



Study of video traffic In telecommunication systems for the purpose of service quality

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ARTICLE INFO

Article History:

Received: 23/5/2018

Accepted: 17/6/2018

Published: Summer 2018

Doi:

10.25212/lfu.qzj.3.3.25

Keywords:

video traffic, quality of service, correlations dimension, fractal.

ABSTRACT

The self-similar network traffic can have a detrimental impact on network performance, including amplified queuing delay, retransmission rate and packet loss rate. Modern network traffic consists of more bursts than Poisson models predict over many time scales. This difference has implications for performance. The video traffic research is important because self-similar nature of network traffic leads to a number of undesirable effects like high buffer overflow rates, large delays and persistent periods of congestion and the severity of these conditions is directly proportional to the degree of self-similarity. On the other hand, the long memory property of self-similar traffic is able to help to forecast traffic for the purpose of quality of service (QoS) provision. This work presents the results of the analysis of video traffic performed and study the structure of the video traffic to identify its characteristic features.

Keywords: video traffic, quality of service, correlations dimension, fractal.

INTRODUCTION

In the telecommunications market, voice and video services, which make up the real-time traffic, occupy a leading position and the number of users of these services is increasing every year. Recent studies show that network traffic for most types of services is a fractal. There are many publications on the structure of modern traffic, but very a small number of works devoted to the study of the fractal nature of video traffic.

There is currently no systematic study estimates the impact of the fractal properties of video traffic on service of quality. There are no common analytical results considering effect of queuing, fractal and Long-range dependence on the traffic QoS of telecommunication network. There are only individual results for particular cases [1-4]. The properties of self-similar traffic are very different from the traditional models of traffic based on Poisson, Markov-modulated Poisson, and related processes [5].

The use of traditional models in networks characterized by self-similar processes can lead to incorrect conclusions about the performance of analyzed networks. These include serious over-estimations of the performance of computer networks, insufficient allocation of communication and data processing resources, and difficulties in ensuring the quality of service expected by network users.

Increasing the types of services and complexity of the telecommunication systems requires the adequate development methods of analysis and synthesis of these systems to obtain reliable estimates of their characteristics. With the different type of networks and different method of allocation network resource for service the traffic, we need to develop models which take into account the actual nature of the message streams and details of the multiservice service traffic for different applications (voice, video, data). Transfer of different services streams provide a single network. Since each service sources may have different data rate or its change during the communication session, so stream of data characterized burst and fractal. In the implementing certain amount of traffic present some large pulsation, relatively low average of traffic level [6,7].

Analyze and study video traffic is important because fractal traffic in voice and video transmission systems degrades service of quality. Methods of modeling and analyzing of network systems based on using of a Poisson flow in these systems and do not give an accurate picture of the processes occurring in the network. Accounting fractal traffic will help to describe and reproduce video traffic more accurately, that will provide an opportunity to obtain the desired quality of service [8,9].

The aim of this work is to study the structure of video traffic to identify its characteristic features. The paper addresses the following tasks: assessed the distribution density, autocorrelation functions (ACF), the energy spectra of the studied time series, determine the degree of fractality (Hurst exponent).

VIDEO TRAFFIC IMPLEMENTATIONS

To study the implementation of frames of the film "war and peace" is being investigated. Initially, the video data was processed by BTTVGRAB and presented as frames with a frequency of 25 frames / sec. Using the TMN encoder, a stream of compressed video. The time series studied are measurements of the volumes (bytes) of consecutive frames. This is the input traffic. once can take any other. Here, three segments with different behavior for 1000 values are selected (Figures 1).

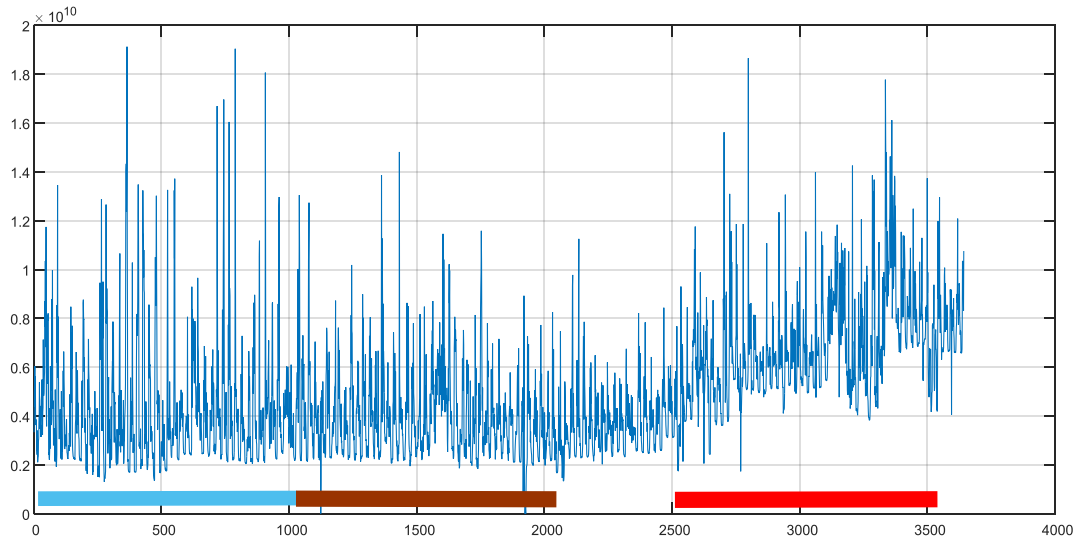


Figure 1. Time series plot of the input video traffic

ANALYSIS OF THE DISTRIBUTION DENSITY

This section shows analysis of the distribution's densities. Evaluation is conducted based on the relative frequency histograms, shown in Figures 2-4. Visual analysis leads to the following conclusion: studied time series do not obey normal distribution.

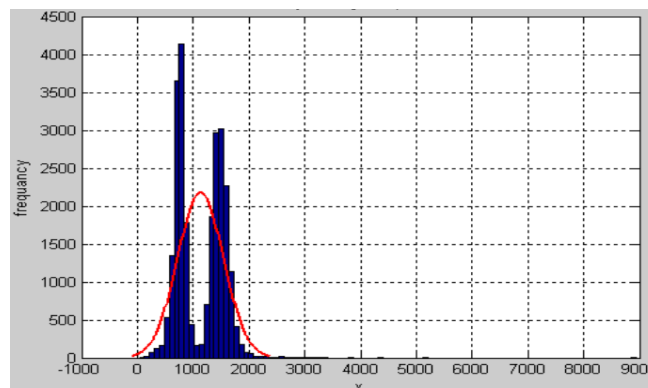


Figure 2. Histograms of distribution density-1

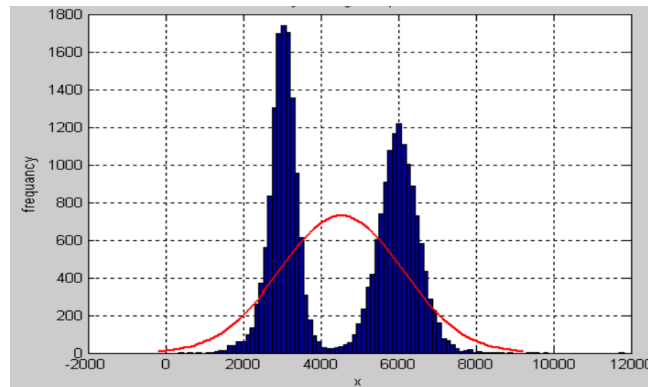


Figure 3. Histograms of distribution density-2

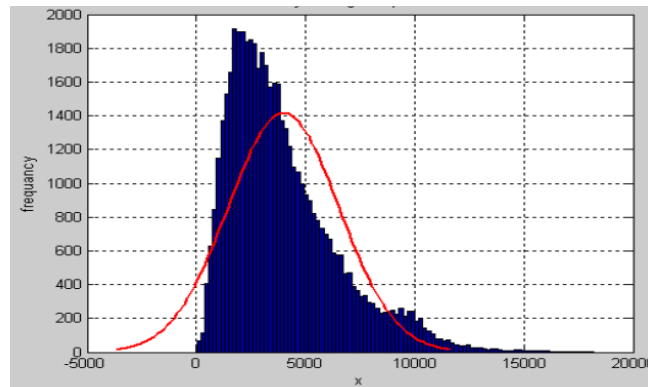


Figure 4. Histograms of distribution density-3

ANALYSIS OF AUTOCORRELATION FUNCTIONS

After analysis of the distribution's densities, one must define if the time series have long-range dependence or short-range dependence.

These are the corresponding correlation functions. They basically talk about a 24 hour periodicity and a fairly strong correlation.

The process X has long-range dependence in order that $r(k) \sim k^{-\beta}, k \rightarrow \infty$ for its autocorrelation functions. The process with long-range dependence are characterized by autocorrelation function, which decreases by power-law with increasing time delay (Lag). In contrast to the processes with long-range dependence, processes with short-range dependence have exponentially decreasing autocorrelation functions of the form: $r(k) \sim e^{-k}, k \rightarrow \infty$

Autocorrelation functions of the studied time series are shown in Figures 5-7. They do not go to zero in the case of large values of k , which indicating the long-range dependence of autocorrelation functions, and the presence of a short- range dependence in all implementations of the studied traffic.

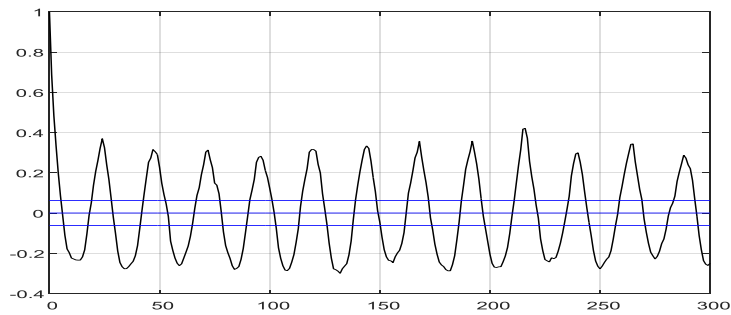


Figure 5. Autocorrelation functions of the first segment of input traffic data

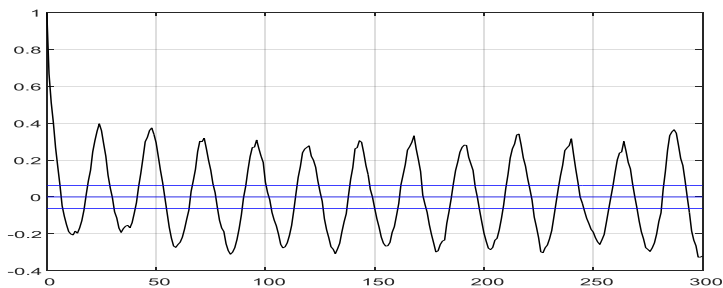


Figure 6. Autocorrelation functions of the second segment of input traffic data

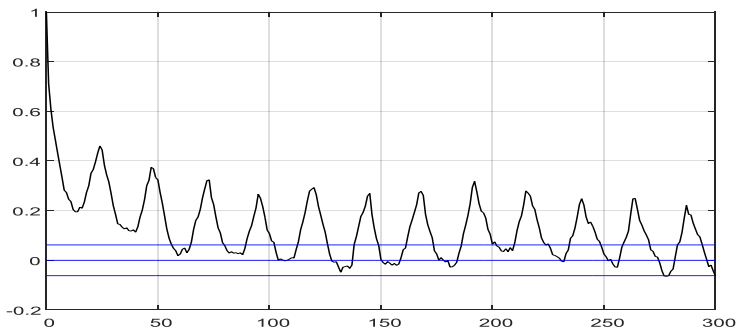


Figure 7. Autocorrelation functions of the third segment of input traffic data

Spectral analysis

In this section calculated the energy spectral of the investigated time series. In the frequency domain long-range dependence leads to a power-law behavior of the spectral density of the process. The process X has long-range dependence, if for spectral density $S(f) = \sum_k r(k). e^{ikf}$ occurred next condition: $(f) \sim f^{-b}$, where $f \rightarrow 0, i = \sqrt{-1}, 0 < b < 4$.

The process with long-range dependence characteristic has a spectral density with a singularity at the origin(zero): spectral density tends to infinity as the frequency f approaches to zero. The energy spectra of implementations are presented in Figures 8-11.

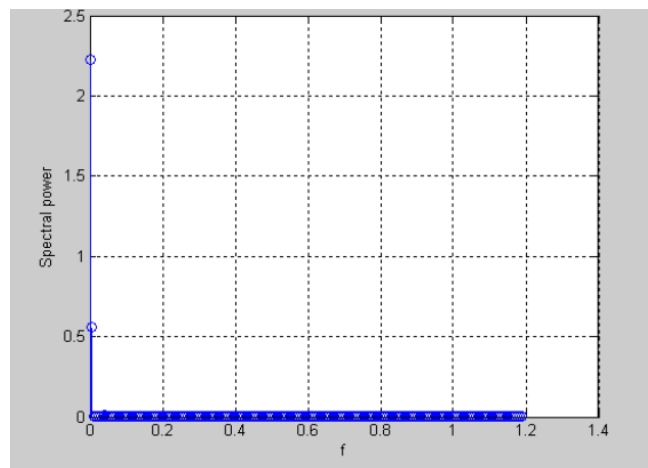


Figure 8. The spectral density of the time series for the first segment

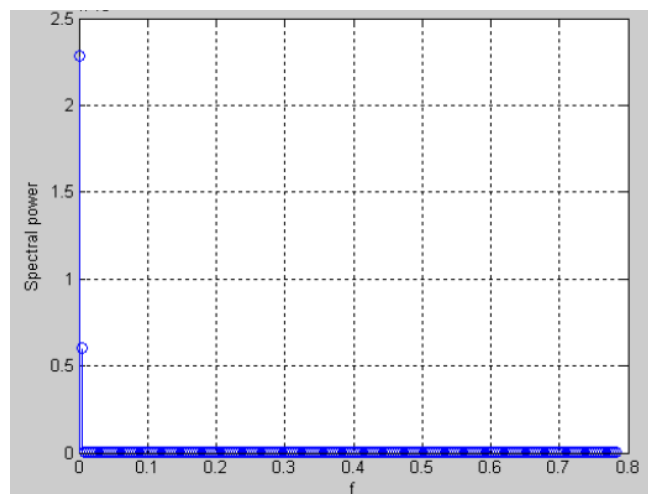


Figure 9. The spectral density of the time series for the second segment

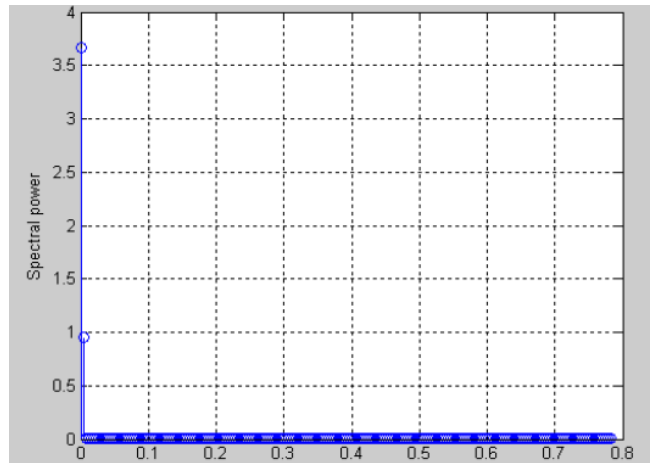


Figure 10. The spectral density of the time series for the third segment

These are multifractal spectra for the corresponding segments of the traffic(figure 11).

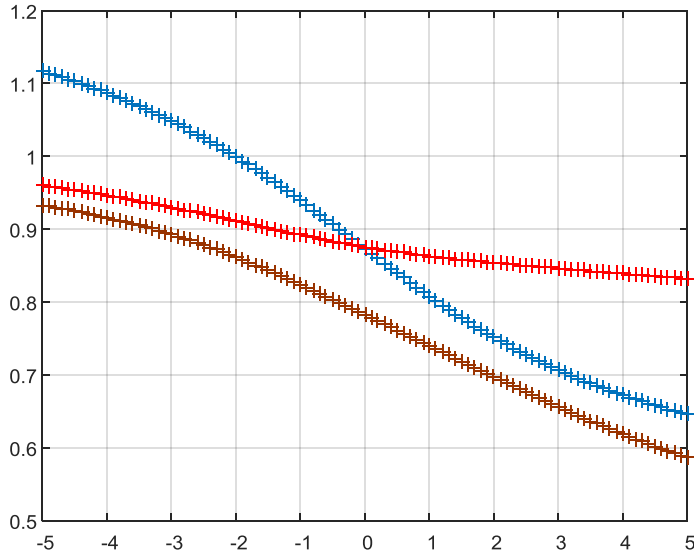


Figure 11. multifractal spectra for the three segments of the traffic

ANALYSIS OF THE HURST EXPONENT

In this section, the Hurst exponent (H) is estimated, which is a measure of the length of the long-term dependence of the process. The value of $H = 0.5$ indicates the absence of long-term dependence. Correlation between events is absent. The series is random, not fractal. The closer the value of H to 1, the higher degree of stability of long-term dependence. At $0 \leq H < 0.5$, the time series is a trend-

resistant (antipersistent). It is more variable than a random series, because it consists of frequent reversals of a slump-rise. At $0.5 < H \leq 1$ the series is trend-resistant. The trend of its change can be predicted. In this paper, the Hurst index is determined using the procedure [4]: for fractal processes with increasing frequency, the value of the spectral density falls according to a power law with exponent b , with $b = 2H-1$. Using this formula, knowing the value of b , one can find the Hurst exponent.

Together with the statistics (\bar{X} - is the average value of the traffic intensity, S_{var} - is the estimate of the coefficient of variation), we have the following characteristics of the traffic sections:

- 1) $\bar{X} = 4.26e9$, $\Delta h(q) = 0.5$, $S_{\text{var}} = 0.6$, $H = 0.75$
- 2) $\bar{X} = 4.0e9$, $\Delta h(q) = 0.33$, $S_{\text{var}} = 0.46$, $H = 0.7$
- 3) $\bar{X} = 6.7e9$, $\Delta h(q) = 0.1$, $S_{\text{var}} = 0.33$, $H = 0.86$

and the following conclusions can be made based on these characteristics:

- The first and second sections have approximately the same intensity, but the correlation (the Hurst exponent) on the first is stronger; In addition, the first section has a large burbot (the presence of bursts), which is determined by the range of $\Delta h(q)$ and S_{var} . Therefore, the first site will require large network resources.
- In the third section, the intensity of traffic increases from $5e9$ to $8.5e9$, H reach large value and, although the burbot is small enough, it also requires more resources.

Since the condition $0.5 < H < 1$ is fulfilled, the series studied are trend-resistant (persistent) and have long-term memory.

CONCLUSIONS

For the processes of video data transmission by packet traffic, it is characteristic of the fractal property, which was discovered in practice. In connection with this peculiarity of network processes is the development of constructive methods for investigating packet traffic. In this paper, for the realization of compressed video traffic, analysis of the distribution density, autocovariance functions and energy spectra is performed. The values of Hurst Exponent were investigated.

The following results were obtained:

1. The time series studied are not subject to normal distribution.
2. The time series studied do not have an exponentially decreasing ACF inherent in random series.
3. The studied time series are persistent and possess long-term memory.

For further research can be the analysis of video traffic by methods of nonlinear dynamics. To improve the efficiency of modern computer networks, it is necessary to create mathematical models that most fully reflect the fractal properties of processes.



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