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Self-Similar Traffic : A New Model for Next Generation ATM Switch

Hong Cai*, Huimin Chen, Yanda Li
Automation Dept. ; Tsinghua Univ., Beijing 100084, China
*E-mail: caihong@jerry.dau.tsinghua.edu.cn

Abstract—This paper gives brief introduction to self-similar process and the estimation of Hurst parameter in the context of time series analysis. Different methods of self-similar traffic generation are compared based on simulation study. We find that aggregating the streams of ON/OFF sources of Pareto distribution leads to self-similarity quickly as the sources become large. The quick traffic generation that approximates real traffic in various time scale is also discussed and its influence to the design, control and analysis of high speed cell-based ATM networks is learnt from the simulation.

1. Introduction:

Recent traffic measurement studies suggest that the self-similarity observed in packet traffic has strong influence in traffic modeling and performance evaluation for future high speed networks[1]. Many traffic models dealing with efficiently describing the fractal or self-similar nature of real traffic traces have emerged such as Fractal Brownian Motion (FBM)[2][3] and aggregation of heavy-tailed ON/OFF sources[4][5]. However, their accuracy and quickness of traffic generation have seldom been discussed via simulation study. In this paper, three traffic generation methods named aggregation of Pareto-tailed sojourn time traffic[6], chaotic map based modeling[7] and random midpoint displacement (RMD) algorithm[8] are compared through time series analysis. We find that the Pareto-tailed traffic generation is more effective and flexible to adjust its time scale to approximate the actual traffic data from various coarse measurements. Simulation study using cell-based queueing and scheduling shows that the cell loss rate and queueing delay may deviate from the queueing analysis[9] by using FBM model. This indicates that in order to deeply understand the impact of self-similarity on performance, the potential factors besides Hurst parameter, such as higher-order statistics, should also be considered.

2. Self-Similar Stochastic Process and Its Quick Traffic Generation

In this section, we briefly discuss on self-similar stochastic process and the methods of quick traffic generation with self-similarity. Details can be found in the references and relative topics listed therein.

Suppose we have a covariance stationary stochastic process $X = (X_1, X_2, \ldots, X_n)$, which has the following autocorrelation structure:

$$r(k) \sim k^{-\beta} L_1(k), \quad \text{as } k \to \infty, \tag{1}$$

where $0 < \beta < 1, L_1$ is a slow variant function in infinity, that is $\lim_{t\to\infty} L_1(tx)/L_1(t) = 1$ for all x>0. then we may say that X is a self-similar stochastic process. The self-similar parameter H, often called Hurst parameter, is the main characteristics of self-similarity in estimating the traffic trace, where $H=1-\beta/2$. There have been many stochastic models that have self-similar phenomenon among which three approaches are widely used for quick generation of traffic sources.

2.1 Pareto-Tailed Sojourn Time Traffic

The traffic model we considered here is aggregated by multiple single ON/OFF traffic sources. Suppose we have N traffic source of the same class, let the ON time of i-th traffic be $\tau^{(i)}$, OFF time be $\theta^{(i)}$. The random variables $\tau^{(i)}$ are i.i.d., their distribution functions are:

$$P(\tau > t) \sim t^{-\alpha}, t \to \infty, 1 < \alpha < 2 \tag{2}$$

(i.e. $\tau^{(i)}$ follows Pareto distribution) having finite mean $a_\tau = E(\tau) < \infty$ and infinite variance.

This formula is quite different with traditional exponential distribution $P(\tau > t) \sim e^{-\lambda t}, t \to \infty$. Or in other word , the distribution in (2) has heavier tail than exponential distribution . Note that α in (2) determines the "tail" of autocorrelation function. It has the relationship with self-similar parameter H that $\beta = \alpha - 1, H = (3-\alpha)/2$.

2.2 Chaotic Map Based Modeling[7]

Chaotic Map based modeling considers the aggregation of well known two state ON/OFF sources. Under the traditional structure of Markovian model, the ON/OFF sojourn time has exponential distribution. On the contrary, using Chaotic Map with either single intermittency or double intermittency to generate traffic sources leads to the distribution that have heavier tail than exponential distribution. Now we show how to generate this kind of distribution through Chaotic Maps. Consider one dimension map, whose state variables evolve like this:

$$x_{n+1}=\begin{cases} f_1(x_n), 0 \le x_n \le d \\ f_2(x_n), d \le x_n \le 1 \end{cases} \quad (3)$$

There is another state variable y_n associated with it(y_n will have value 0 or 1 according whether x_{n+1} takes the form of f_1 or f_2). When $y_n = 1$ a batch of k cells are generated, when $y_n = 0$, no cell is generated. Different $f_1(x), f_2(x)$ will bring about different result (details in [7]):

1) Linear function segment will generate ON/OFF sojourn time that exhibit geometry distribution

$$P(t > l) \propto ce^{-l} \quad (4)$$

2) Nonlinear segment like $f(x) \approx \varepsilon + x + cx^m$ will generate Pareto type ON/OFF sojourn time

$$P(t > l) \propto l^{-\frac{1}{m-1}}, l \to \infty \quad (5)$$

The advantage of chaotic map is that this kind of deterministic representation is suitable for performance analysis. Suppose the source generate a batch of k cells in ON period, the system's queue (or buffer occupancy) will evolve like this:

$$l_{n+1} = \max(l_n - 1, 0) + ky_n(x_n) \quad (6)$$

$$x_{n+1} = f(x_n) \quad (7)$$

2.3 Random Midpoint Displacement Algorithm[8]

Random Midpoint Displacement (RMD) algorithm is used for FBM process generation in a given time interval. If the trajectory of FBM Z(t) is to be computed in [0, T], then we start out by setting Z(0)=0 and Z(T) from a Gaussian distribution with mean 0 and variance T^{2H} . Next, Z(T/2) is calculated as the average of Z(0) and Z(T) plus an offset. The offset is a Gaussian random variable with a standard deviation given by T^{2H} times the initial scaling factor $s_1 = 2^{-H} s_0 = 2^{-H}\sqrt{1-2^{2H-2}}$. We then reduce the scaling factor by $\frac{1}{2^H}$, and the two intervals from 0 to T/2 and from T/2 to T are further subdivided, and so on. The packet arrival process of traffic A(t) can be written as

$$A(t) = Mt + \sqrt{aM}Z(t) \quad (8)$$

where M is the mean rate, a is the peakedness factor which is defined as the ratio of variance to mean of the number of cells in a unit time interval.

3. Comparison of Traffic Generation Methods by Estimating Hurst Parameter

In this section we provide a quantitative assessment of traffic traces generated by different methods by using a number of statistical tools, including R-S (Rescaled adjusted Range statistic) analysis, Variance-Time analysis and IDC (Index of Dispersion for Counts) analysis(for details see [10]). We use a counter for traffic collection to estimate H-value and compare the discrepancies between the estimated value and the target value among different methods of traffic generation. The traces generated by different methods should be easy to calculate, conform to target H-value in all desired scale, and easy to be used for performance evaluation.

In generating the Pareto-tailed traffic sources, we use the distribution function of the sojourn time as

$$F(x) = 1-(a/x)^{\beta}, a, \beta \ge 0, x \ge a \quad (9)$$

If $\beta \in (1,2)$, then the distribution has finite mean and infinite variance so that $H \in (0.5,1)$. We will demonstrate that changing location parameter a affects the scale of measurement in approximating the real self-similar traffic. Double intermittency map[7] is used in chaotic map based modeling that makes the single source have heavy-tailed sojourn time in ON period. In RMD algorithm, different level of aggregation of A(t) is used to refine the self-similar interpolation in a given time interval. The traffic traces to be analyzed by R-S, variance-time and IDC plots are firstly changed to a count process with given count interval. In comparison of the three different traffic generation methods, we first limit the count sample time to be 1ms and enlarge the total number of aggregation with ON/OFF sources as well as interpolation times of FBM sources to observe the estimated H-value with the count process that approximates the target H-value in a long trace traffic collection.

We find that aggregating Pareto-tailed ON/OFF sources is more suitable to generate self-similar traffic that approximates the desired H-value for long time of counts. In our analysis, we use over 10^6 cell counts to generate the traffic series and trunk them to fit different plots. In Fig. 1, the location parameter a is ranged from 10 to 50 cells for the long traces. It is shown that the estimated H is nearly the same as the target value though there is a large fluctuation in small time scale. Since R-S analysis has less variance in estimation shown as in Fig. 1, we use this statistical method to compare the time scale of self-similarity in traffic generation. In chaotic map, one step of iteration in ON period generates 10 cells while it maintains the same time span for cell service in OFF period. The traffic generated by RMD algorithm has the same time interval as the collection of aggregated ON/OFF sources. Fig. 2 shows that in RMD algorithm, the estimated Hurst parameters can differ from their target values (marked in graph) especially when H is large. When the observed time interval is long, RMD needs more times of fractal interpolation to achieve a finer scale of arrival counts. Further more, the traffic should be generated in advance for performance evaluation when applying RMD algorithm. Chaotic Map based modeling shows slow convergence to self-similarity through aggregation and we find the total aggregation should be over 1000 to achieve the accuracy of estimated H in the range of time scales shown by Pareto-tailed method.

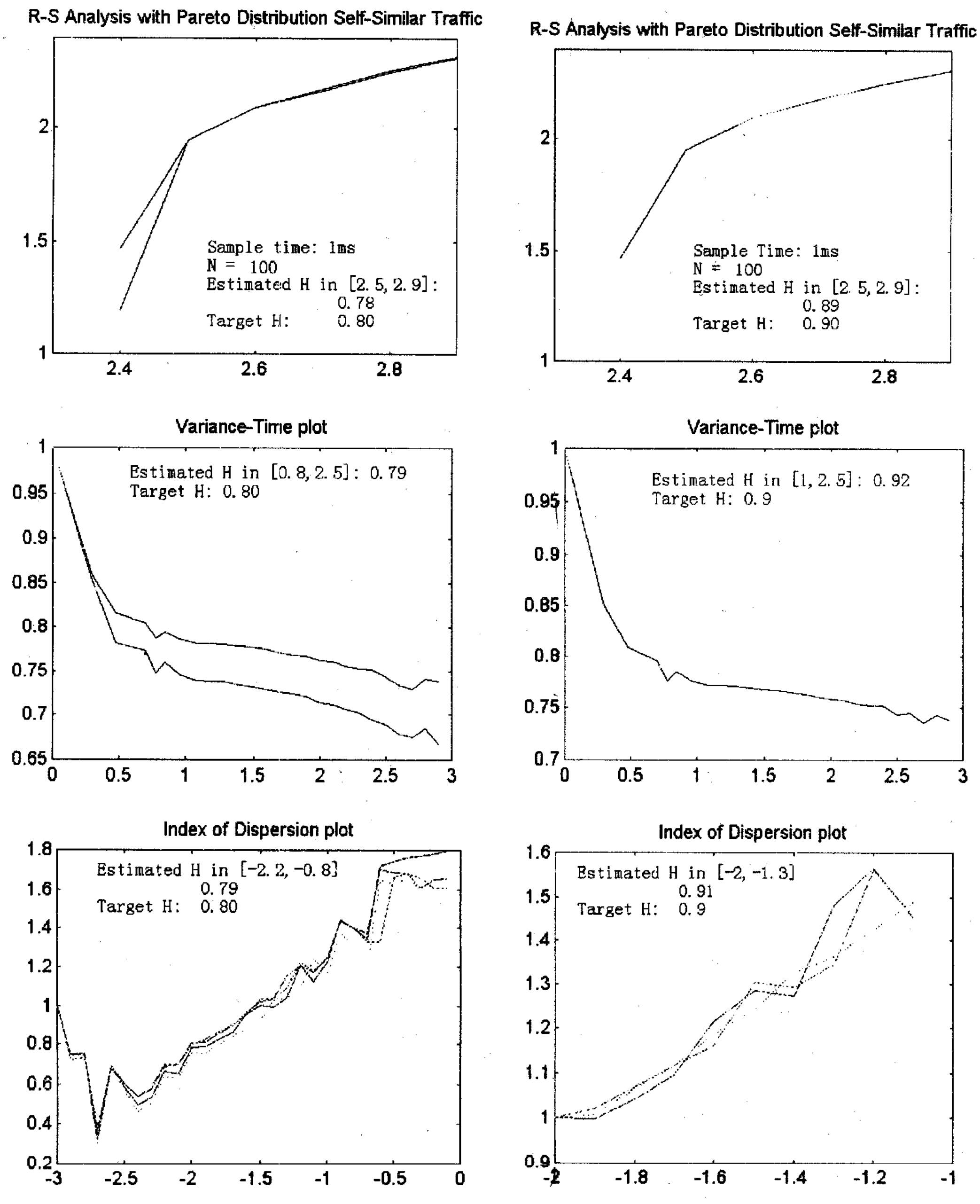

Fig. 1 Statistical Analysis of Pareto-Tailed Self-Similar Traffic

In Fig. 2, we can see that when the sample time is changed to 10ms, the Pareto-tailed traffic aggregation maintains self-similarity for a few hours of counts except for a changes to 200 cells. Thus we can tune the time scale to the desired self-similarity by changing a, and enlarge the observed time span of desired target H-value by adding more traffic sources. One point can be drawn from our extensive study of self-similar traffic generation that count process associated with i.i.d. Pareto interarrivals appears like the desired self-similarity over many time scales when the multiplexed sources are large enough.

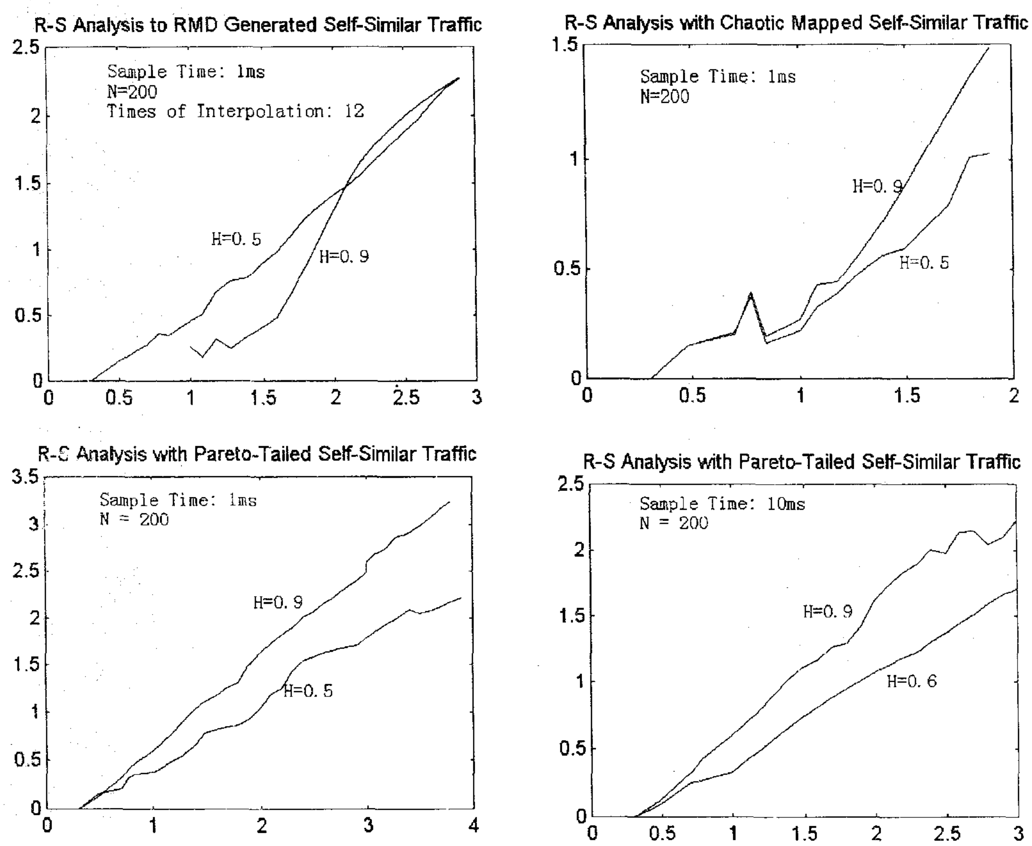

Fig. 2 Comparison of Different Traffic Generation Methods by R-S Analysis

4. Performance Analysis

In this section, we use Pareto-tailed traffic generation to approximate the asymptotically self-similar input traffic and study the performance of an ATM buffer. Simulation results of the queueing behavior tend to have remark difference from the theoretical results shown as in [9] even when the number of aggregated sources is as large as 1000. In simulation, the intensity of the aggregation traffic is 0.2, the mean of active period length in each source is 20 in cell unit time and H tends to be 0.8 as drawn in Fig. 1. When the number of sources becomes large and the traffic load is fixed, we observe that the loss probability decreases with buffer size neither in consistently algebraical form, nor stretched exponential one derived from FBM traffic model.

Fig. 3 shows that the aggregation traffic has faster buffer decay rate in small buffer condition than that from theoretical results based on M/G/1 model in [7].

We believe that the differences of some higher order statistics between the exact self-similar traffic and its approximation of real traffic data have significant influence on the queue length distributions and more in-depth work should be done to associate our empirical results with the design and control of ATM multiplexers and switches.

5. Discussion and Conclusions

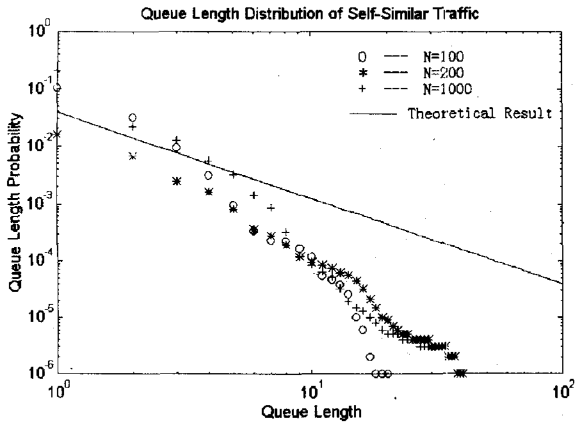

Fig. 3 ATM Queue Length Distribution
N: Number of sources

In this paper, we first give the mathematical model of self-similar traffic and describe some quick traffic generation methods that approximates real LAN traffic data in the observed time scale with desired H-value. We use time series statistics to estimate the Hurst parameter and find that the aggregated traffic with Pareto-tailed sojourn time shows more accuracy of self-similarity and easy to be applied to performance analysis with less computation time. In simulation, the observed cell loss rate and queue length distribution do not conform to the theoretical results based on FBM model when using Pareto-tailed traffic sources. This paradox can be explained by higher order statistics other than the Hurst index used in traffic generation. Future work should concentrate on the physical basis of self-similarity in various applications and use multi-resolution analysis to evaluate the effect of queueing behavior. Importance Sampling(IS)[11] should also be introduced for cell-based network simulation to get further results in condition of very small cell loss rate, which is useful for designing next generation ATM switches.

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