Fractal Behavior of Video and Data Traffic

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Abstract

A fractal is a function or a process in which an identical motif repeats itself on an ever diminishing scale. The motif of a fractal can be a feature influenced by chance. Fractals can be found in nature everywhere, for instance the surface of the moon is a fractal, where the motif of craters is repeated in a scale from inches to miles. It is created by random collisions with space objects. Fractals are also called self-similar, because they show the same picture when looking at them in different scales. Fractals can be found in the load profile of data and video traffic, too. Fractal behavior has serious consequences for the modeling, design and operation of packet switched networks like ATM. They are: 1) no smoothing effect while traffic is multiplexed and, 2) unpredictable burst lengths. This leads to difficulties in buffer dimensioning and in traffic control schemes. Understanding and modeling the fractal behavior is a new research challenge. More knowledge is needed to understand reasons for the fractal properties and to model them in order to design networks, services and even applications with regard to it. There are several methods to find out fractal properties of data and video traffic. One of them, the so called pox diagram, will be applied. We will show results achieved by application of this approach on measured video traffic. Additionally results of other measurement in data networks and in the Internet will be presented.

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1 Introduction

Modeling of the load of communication systems often is based on statistical assumptions which are easy to handle either analytically or by simulation. Dimensioning of critical system parts like buffers, based on this modeling, sometimes fails under certain real life load conditions. The reason is, that traffic sources do not behave like their models. Fractal properties of real sources have been found to cause this unexpected behavior.

So a bundle of question arise: Where are these properties to be expected? How can they be described or even modeled? Where do they come from? What consequences do they have and how can one come along with them?

Up to now there are some investigations describing the phenomenon in one or the other context, all of them on a high theoretical level. Traffic engineers are frightened by messages like '*Poisson* modeling fails' or even 'burst traffic is unpredictable'. Indeed, fractal or self-similar traffic properties can cause a variety of problems to communication systems, mainly if Quality of Service is concerned.

This paper tries to give some explanation about self-similarity at all and summarizes the state of the art. Its special focus are ATM systems as own measurement has been done in an ATM environment. Conclusions raise some questions and directions to think about the answers. All this is to sensitize the research community to the subject.

The rest of the paper is organized as follows: First, I describe some technical meaning of fractals and self-similarity (section 2). Following, one method of finding fractal properties will be introduced (section 3). I then give a description of the measurement I did in an ATM network and their findings, this will be followed by scanning other findings from the literature (section 4) and a brief description of the serious consequences of fractal traffic for ATM systems (section 5). I finally end up with conclusions and some remarks on future work (section 6).

2 Fractals and Self-similarity

2.1 Fractals in Nature

A fractal is a geometrical figure in which an identical motif repeats itself on an ever diminishing scale [LAU91]. A very intelligible example is the so called logarithmic spiral, as shown in Figure 1. This spiral always shows the same picture, no matter what the scale of view is. In Figure 1, the logarithmic spiral is plotted in two different scales of r in polar coordinates (r,θ). The logarithmic spiral is called a protofractal. The motif of the logarithmic spiral is the spiral itself.

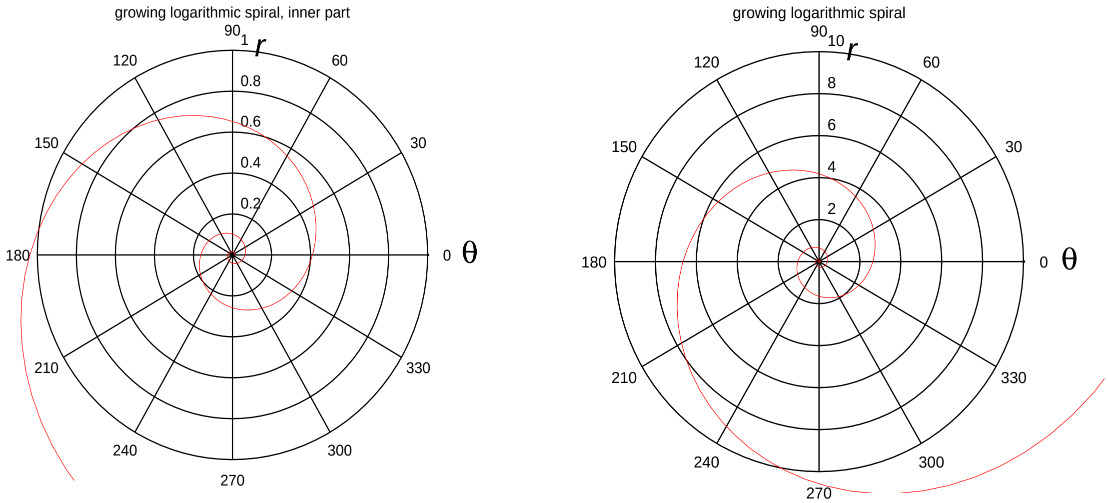

FIGURE 1. Growing Logarithmic Spiral

The motif of a fractal can be influenced by chance. The motif of the fractal in Figure 2 is an angle of 90 degrees with its two legs. The length of both legs is influenced by chance. The fractal grows from its root in the middle. During each iteration a new angle grows at each end of all angles of the previous generation. All length disturbances are calculated using random numbers from the same distribution. Generations look similar, because some basic features (angle) and the statistics of other features (leg length) are the same. Fractal and statistical properties are superpositioned. The tree in Figure 2 looks much more natural than it would look without the influence of coincidence.

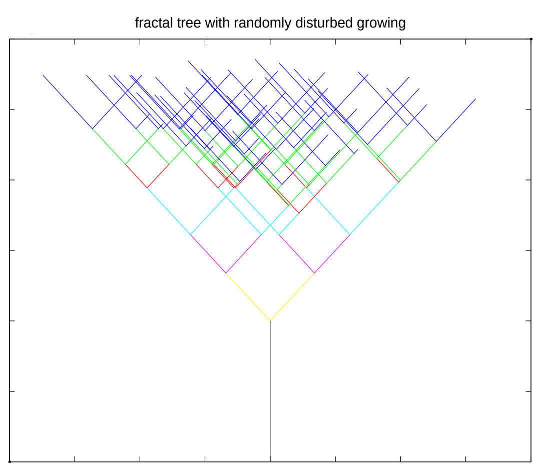

FIGURE 2. Fractal Tree

Having this in mind, fractals can be found in nature everywhere. The logarithmic spiral is the plan for the growth of the Ammonite, and tree fractals can be found in real trees. One impressive example is the surface of the moon. The surface of the moon is a fractal, where the motif of craters is repeated in a scale from millimeters to kilometers. It is created by random collisions with space objects of different size.

Fractals are also called ***self-similar***, because they show the same picture when looking at them in different scales, as you will always see craters on the moon's surface when looking from the earth and from 1cm above the surface as well. Figure 3 gives an impression. ***Self-similarity*** is another term for fractal behavior.

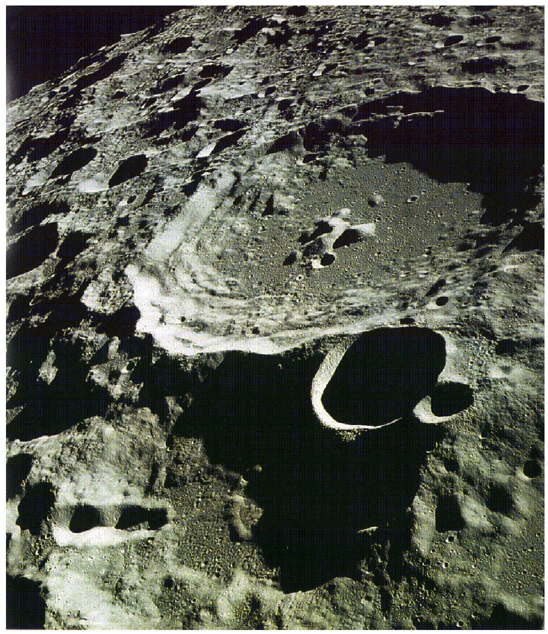

FIGURE 3. The Moon's Surface

An example similar to the moon's surface, but simpler because it is two dimensional and it can be found on earth, are coast lines. Imagine the following experiment:

- Measure the coast line of California on a country map using a 5 mm meterstick by counting how many meterstick steps you have to make to walk along the whole coast line.
- Do the same on a hiking map using the 5 mm meterstick again.

The result of the experiment will be that there are differences in the total length of the coast line. The experiment is called *Richardson*'s experiment [LAU91]. When plotting the total length found for a specific coast line versus the used measur ement unit in a double logarithmic plot, the values concerning one specific coast will be closed to a straight line. This is, because coast lines are fractal. The slope of the line in the plots resulting of *Richardson*'s experiment indicates a ***fractal dimension***. It gives some information about the degree of meandering of the coast line in just one parameter. Figure 4 shows an example of the plot. Expressing a fractal dimension is a basic idea I will use in this paper to describe the fractal behavior of video and data traffic, too.

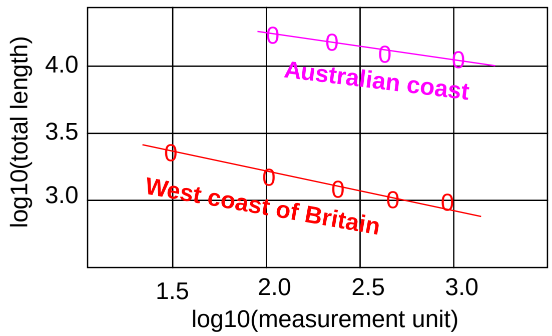

FIGURE 4. ***Richardson*'s Experiment**

2.2 Mathematical Meanings of Self-similarity

Investigating measurement series having fractal properties, this feature expresses itself by a couple of observations. Assume a time series **X** = (X_t; t = 0, 1, 2...) and aggregated series $\mathbf{X}^{(\mathbf{n})}$ = ($X_k^{(n)}$: k = 1, 2, 3 ...), created by summing the original series **X** over non overlapping blocks of size **n.**

First, the autocorrelation function **r(k)** = $E[(X_t - \mu)(X_{t+k} - \mu)]$ of all aggregated series is the same, it is invariant of **n**.

Second, **r(k)** is approximate $\mathbf{k}^{-\beta}$ with $0 < \beta < 1$ as **k** becomes infinite. This corr elation function decays hyperbolically and is non summable. This feature is called long range dependence.

Third, the variance of samples of size **n** from such series do not decrease as a function of **n** but rather by $\mathbf{n}^{-\beta}$. This feature is called slowly decaying variances.

Fourth, the power spectrum of such series **X** is hyperbolic and rising to infinity at frequency zero. The power spectrum is hyperbolic.

Last but not least the probability **P[X>=x]** is about $\mathbf{x}^{-\alpha}$ as **x** becomes infinite. α is between 0 and 2. The asymptotic shape of **P** is hyperbolic. The distribution is called heavy-tailed.

3 Exploration Methods

There are several methods, based on long range dependencies ([LEL93] and [MAN69]), slowly decaying variances (variance-time plots, [LEL93]), power spectrum slope (periodograms, [LEL93]) and new approaches like in [CRO95].

One method has been investigated and used for this paper: ***Rescaled Range Statistics*** [LEL93], [MAN69]. It is based on long range dependencies. The data we will analyze describes the investigated traffic as time series, for instance the number of ATM cells in one time unit. To find long range dependencies, measur ed data has to be evaluated in different time-scales.

The same sample of cell numbers versus time has to be cut into pieces, so called lags. Cuts have to be done several times, varying the number and length of lags. The length of the lags **n** is the time base for further investigations. It is the number of observations in the lag, in our case a number of consecutive time intervals. Figure 5 shows an example for cutting a sample one time into seven pieces and another time into 14 pieces.

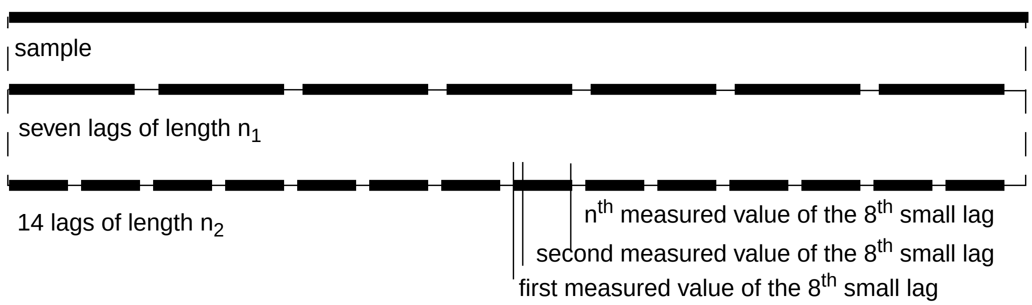

FIGURE 5. Cutting a Sample into Lags

For each **n**, a number of lags are selected randomly. This number of lags must be the same for all values of **n**. It is obvious, that in the example above, the number of selected lags must not exceed seven.

For selected lags, two parameters are calculated:

- $\mathbf{R(n) = max(0, W_1, W_2,..., W_n) - min(0, W_1, W_2,..., W_n)}$
  with $\mathbf{W_i = (X_1 + X_2 + ... + X_i) - i\overline{X}(n)}$ is the *sample range* of the lag.
- $\mathbf{S^2(n)}$ is the *variance* of the set $\{\mathbf{X_1 + X_2 +... + X_n}\}$ of one lag.

From [LEL93] we can learn, that for short range dependent sets of observations the expected value $\mathbf{E[R(n)/S(n)]}$ is about $\mathbf{c_0 n^{1/2}}$. Contrary to that, for long range dependent sets of observations $\mathbf{E[R(n)/S(n)]}$ is about $\mathbf{c_0 n^H}$ with $\mathbf{0.5 < H < 1}$. **H** is equal to $\mathbf{1- \beta/2}$ (refer to section 2.2) and $\mathbf{c_0}$ is a constant of minor importance. The following steps describe how to evaluate $\mathbf{E[R(n)/S(n)]}$ graphically.

- The quotients of **R(n)** and the corresponding **S(n)** have to be calculated.
- After that, the mean of all quotients belonging to one **n** have to be calculated.
- The quotients and their means are plotted in a double logarithmic plot versus **n**, the so called POX diagram.

Figure 6 contains a POX diagram. **R/S** quotients are marked by dots. Their means are marked by '+'. There are seven quotients per **n**. The plots form a straight line. The slope of this line is called the *Hurst* parameter **H**. If there is no fractal behavior, **H** is circa 0.5. An **H** of greater than 0.5 is a sign for self-similarity or fractal behavior. The greater **H**, the greater is the fractal dimension of the investigated traffic. Again, one parameter expresses the fractal behavior.

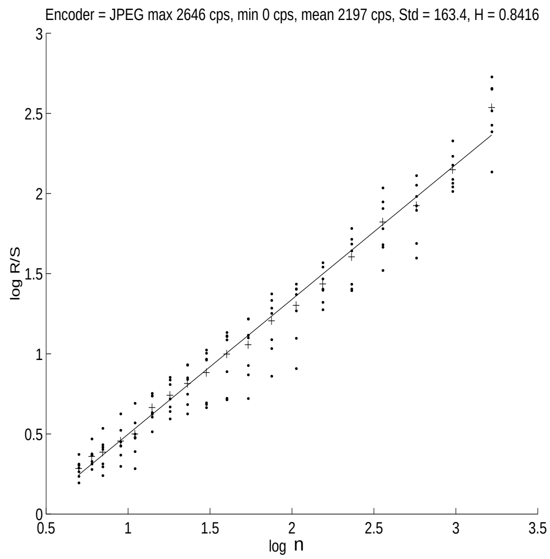

FIGURE 6. Example POX Diagram

4 Traffic Measurement and Results

4.1 Experiment Description

All measurement has been done with video traffic in the MAY network [HTTP1] using the configuration presented in Figure 7. The workstation performing the measured sources was a *sparc5* workstation running *Solaris2.5* equipped with a *SunVideo* board and an *Interphase ATM board* [HTTP2]. The ATM cell stream was linked to a *LattisCell ATM Switch Model 10114-SM* [HTTP3]. This Switch offers 16 Sonet/SDH 155Mbit/s ports. A tool named `atmstat` was used to measure the ATM cells arriving in each second.

Different video encoders used in the `vic` tool were used to encode a video stream from a camera: H261, JPEG and, NV, a special Xerox invented format. The `vic` program offers some possibilities to tune encoding and transmission quality. There can be chosen a frame rate and a transmission rate. Nevertheless these predefined values are adapted during transmission to the workstations performance constraints. For all experiments, the predefined frame rate and transmission rate have been selected for the highest quality transmission. That is, 30 fps frame rate and 3072 kbps transmission rate.

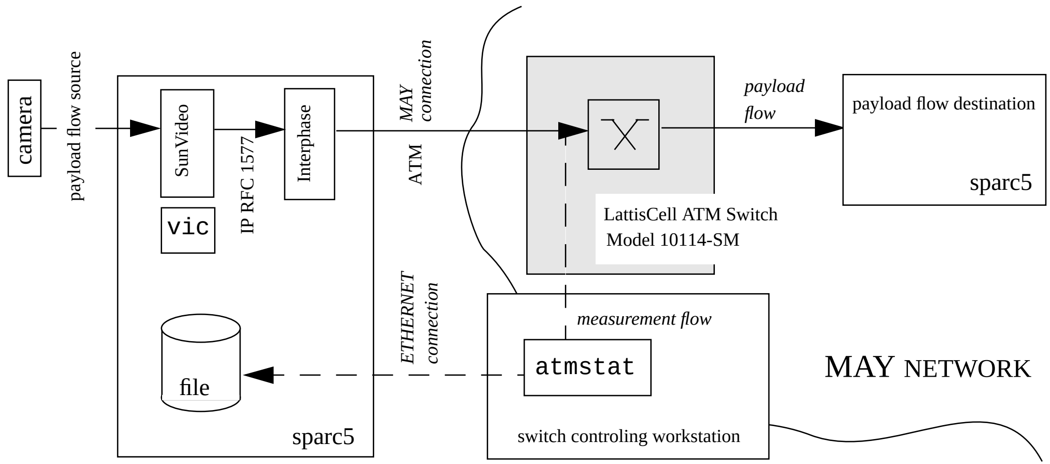

FIGURE 7. Measurement Configuration

The `vic` encoder produces UDP frames which are packed into IP packets (Classical IP RFC 1577), as to be seen in Figure 8. To the UDP (User Datagram Protocol) packets there are added 8 bytes for the UDP header, 20 bytes for the IP (Internet Protocol) header, plus 8 bytes for the PDU trailer of the AAL5.

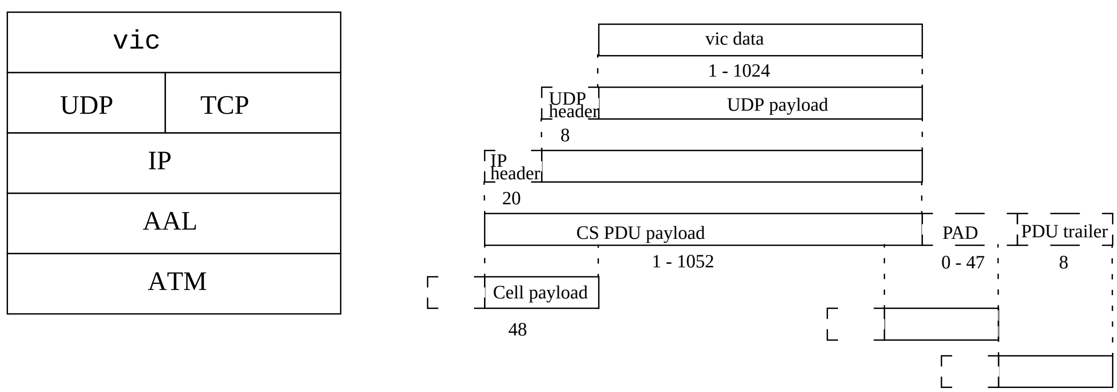

FIGURE 8. Protocol Stack

4.2 Results

The following plots are cell rate versus time plots of the measurement described above. The average cell rate is indicated by a grey solid line. The time resolution of the plots is one second.

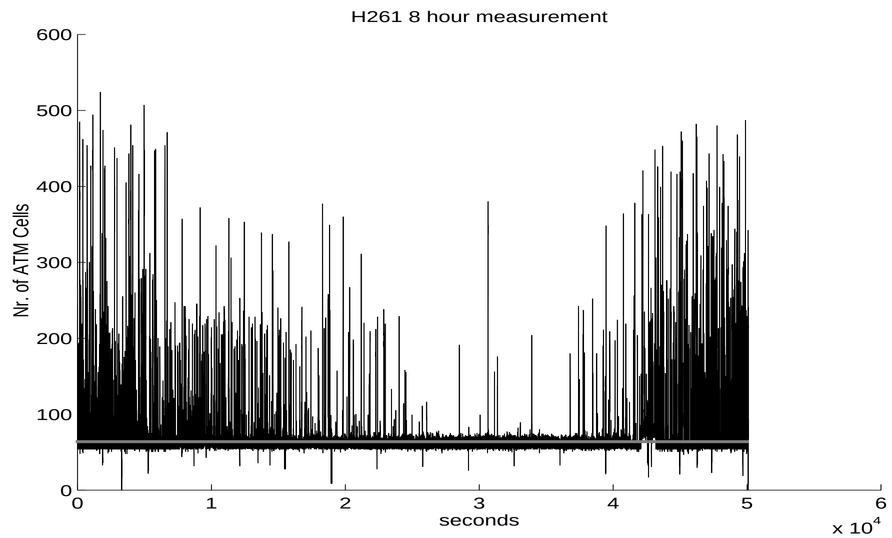

FIGURE 9. H261 Time Plot

For H261 there was a minimum cell rate of about 50 cells per second. Cell rates below this are probably caused by workstation's performance problems, as for instance the zero cell rate short after the beginning of the measurement is caused by the screen lock procedure. Most of the time the cell rate is near the mean of 80.43 cps. The burstiness as the quotient of peak cell rate and mean cell rate is 10.8. The measurement shows impressively, that the essential of this encoding scheme is a low lasting cell rate, superimposed by spikes when pictures are updated due to scene changes.

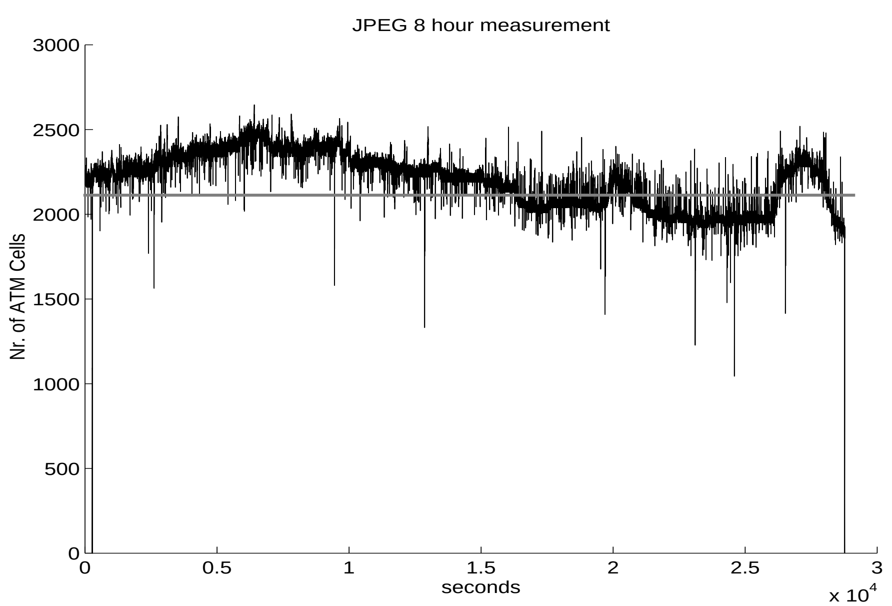

FIGURE 10. JPEG Time Plot

The behavior of the JPEG encoder is much different. You will find variations around a mean cell rate, i.e. the cell rate varies to high and to low values. Even the mean cell rate itself varies. There are variations in a minute time-scale and they are superimposed by variations in a hour time-scale. Runaways to low cell rates are caused by the workstations behavior, as for the H261 encoder. The JPEG mean cell rate is the highest of all measured encoders, but the variance is one order of magnitude below the mean, which differs from other encoding schemes, too.

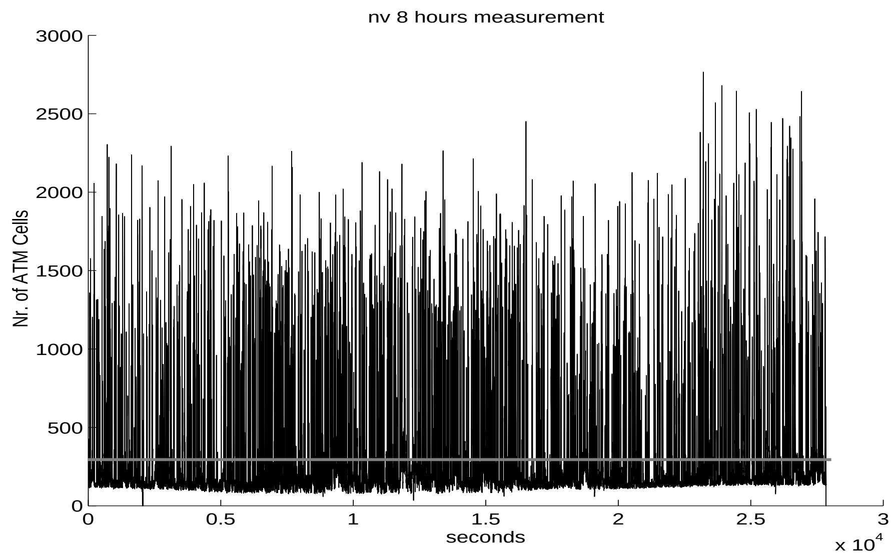

FIGURE 11. NV Time Plot

The NV encoding scheme behaves quite similar to the H261 scheme. Spikes are higher than in the H261 scheme. The burstiness measured for one second intervals is about 250. Zero cell rates are runaways for these measurement, too.

All measurement was tested according to self-similarity. The following plots show the self-similarity tests. The lag size ranges from 5 seconds to a size where at least 7 non overlapping lags could be built from the measured data. The quotients **R/S** are plotted by single dots, the mean of the quotients corresponding to a specific **n** are marked by '+' and the solid line shows a regression line of the means to find the slope. The figures show, that all 3 encoders have fractal behavior, especially the JPEG decoder shows a high value of **H**.

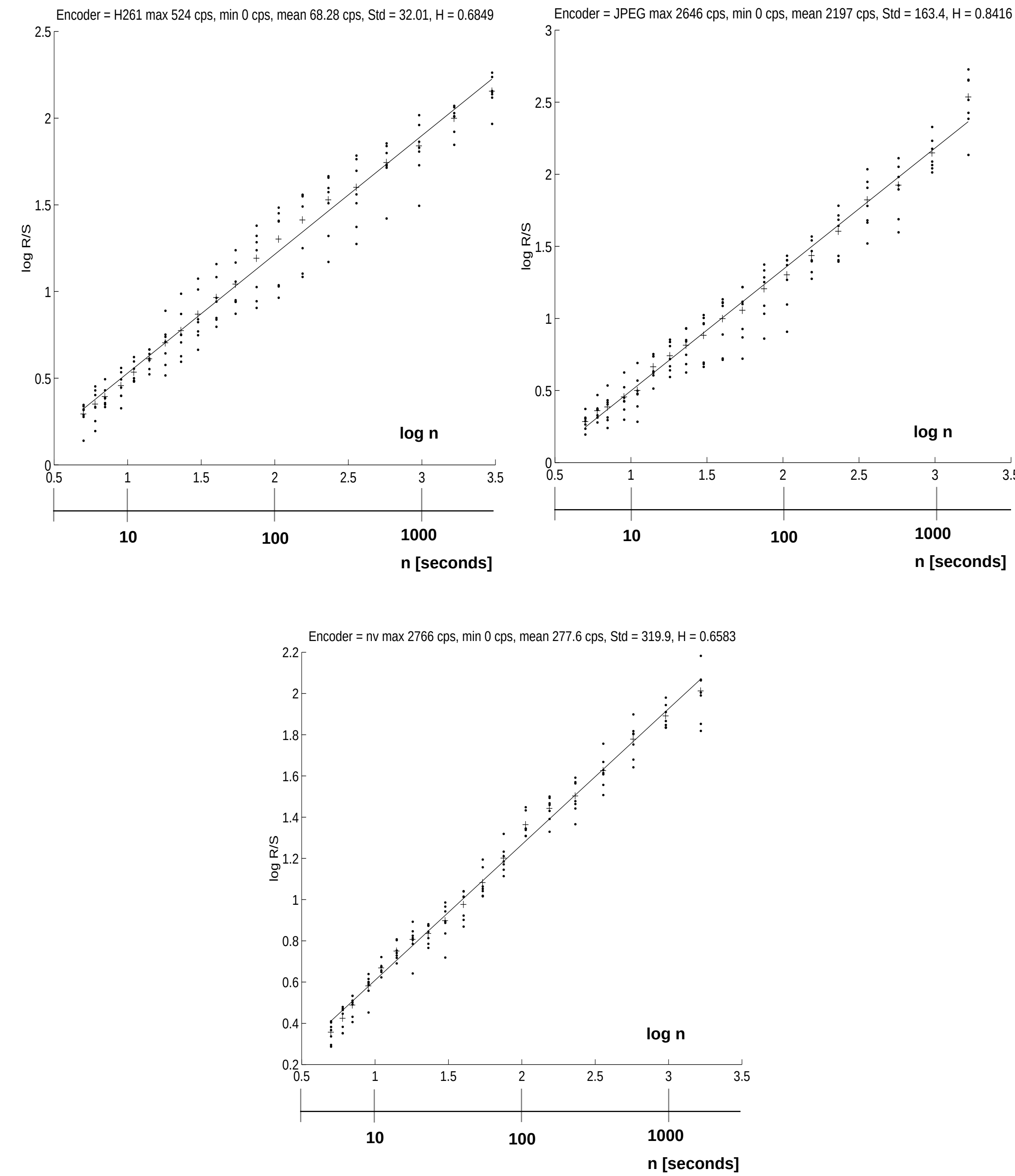

FIGURE 12. Self-similarity Test of the Encoders

As shown in [LEL93], this feature manifests when several cell streams are multiplexed. In theory, when sequences of the same **H** are multiplexed, this should result in the same **H** again for the multiplexed sequence. For that reason, the following has been performed with the measured data: Each data set of approximately 8 hours length was cut into 10 pieces first and then these 10 streams were multiplexed to one stream using an idealized loss free multiplexer. The cut of the original stream results in streams of approximately the same **H**. On the multiplexed stream, the same procedure for self-similarity testing as for the original data was applied. After that, the same has been done cutting the original date into 100 pieces, simulating the multiplex of 100 cell streams.

Table 1 summarizes all experiment statistics and results.

TABLE 1. Experiment Statistics and Results

						H		
Encoder	**Measure-ment Time**	**sum cells**	**max cells per sec**	**mean cells per sec**	**std**[a]	**Single Cell Stream**	**10 Multi-plexed Streams**	**100 Multi-plexed Streams**
H261	50,094 s	3,420,462	524	68.2809	32.0104	0.6849	0.7319	0.7648
JPEG	28,782 s	63,221,534	2,646	2,196.6	163.3749	0.8416	0.7146	0.6243
NV	27,845 s	7,730,465	2,766	277.6249	319.8612	0.6583	0.7216	0.7230

a. std ... Standard Deviation of the number of cells per second

The *Hurst* parameters of the multiplexed streams are more or less in the same range as for the single streams. It must be taken into account, that the POX diagram is just one test for self-similarity and there might be different values for **H** in different parts of the sequences. Further investigation is necessary, in particular to check the JPEG results.

4.3 Comparison to Other Published Results

In [LEL93], one of the basic papers concerning self-similarity of traffic in communication systems, *Bellcore* investigated Ethernet traffic to very active file servers inside a LAN, traffic between parts of a LAN inter connected by a bridge, external traffic of an Ethernet LAN and Internet traffic. There were found *Hurst* parameters **H** between 0.53 and 0.99. **H** was increasing for more aggregated traffic (more users) and with moving from low to heavy traffic of the individual users.

In [CRO95] sequences of file requests were used to measure bursts in terms of bytes versus time. *Hurst* parameters of about **H** = 0.8 were found, caused by the distribution of WWW document sizes, caching, user reaction time and traffic aggregation in LANs. It was found, that sources behave like ON/OFF sources with heavy-tailed ON and OFF period lengths.

In [GRI95] file system traces in a Sprite file system for events like ‘open’, ‘close’, ‘block transfers’, ‘delete’ and ‘directory use’ were used to search for fractal properties. All these file system events require communication, so kernel calls to client machines were monitored with a precision of 10 ms. The analysis was made by application of different detection methods. There were found *Hurst* parameters **H** between 0.54 and 0.99.

In [ROS95] several video sequence were analyzed. They were all encoded with MPEG. *Hurst* parameters were between 0.51 and 0.99. The paper concluded, that apart from exceptions a larger **H** reflects a larger amount of movement in the video sequence.

5 Consequences of Fractal Traffic

The most serious consequence of self-similar traffic concerns the size of bursts. Within a wide range of time-scales, the burst size is unpredictable, at least with traditional modeling methods. This has some very practical meanings for buffer dimensioning and service creation:

- buffers for fractal traffic cannot be dimensioned using *Poisson* modeling,
- cell loss guarantees based on *Poisson* traffic assumptions will fail,
- connection admission based on knowledge about a natural burst length will fail,
- *Poisson* modeling based congestion control schemes can fail and,
- variable bit rate services are especially difficult to design.

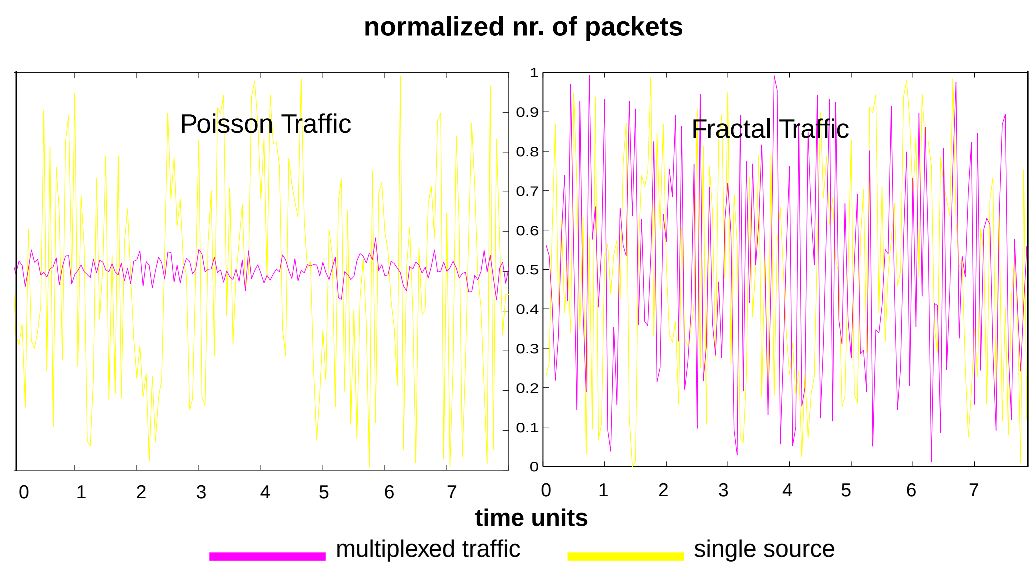

FIGURE 13. Statistical Multiplexing of *Poisson* and Fractal Traffic

The rigidity of *Poisson* modeling can be illustrated by the following comparison. Assume several traffic streams of *Poisson* traffic on one hand and a number of fractal traffic streams on the other hand. If these traffic is multiplexed, *Poisson* with *Poisson* and fractal with fractal, it can be observed, that the characteristic of the multiplexed *Poisson* traffic becomes smooth, as to be seen in the left part of Figure 13. It is obvious that dimensioning of any resources can easily be based on this feature. For fractal traffic, multiplexing the same number of traffic streams leads to a less smooth traffic, also to be seen in the right part of Figure 13. Any resources must be dimensioned for a much higher peak to mean ratio of the resulting traffic stream than in the *Poisson* case.

6 Conclusions and Future Work

There must be much more research about fractal traffic. One topic is the reasons for it. Knowing them, we could either create applications with less fractal traffic or systems getting along with fractal traffic or both. In any case there is an advantage from knowing self-similarity parameters and using them in new modeling techniques. Learning about the possible reasons has started in [CRO95], for instance. One step towards less self-similar traffic producing applications is the comparison of different video encoders.

Some of the crucial questions are:

- Is fractal traffic created by the encoding techniques or the content, that means is it immanent to the transmitted data?
- Does self-similarity become the more important the more encoding is done because encoding removes redundancy from the data?
- Has self-similarity to do with human perception because video encoding schemes are designed to show the human brain what it likes?
- Or is the reason, that as well data sources as video sources are not memoryless?

To find answers there is necessary:

- an in depth analysis of previous investigations of self-similarity in packet traffic,
- a completion of the theoretical background by exploring mathematical views on self-similarity and by exploring how other sciences deal with self-similarity (e.g. physics, geology etc.),
- the development of customized test methods and parameter sets,
- an analysis of a broad spectrum of traffic to get universal knowledge about relations between applications and traffic features and about reasons for fractal behavior and,
- the development of modeling approaches for self-similarity to be able to assist application, network and service design by analytical modeling and simulation.

Superposition of ON-OFF sources with heavy tailed ON- and OFF- length distributions is one of the possible modeling approaches. To summarize, more theory is necessary, but only worth combined with extensive measurement.

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