=\sum_{l=0}^{M-1} w(l)\cdot d(n-l) \tag{4}$$

Where, $W=[w(0),w(1),\cdots,w(M-1)]^T$ are coefficients of the prediction filter, $D(n)=[d(n),d(n-1),\cdots,d(n-M+1)]^T$ is the input sequence and $p(n+k)$ is the estimates of k step. Prediction error is given as follows:

$$e(n)=p(n+k)-d(n+k)=p(n+k)-W^T D(n) \tag{5}$$

Optimal linear prediction on mean squared error sense should make the mathematical expectation of mean square error $\xi = E[e^2(n)]$ to obtain the minimum. LMS algorithm is a gradient search algorithm, the prediction coefficients W alters over time, of which the adjustment process depends on the feedback of error $e(n)$. When prediction initiate, we first estimate to set the coefficient of the initial value $w(0)$, then update coefficient W using equation (6) and use the updated coefficients for the next prediction.

$$W(n+1)=W(n)+\frac{\beta\cdot e(n-k)\cdot D(n-k)}{\left\|D(n-k)\right\|^2} \tag{6}$$

Where $\left\|D(n-k)\right\|^2 = D(n-k)^T\cdot D(n-k)$, β is step adjustment factor meet $0<\beta<2$, if β is greater, the prediction convergence is quicker and response to the signal changes is more rapid, but the fluctuations after the convergence is greater too. On the contrary, if β is smaller, the prediction convergence is slower, but the fluctuations after the convergence is smaller too. As to the wavelet coefficients $d(k)$ at time k, $\{p(k+1), p(k+2), \cdots, p(k+i)\}$ need to be estimated. We adopt an iterative prediction method, the iterative relationship is given as following:

$$\begin{cases} p(k+1) = f(d(k), d(k-1), \cdots, d(k-i+1)) \\ p(k+2) = f(p(k+1), d(k), \cdots, d(k-i+2)) \\ \quad\quad\quad\quad \cdots\cdots \\ p(k+i) = f(p(k+i-1), p(k+i-2), \cdots, d(k)) \end{cases} \tag{7}$$

Where $f(x)$ is the LMS prediction operator.

With wavelet packet decomposition, original video traffic with complex properties of long-range and short-range dependence can be transformed into a sequence in wavelet domain with short correlation. On this basis, by utilizing LMS algorithm to achieve approximate prediction of the wavelet coefficients after the wavelet packet transform, we can realize the real-time video traffic prediction algorithm, which is described as followings:

- Step 1: conduct wavelet packet decomposition on each group of video frames acquired and output sequence of wavelet coefficients;
- Step 2: use LMS algorithm to predict the next set of wavelet coefficients in the wavelet domain with the new acquired wavelet coefficients;
- Step 3: conduct inverse wavelet transform with predicted wavelet coefficients, then the prediction of video traffic in the next time window is realized;
- Step 4: every time new video frame traffic is acquired, traffic data should be recorded, then repeat step 1, 2, 3.

4 Simulatioin and Analysis

In this paper, experimental video "StarWars" and "News" are chosen from the MPEG4 video trace database of Berlin university. These Video adopt MPEG-I compression standard , with QCIF format, frame rate set to 30fps, and quantitative parameters is fixed at 10, 14 and 18.

First of all, NMSE (Normalized Mean Squared Error) is introduced to evaluate performance of our algorithms. NMSE is defined as follows:

$$NMSE = \frac{1}{\sigma^2}\frac{1}{N}\sum\left[x(t) - \overline{x}(t)\right]^2 = \frac{1}{N}\sum\left[x(t) - \overline{x}(t)\right]^2 \Big/ Var(x(t)) \tag{8}$$

Where $x(t)$ is the actual frames at time t, $\overline{x}(t)$ is the prediction of $x(t)$. N is the number of predict test, σ^2 is the variance of the observed sequence, 1024 frames are randomly extracted from "Star Wars" and "News". Prediction is conducted on follow-up continuous 200 frames, and the prediction performance is studied.

In order to reduce the prediction time and avoid constantly modify of the model, we adopt an iterative prediction method and video traffic signal is decomposed with *db*1 wavelet and wavelet packet. The optimal wavelet decomposition tree expansion is given below.

$$S = AAAA4 \oplus DAAA4 \oplus ADAA4 \oplus DDAA4 \oplus DA2 \oplus D1 \tag{9}$$

When the length of video traffic prediction is set to 256 frames, the length of each wavelet coefficient need to be predicted is shown in Table 1.

Table 1. Wavelet Coefficients Information

Wavelet level	coefficient Length of wavelet	Coefficient Length of wavelet to be predicted
AAAA4	64	16
DAAA4	64	16
ADAA4	64	16
DDAA4	64	16
DA2	256	64
D1	512	128

Figure 2 shows wavelet packet decomposition and coefficients prediction of "News" frame sequence. Figure 1(a) indicates prediction result of AAAA4 wavelet packet coefficients. This wavelet packet coefficient reflects the trend of signal change. Prediction performance of wavelet packet coefficients DAAA4, ADAA4, DDAA4, DA2 and D1 are shown respectively in Figure 1(b), 2(c), 2(d), 2(e), 2(f).

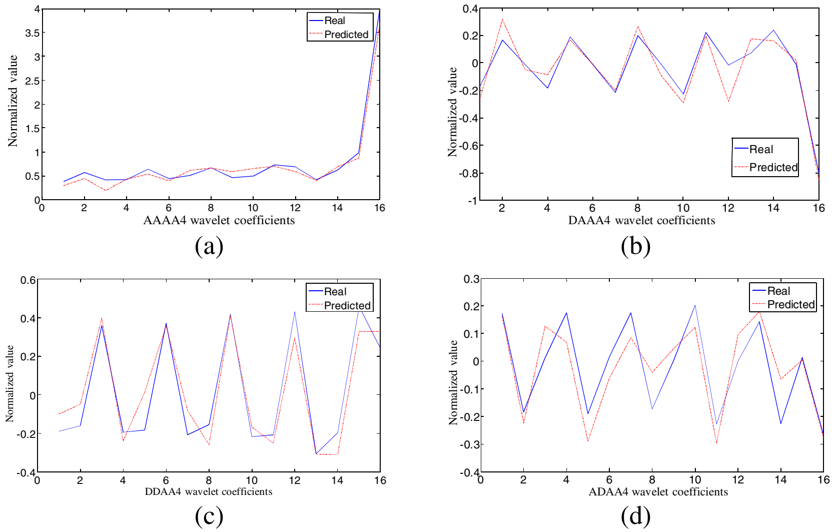
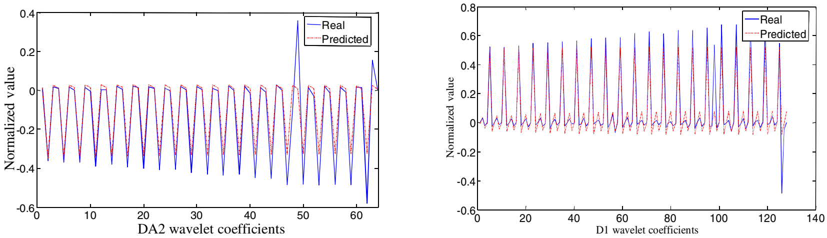


Fig. 1. Wavelet packet decomposition and coefficients prediction



(e) (f)

Fig. 1. (*Continued*)

Figure2 shows prediction of "News" traffic after inverse wavelet transform.

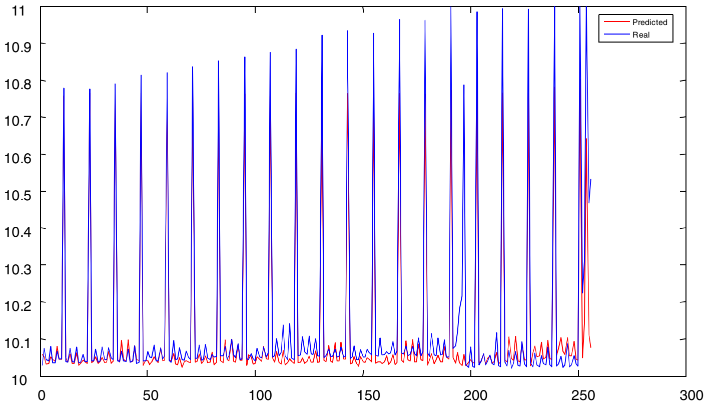


Fig. 2. Prediction of "News" traffic after inverse wavelet transform

From Figure 1 and Figure 2, we can see that prediction of the wavelet coefficients based on wavelet packet decomposition can accurately predict both the variation trend and the bursty behavior of video traffic, which verifies the validity of this algorithm on the long-term prediction.

5 Conclusions

In this paper, we propose a real-time video traffic prediction algorithm based on wavelet packet decomposition. Compared with conventional video traffic prediction method, the proposed algorithm greatly improves the accuracy of long-term prediction. Owing to the ability of following the trend of the video traffic variation accurately and the capability of capturing bursty traffic of real-time video signal, this video traffic prediction algorithm provide a new method to realize bandwidth resource management in a network with long delay and constrained bandwidth.

References

1. Lazar, A.A., Pacifici, G.: Control of resources in broadband networks with quality of service guarantees. IEEE Communications, 66–73 (1991)
2. Chong, S., Li, S., Ghosh, J.: Predictive dynamic bandwidth allocation for efficient transport of real-time VBR video over ATM. IEEE Journal of Select Areas Communication 13, 12–23 (1995)
3. Alarcon-Aquino, V., Barria, J.A.: Multiresolution FIR neural-network-based learning algorithm applied to network traffic prediction. IEEE Transactions on Systems, Man, and Cybernetics-Part C: Applications and Reviews 36(2), 208–220 (2006)
4. Leland, E., Taqqu, M.S., Willinger, W., et al.: On the self similar nature of Ethernet traffic (extended version). IEEE/ACM Transactions on Networking 2, 1–15 (1994)
5. Beran, J., Sherman, R., Taqqu, M.S., Willinger, W.: Long-range dependence in variable-bit-rate video traffic. IEEE Transactions on Communication 43, 1566–1579 (1995)
6. Paxson, V., Floyd, S.: Wide-area traffic: the failure of possion modeling. IEEE/ACM Transactions on Networking 3, 226–244 (1995)
7. Crovella, M., Bestavros, A.: Self similarity in world wide web traffic: Evidence and possible causes. IEEE/ACM Transactions on Networking 5, 835–846 (1997)
8. Tsybkov, B., Georganas, N.D.: On self-similar traffic in ATM queues: definitions, overflow probability bound, and cell delay distribution. IEEE/ACM Transactions on Networking 5(3), 397–409 (1997)
9. Mallat, S.: Theory for multi-resolution signal decomposition: the wavelet representation. IEEE Trans. Pattern Anal. Machine Intell. 11, 674–693 (1989)
10. Sarvotham, S., Riedi, R., Baraniuk, R.: Connection level analysis and modeling of network traffic. In: Proc. IEEE/ACM Network Measurement Workshop, pp. 99–103. ACM Press, San Francisco (2001)
11. Tewfik, A.H., Kim, M.: Correlation structure of the discrete wavelet coefficients of fractional brownian motion. IEEE Transactions on Information Theory 38(2), 904–909 (1992)
12. Wang, S.Y., Zhu, G.X., Tang, Y.Y.: Feature extraction using best wavelet packet transform. Acta Electronica Sinica 31(7), 1035–1038 (2003)
13. Adas, A.: Using adaptive linear prediction to support real-time VBR video under RCBR network service model. IEEE Transactions on Networking 6(5), 635–644 (1998)
14. Iera, A., Molinaro, A., Marano, S.: Call admission control and resource management issues for real-time VBR traffic in ATM-satellite networks. IEEE Journal on Selected Areas in Communications 18(11), 2393–2403 (2000)
15. Su, X.X., Chang, S.J., Xiong, T., et al.: Online VBR video traffic prediction using neural network. ACTA Electronica Sinica 33(7), 1163–1167 (2005)
16. Mao, G., Liu, H.: Real time variable bit rate video traffic. International Journal of Communication System 20(4), 491–505 (2006); Akyildiz, I.F., Su, W., Sankarasubramaniam, Y., Cayirci, E.: A survey on sensor networks. IEEE Communications Magazine 40(8), 102–114 (2002)