Multi-fractal Modeling of Network Video Traffic and Performance Analysis

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Abstract

As the network scale expanding and network business demand increasing sharply, network behavior prediction problems are constantly emerging, such as network detection need to complete the description of the modern network traffic characteristics, to set up the mathematical model, aimed at more efficient use of network resources and ensure the implementation of network QoS. Firstly, described the multi-fractal model of network video traffic and analyzed the influence factors of the simulation sequence of the model. Secondly, designed the algorithm and utilized Haar wavelet to express the simulation sequences of the multi-fractal model and analyzed those long range dependence (LRD), the simulation sequence of multi-fractal model with Haar wavelet is the most close to real video traffic. Thirdly, proposed a controlling method of the LRD of multi-fractal model, relation of edge distribution and the relevance function of the coefficient from the point of theory view. Finally, the early scale coefficients are modeled with AR and the connection is constructed on the short range dependence (SRD) of the early scale coefficients and LRD of finally traffic sequence, realized the precise control sequence on LRD. Experiments shown the stability of multi-fractal model and the consistency of LRD are improved.

Key words: Multi-fractal, Network traffic, Performance analysis, Haar wavelet

1 Introduction

In network transmission, network traffic influences the transmission quality of the actual network. With discover of self-similarity, the measurement, modeling and traffic control become an important problem with the fractal and multi-fractal theory [1-3].

Since fractal theory reveals the form of the whole and the parts is similar, and it shows the new form or the new order between he whole and the parts, orderly and disorder, complex and simple. Self-Similarity of fractal form may be identical, also may be the statistics [4]. The fractal model of network traffic shows three phases, the first is the traditional model such as Poisson, Markov and ARMA, the second is self-similarity model such as the FGN, FBM and FARIMA, and the third is multi-fractal model such as MWM and MFM [3-5].

During the modeling of network video traffic, researchers have caught up with many mathematical models, however, these models are limited in description of video traffic, for example, AR and Markov models can only show the SRD characteristic, FARIMA model can show the SRD and LRD characteristics but cannot perform multi-scale analysis on video traffic. WIG is a wavelet model, but it is set up based on stationary Gaussian distribution, therefore the multi-fractal model has both multi-scale analysis characteristic of wavelet and multi-fractal analysis characteristic, making it a hot topic in research on network video traffic model [6-8].

With the wide application of multimedia technology, network video traffic will have a large proportion in the Internet network traffic. Based on previous results, some innovative works were carried out for multi-fractal model of network traffic, such as analysis, modeling, predict and control of network video traffic [8-11].

2 Design Idea of the Model

For the multi-fractal analysis of MPEG-4 video traffic, those I frame, P frame and B frame are correlation. We analyzed the edge distribution properties and correlation of I frame for the scale factors, and used less statistical parameters to estimate the long correlation, and established the basis of the multi-fractal model for network video.

During the modeling of MPEG-4 traffic, MPEG-4 video contains I, P and B frames, among which I frame is firstly disintegrated to set up multi-fractal modeling sequence and then a network video model is set up based on the correlation in traffic group [3-6]. The process of I frame modeling of video traffic is shown as Figure 1.

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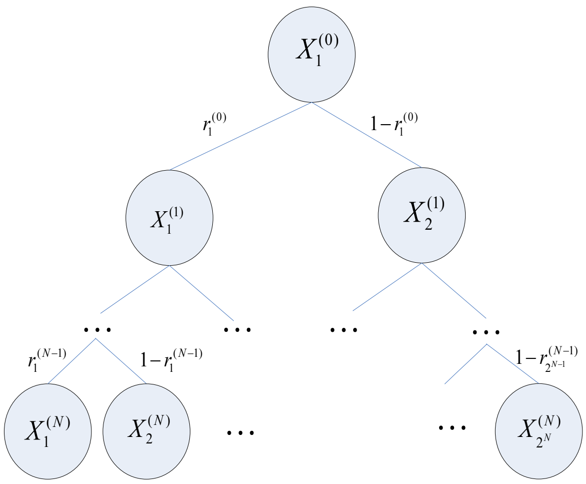


Figure 1. The multi-fractal model

During the modeling of video traffic, time sequence is usually used to show the distribution characteristic of network traffic. The process of generating ratio coefficient between the thickest wavelet coefficient and scale coefficient with β factor consists of repeated narrowing of a given set into a smaller subset, which reflects an iteration process. Assuming the coefficient is $X_i^{(0)}$, the coefficient $X_i^{(j)}$ and factor $r_i^{(j)}$ are calculated by the formula (1).

$$\begin{gathered} X_i^{(j-1)} = X_{2i-1}^{(j)} + X_{2i}^{(j)} \\ r_i^{(j)} = \frac{X_{2i-1}^{(j)}}{X_i^{(j-1)}}; j = 1,2,\cdots,N; i = 1,2,\cdots,2^j \end{gathered} \tag{1}$$

If the coefficient $X_i^{(0)}$ and $r_i^{(j)}$ are defined, the sequence $\{X_i^{(N)}, i = 1,2,\cdots,2^N\}$ and the simulated sequence $\{X_i, i = 1,2,\cdots,2^N,\cdots,2^{N+M},\cdots\}$ are conducted to get by the iteration calculation with the thinnest scale. So that the traffic simulation sequence with the same or approximate ACF characteristic and multi-fractal feature as the original video traffic is obtained.

If $X(t)$ is one-dimension time sequence, so $X(t)$ is non-negative and the $U_{j,k}$ obtained for any j, k by reverse transformation is also non-negative and $|W_{j,k}| \le U_{j,k}$, which may be defined as follows:

$$W_{j,k} = A_{j,k} U_{j,k} \tag{2}$$

The factor $A_{j,k}$ describes the relationship between the scale function and wavelet function of the same grade, where $A_{j,k}$ is a random variable on [0,1]. That can be calculated as follows:

$$\begin{aligned} U_{j,k} &= 2^{-1/2}(U_{j+1,2k} + U_{j+1,2k+1}) \\ A_{j,k} &= C U_{j+1,2k} / U_{j,k} \end{aligned} \tag{3}$$

where C is a constant. When a Haar wavelet is used, the relationship of $A_{j,k}$ and $r_i^{(j)}$ can be obtained as follows:

$$A_{j.k} = 2r_i^{(j)} - 1, i = k - 1 \tag{4}$$

During the process of modeling, the initiative value of model is the thickest scale coefficient $U_{0,0}$ based on which the scale coefficient sequence $U_{n,k}$ is calculated by repeated iteration and the model sequence is obtained at last.

$$\begin{aligned} U_{j,k_j} &= 2^{-j/2} U_{0,0} \prod_{i=0}^{j-1} [\frac{1+(-1)^{k_i'} A_{j,k_j}}{2}] \\ W_{j,k_j} &= 2^{-j/2} A_{j,k_j} U_{0,0} \prod_{i=0}^{j-1} [\frac{1+(-1)^{k_i'} A_{j,k_j}}{2}] \end{aligned} \tag{5}$$

3 Design of Modeling Algorithm

A simulated sequence is generated by multi-fractal model, $U_{0,0}$ is the initial condition of the algorithm and is taken by the β distribution. When $M>0$, the multi-fractal model algorithm is shown as [7-11]:

Step 1: let $J=0$ and generate $U_{0,0}$ with the largest scale;

Step 2: get the factor $A_{j,k}$ based on $\beta_{-1,-1}(p_j, p_j)$ with j scale;

Step 3: calculate $U_{j+1,2k}$ and $U_{j+1,2k+1}$ by formula (3), so get $U_{j,k}$ and $W_{j,k}$ with j scale;

Step 4: perform step 2 and step 3 for another n-1 times.

The generated discrete sequence can be expressed as follows:

$$\begin{gathered} X[k] = 2^{-n/2} U_{0,0} \prod_{i=0}^{n-1} [\frac{1+(-1)^{k_i'} A_{j,k_j}}{2}] \\ A_{j,k} \approx \beta(p_j, p_j) \\ p_j = \frac{\eta_j}{2}(p_{j-1}+1) - \frac{1}{2} \\ k_j = \sum_{i=0}^{j-1} k_j' 2^{j-1-i}, i = 1,2,\cdots,n-1 \\ \eta_i = \frac{E[W_{j-1,k}^2]}{E[W_{j,k}^2]} = \frac{2E[A_{j-1}^2]}{E[A_j^2](1+E[A_{j-1}^2])} \end{gathered} \tag{6}$$

When k_0' is dentically equal to 0, k_i' is the direction of the time shift. If k_j' is equal to 1, then k_j transmits to the right, else if k_j' is equal 0, then k_j transmits to the left. The scale coefficient is generated by β distribution, and the wavelet coefficient and scale coefficient of each layer is generated in the variable iteration process for Haar Wavelet.

4 Multi-fractal Analysis

It is known from the design of multi-fractal model that the simulated sequence is obtained by repeated iteration of the ratio between scale coefficient and wavelet coefficient. To determine the multi-fractal characteristic of the sequence, a fractal function based on the wavelet coefficient should be set up. The function is as follows:

$$S(q,j)=\sum_{k}\left|2^{\frac{-j}{2}}dx(j,k)\right|^{q} \tag{7}$$

Where j is scale and $d_x(j,k)$ is wavelet coefficient. It is known from the analysis on formula (7) that when an sudden change occurs to the video traffic or, in other words, an exceptional change occurs to the signal, which contributes to sudden increase of wavelet coefficient, such change of the coefficient may directly affect various scale coefficients and amplified by its q moment, therefore it is very effective to use the fractal function to judge the local sudden change.

Therefore, the multi-fractal analysis on video traffic shall be performed in the following three steps:

Step 1: during the experiment, let q=1, q=1.75, q=2.5, q=3.25 and q=4, and calculate the $S(q, j)$ of simulated and original traffic sequence when β factor, point mass factor and hybrid factor are adopted respectively and draw the two-dimension $S(q, j)\sim j$ curve as shown in Figure 2. As our observation, in Figure 2(b), when q value is larger and scale is smaller and in Figure 2(c), when q value is larger and scale is larger, the value of fractal function is smaller than that of the original traffic; only Figure2(d) shows that the generation traffic of hybrid model displays the multi-fractal feature of original traffic favorably.

Step 2: the above figures clearly show the change of $S(q, j)$ for different q. To describe the multi-fractal feature of traffic in a more straightforward manner, the fractal function is used to define the scale exponent by the formula (7).

$$\tau(q)=\lim_{j\to\infty}\inf\frac{\log_2 S(q,j)}{\log j} \tag{8}$$

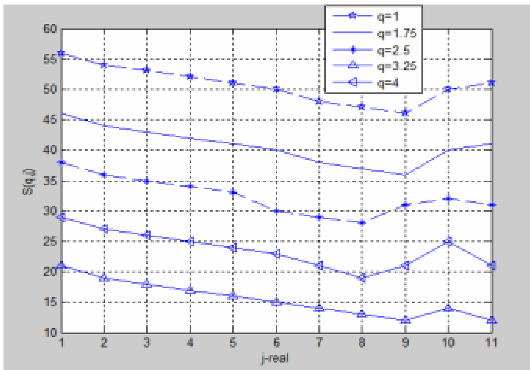
According to formula (8), if $\tau(q)$ is in linear relation with q, the traffic sequence can be judged as a single-fractal process and, on the contrary, if $\tau(q)$ is not in linear relationship with q, the traffic sequence can be judged as a multi-fractal process.

The $h(q)$ function is introduced to further simplify the above calculation:

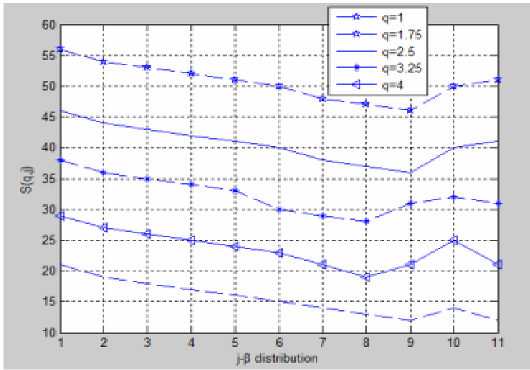
$$h(q)={}^{\tau(q)}\!/_{q} \tag{9}$$

In the formula (9), the problem is converted from the determination of relation between $\tau(q)$ and q into determining whether $h(q)$ is a constant. Therefore, $h(q)$ is a constant for a single-fractal process and not for a multi-fractal process.

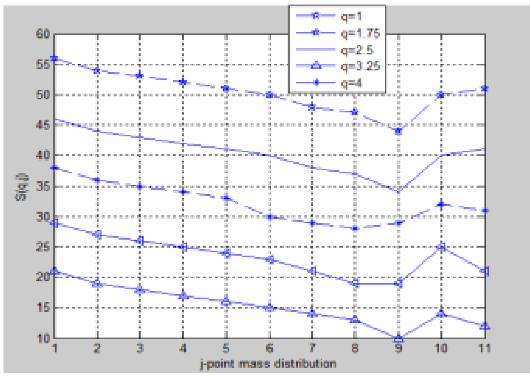
The $h(q)$ of generation traffic of three different factor models is calculated and shown in Figure 3, where $h(q)$ is a straight line, so their generation traffic has the multi-fractal feature. It can be further determined by the proximity that the generation traffic of hybrid factor can better reflect the characteristic of original traffic.



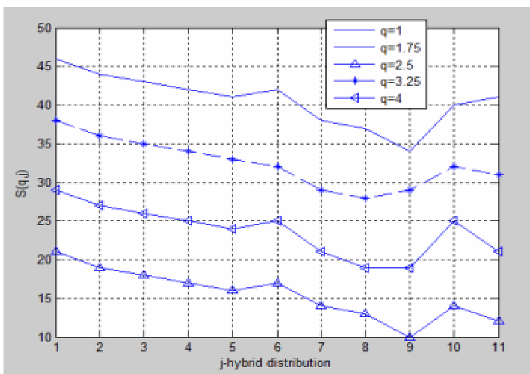
(a) Original traffic



(b) Generation traffic of β factor



(c) Generation traffic of Point-mass factor



(d) Generation traffic of hybrid factor

Figure 2. The logarithm graph of scale-segmentation function

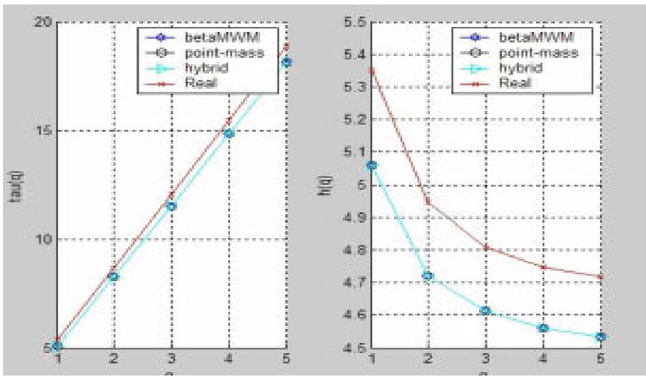


Figure 3. The index analysis graph of trafficscale

Step 3: the wavelet coefficient can satisfactorily describe the detailed changes of signal. To further study the characteristic of original traffic and simulated traffic, we compare the standard deviation of wavelet coefficients for various scales of the original traffic and simulate traffic sequence and the standard deviation can reflect the change characteristic of data or be used to determine whether a set of data is similar or consistent, as shown in Figure 4.

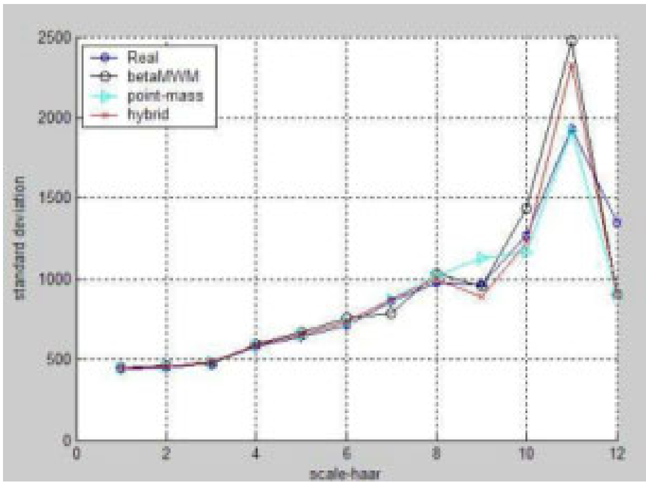


Figure 4. The standard difference of wavelet coefficient

The standard deviation of wavelet coefficients in Figure 4 shows that the simulated traffic of hybrid factor multi-fractal model is closest to the real traffic. The follows are concluded from analysis on the above experiment:

(1) In the model, it is not mandatory to select β distribution for the random variable factor $A_{j,k}$ and any other distribution may be selected based on the characteristic of signal.

(2) For hybrid factor multi-fractal model, β distribution model is selected for thick scale and point-mass distribution model is selected for thin scale, which can control the second moment of wavelet coefficient better, solve the problem in matching of energy decay and keep the heavy-tailed distribution and self-similarity characteristics of the generation traffic.

5 Performance Analysis

In the experiment, the video traffic with MPEG-4 comes from TNK of Technische Universität Berlin whose address is http://www.tkn.tu_Berlin.de/research/trace/trace.html. The characteristic parameters of traffic are shown in Table 1.

Table 1. Statistical properties of traffic

Name	Average bps	P/M value	Compression ratio
Video I	223655.50	6.50	60.4
Video II	876553.45	4.55	20.30

We try Daubechies wavelets with different vanishing moment N, adopt video generation by multi-fractal model and conduct performance analysis and comparison with the video traffic.

(1) Analysis on fractal function and scale logarithm diagrams shows that the multi-fractal model of Daubechies-5 wavelet can reflect the sudden feature of actual video traffic better than the multi-fractal model of Haar wavelet.

(2) Other wavelets with higher vanishing moments have similar performance with Daubechies-5 and much poorer performance in simulation, which is related to selecting β distribution for these scales.

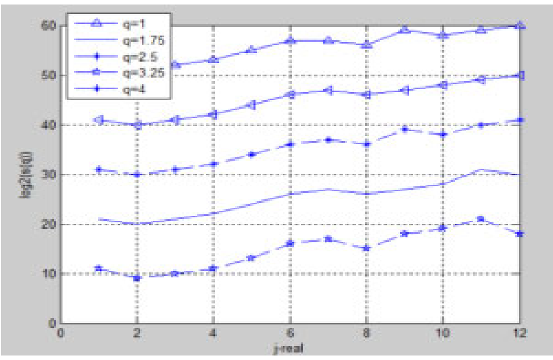
(3) The model performance is evaluated for Daubechies wavelet with different vanishing moments and the result shows that the selection of vanishing moment has impact on the model performance, which is less significant than the impact of selection of wavelet base function on the same.

Therefore, during the analysis on impact factors of model, for example, the analysis of impact of selection of wavelet and wavelet vanishing moment on model, it was concluded that the Haar wavelet has the shortest support set and the smallest vanishing moment and it is both a type of Daubechies wavelet and the simplest function, so the most desirable result can be achieved by using Haar wavelet in model.

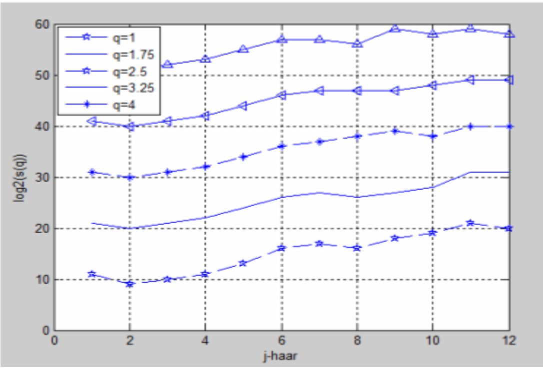
5.1 Margin Distribution Analysis

The correlation between two traffics is generally determined by their margin distribution. The most commonly used method is QQ diagram, a method to verify the similarity of two probability densities by diagram. If two sets share the same or similar function, all points in QQ diagram will form a straight line with slope angle of 45 degrees and otherwise, will deviate from the straight line and more significantly the two distribution functions differ. The simulation results are shown in Figure 5 and Figure 6.

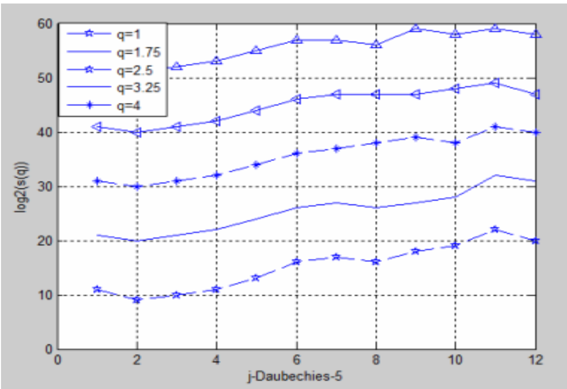
The video traffic (the original traffic comes from TNK of Technische Universität Berlin whose address is http://www.tkn.tu_Berlin.de/research/trace/trace.html) is used in experiment.



(a) The original traffic of Video I



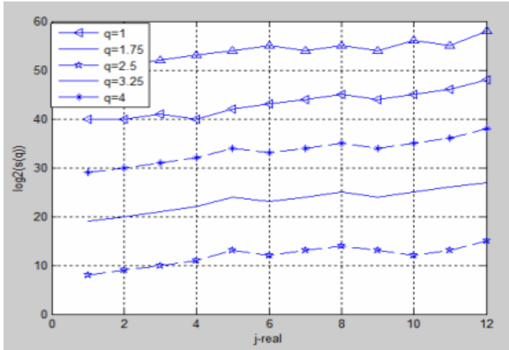
(b) The multi-fractal generation traffic with Haar Wavelet



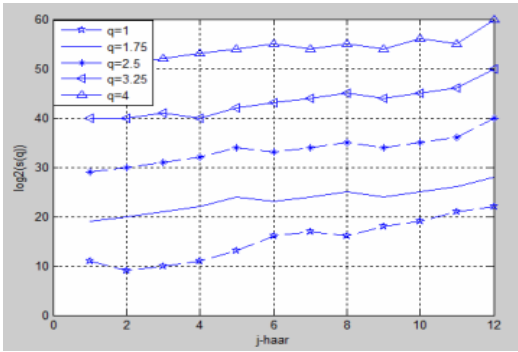
(c) The multi-fractal generation traffic with Daubechies-5 Wavelet

Figure 5. The NO. 1 logarithm graph of scale-segmentation function

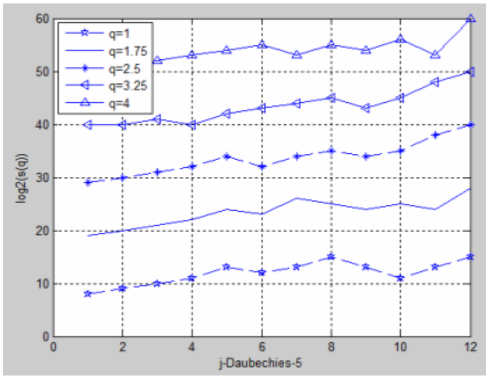
Step 1: the video traffic is disintegrated into I frame, P frame and B frame, each frame is simulated in video and by multi-fractal model respectively to generate simulated video traffic based on multi-fractal model, then the simulated traffic distribution function of I frame, P frame and B frame and original traffic are compared in QQ diagram to determine their similarity. As shown in Figure 7, we can determine that the multi-fractal model has better capability to approach the margin distribution.



(a) The original traffic of Video II



(b) The multi-fractal Generation traffic with haar Wavelet



(c) The multi-fractal generation traffic with Daubechies-5 wavelet

Figure 6. The NO. 2 logarithm graph of scale-segmentation function

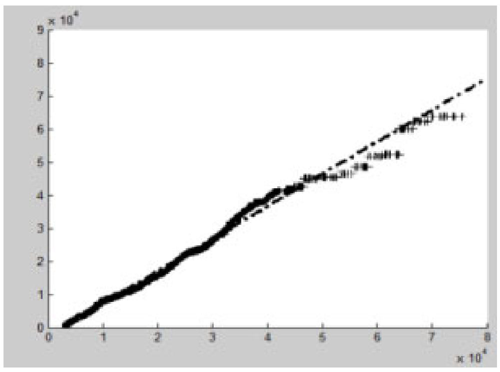


Figure 7. Correlation among Videos

Step 2: double-log curve is drawn to determine the similarity between β and *pm* distribution.

The video traffic has the multi-fractal characteristic and non-strict self-similarity, so the similarity between the model-generated traffic and the original traffic is firstly concerned in model performance analysis, however, only when the selected factor fits the feature of traffic, the similarity between the generation traffic and the original traffic will be high.

This section sets up the multi-fractal model for I frame sequence and selects two commonly used factor distributions, namely, β distribution and point set pm distribution. A piling process is defined as follows:

$$X^m(n) = \frac{1}{m}(X_{mn-m+1} + \cdots + X_{mn}),\ n = 1,2,\cdots \quad \textbf{(10)}$$

We calculate $X^m(n)$, then get $Var(X^m(n))$ and finally draw the two-dimension curve of $log_2(X^m(n))\_log_2(Var(X^m(n)))$. With this piling process, the original traffic and simulated traffic of β distribution model and *pm* model for I frame, $X^m(n)$ and $Var(X^m(n))$ are obtained and then three $log_2(X^m(n))$-$log_2(Var(X^m(n)))$ curves are drawn as shown in Figure 8.

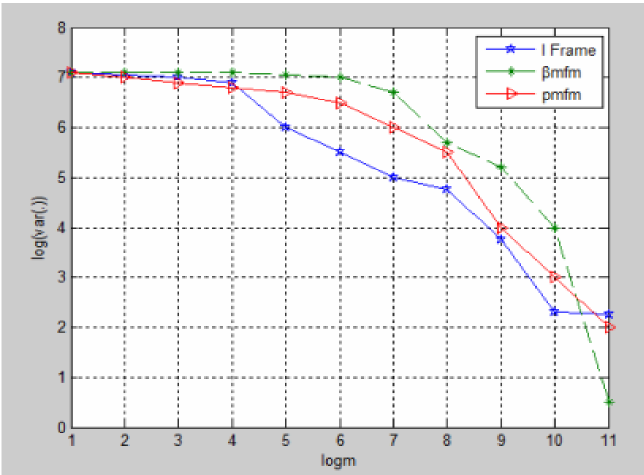


Figure 8. Correlation of β distribution and *pm* distribution

(1) The β distribution model, *pm* model and original traffic for I frame sequence are all close to each other, which fully confirms that β distribution model and *pm* model have better capability to approach margin distribution. The β distribution model and *pm* model have great differences and both deviate from the I frame of original traffic.

This means in all scales, they cannot ensure the statistical distribution accuracy of factor models. As shown in Figure 8, the great differences for same scales will cause the large error in approximation effect.

Step 3: the minimum error of wavelet coefficient is estimated by the K-L distance.

On this basis, the sudden change during wavelet coefficient evaluation creates an excessively large wavelet coefficient, which transmits the deviation through the process of iteration of multi-fractal model and affects the generation sequence of model. To solve the problem of deviation of β and pm distribution models, the Kullback-Leiblar (KL) distance judging method is introduced in estimation of wavelet coefficient to control the amplification and transmit of coefficient.

The K-L distance method is used to calculate the entropy of different distributions to judge their similarity. The K-L distance between discrete distributions $p=\{p_1, p_2,..., p_n\}$ and $q=\{q_1, q_2,..., q_n\}$ is defined as follows:

$$KL(p,q) = \sum_i p_i \cdot \log_2(p_i / q_i) \quad \textbf{(11)}$$

With the same video traffic and based on pm distribution model, the wavelet coefficient for each moment is estimated by the minimum error judgment, which is defined as PMFM model and the $log_2(X^m(n))\_log_2(m)$ curve is drawn as shown in Figure 9. This model has better capability to approach margin distribution than β and pm distribution models.

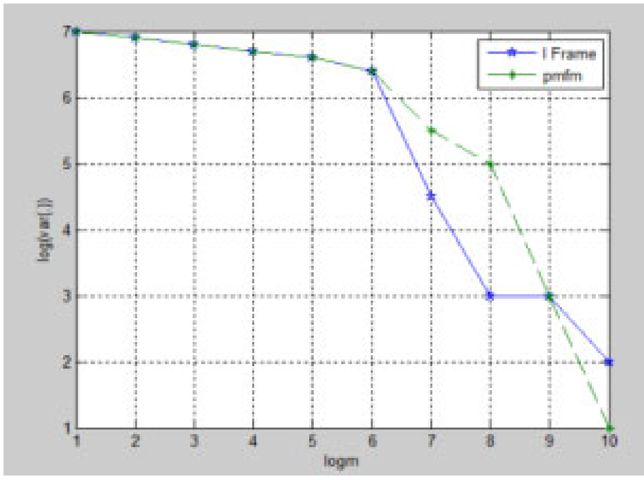


Figure 9. Correlation test of video models

5.2 Multi-fractal Spectral Analysis

The video traffic has the multi-sequence characteristic and no quantitative method for calculating irregular and multi-sequence spectrum exists at present, therefore, the shape-similarity judgment method is used for research on multi-fractal spectrum of video traffic. The model generating a traffic spectrum function curve that is most approximate to the original traffic spectrum function, will be determined as the optimal model.

The comparison parameters for models are defined as follows:

(1) δf is defined as width, which reflects the difference between maximum and minimum probabilities in video traffic sequence.

(2) $\triangle\alpha$ is defined as height, which reflects the fluctuation of video traffic sequence.

This section draws the spectrum functions of β

distribution model, pm model, PMFM model and original traffic as shown in Figure 10. The two parameters, δf and $\triangle\alpha$ are used to determine that the PMFM model is most approximate to the spectrum function of the original traffic and this video model is most consistent with the original video traffic.

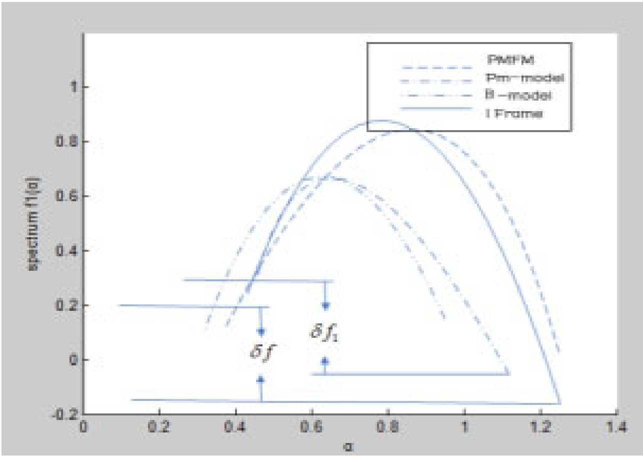


Figure 10. Comparison of Spectrum Function

6 Conclusion

In this paper, describes the idea of multi-fractal modeling for I frame of network video traffic of MPEG-4, provides the model algorithm, utilizes the Haar wavelet and β distribution to generate initial settings, finally takes advantage of the correlation within the video traffic group to generate simulated video traffic and conducts performance analysis, including margin distribution and multi-fractal spectral analysis. It verifies the correctness of model. The future work will focus on network traffic modeling for many information sources, better suited to the needs of the Internet.

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Biographies

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