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Abstract
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Keywords
ACF, HEAF(2), LRD, Self-similarity

Disciplines
Computer and Systems Architecture | Digital Communications and Networking | Hardware Systems | Systems and Communications

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Karim Mohammed Rezaul, Vic Grout

***Abstract*—The intensity of Long-Range Dependence (LRD) for communications network traffic can be measured using the Hurst parameter. LRD characteristics in computer networks, however, present a fundamentally different set of problems in research towards the future of network design. There are various estimators of the Hurst parameter, which differ in the reliability of their results. Getting robust and reliable estimators can help to improve traffic characterization, performance modelling, planning and engineering of real networks. Earlier research [1] introduced an estimator called the Hurst Exponent from the Autocorrelation Function (HEAF) and it was shown why lag 2 in HEAF (i.e. HEAF (2)) is considered when estimating LRD of network traffic. This paper considers the robustness of HEAF(2) when estimating the Hurst parameter of data traffic (e.g. packet sequences) with outliers.**

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I. INTRODUCTION

The Long-Range Dependence (LRD) property of traffic fluctuations has important implications on the performance, design and dimensioning of the network [2]. A simple, direct parameter characterizing the degree of long-range dependence is the *Hurst parameter*. The Hurst exponent (or Hurst parameter, *H*), which more than a half-century ago was proposed for analysis of long-term storage capacity of reservoirs [3], is nowadays used to measure the intensity of LRD in network traffic. A number of methods have been proposed to estimate the Hurst parameter. Some of the most popular include the aggregated variance time (V/T) [4], Rescaled-range (R/S) [2, 3], Higuchi method [5], wavelet-based method [6, 7] although there are many othrs. In all these methods, *H* is calculated by taking the slope from a log-log plot. So far the wavelet-based Hurst parameter has acquired popularity in estimating LRD traffic. However the study [8] explores the advantages and limitations of wavelet estimators and found that a traffic trace with a number of deterministic shifts in the mean rate results in steep wavelet spectrum which leads to overestimating the Hurst parameter. The intensity of long-range dependence is measured for file size or document size [9], packet counts (number of packets per unit time) [10, 11, 12], interarrival time [13, 14], frame size [15], connection size [16], packet length [17], number of bytes per unit time [2], Bit or byte rate [18] and so on.

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This paper continues work on the new estimator introduced earlier which is named Hurst Exponent by Autocorrelation Function (HEAF) [1]. HEAF estimates *H* by a process which is simple, quick and reliable. In order to investigate the robustness of HEAF(2), two different types of simulation studies were performed. The first one is using fractional Gaussian noise (fGn) sequences generated by the Dietrich-Newsam algorithm [19, 20], which generates exact self-similar sequences. The second one is using a fractional autoregressive moving average (FARIMA) process [21, 22]. Stationarity is assumed for these kinds of classical models (FARIMA and fGN) because it is convenient from a theoretical point of view, especially to check the validity of any hypothesis. The sequences generated by these models show a bell-shaped (i.e. Gaussian) curve either exactly or with small variation. However, our concern in this research is to determine whether, in the case that the underlying process is not FARIMA or fGN, HEAF(2) can still capture the long-range dependency of the traffic. We investigate what role HEAF(2) can play to yield an estimate with a good degree of accuracy if the traffic is nonstationary. For instance, if the data traffic possesses outliers, we consider how to estimate H by eliminating these outliers to have satisfactory and reliable information.

The paper is organised as follows. Section II describes the definitions of self-similarity, long-range dependence and autocorrelation function. Section III introduces the HEAF estimator. Section IV describes about the robust versions of autocorrelation function. Finally the results are presented in section V.

II. SELF-SIMILARITY , LONG-RANGE DEPENDENCE AND AUTOCORRELATION FUNCTION

In general two or more objects having the same characteristics are called self-similarity. A phenomenon that is self-similar looks the same or behaves the same when viewed at different degrees of magnification or different scales on a dimension and bursty over all time scales. Self-similarity is the property of a series of data points to retain a pattern or appearance regardless of the level of granularity used and is the result of long-range dependence in the data series. If a self-similar process is bursty at a wide range of timescales, it may exhibit long-range- dependence. In general lagged autocorrelations are used in time series analysis for empirical stationary tests. Self-similarity manifests itself as long-range dependence (i.e., long memory) in the time series of arrivals. The evidence of very slow, linear decay in the sample lag autocorrelation finction (ACF) indicates the nonstationary behaviour [23]. The research [24] show that Internet traffic is nonstationary.

Long-range-dependence means that all the values at any time are correlated in a positive and non-negligible way with values at all future instants. For a continuous time process $Y = \{Y(t), t \geq 0\}$ is self-similar if it satisfies the following condition [25]:

$$Y(t) \overset{d}{=} a^{-H} Y(at), \quad \forall a > 0, \quad and \quad 0 < H < 1$$

where H is the index of self-similarity, called Hurst parameter and the equality is in the sense of finite-dimensional distributions.

The stationary process X is said to be a long-range dependent process if its autocorrelation function (ACF) is non-summable [26] meaning that $\sum_{k=-\infty}^{\infty} r_k = \infty$

The details of how ACF decays with k are of interest because the behaviour of the tail of ACF completely determines its summability. According to [3], X is said to exhibit long-range dependence if

$$r_k \sim L(t) k^{-(2-2H)}, \quad as \ k \to \infty \qquad (2.1)$$

where $\frac{1}{2} < H < 1$ and $L(.)$ slowly varies at infinity, i.e.,

$$\lim_{t\to\infty} \frac{L(xt)}{L(t)} = 1, \quad \text{for all } x > 0$$

Equation (2.1) implies that the LRD is characterized by an autocorrelation function that decays hyperbolically rather than exponentially fast.

III. HEAF: A 'Hurst Exponent by Autocorrelation Function' estimator

A new estimator has been introduced [1] by extending the approach of Kettani and Gubner [27]. As in [27], for a given observed data X_i (i.e. $X_1, \ldots\ldots, X_n$), the sample autocorrelation function can be calculated by the following method:

$$\text{Let } \hat{m}_n = \frac{1}{n} \sum_{i=1}^{n} X_i \qquad (3.1)$$

$$\text{and } \hat{g}_n(k) = \frac{1}{n} \sum_{i=1}^{n-k} (X_i - \hat{m}_n)(X_{i+k} - \hat{m}_n), \qquad (3.2)$$

where k=0,1, 2, ….., n,

$$\text{with } \hat{s}_n^2 = \hat{g}_n(0). \qquad (3.3)$$

Then the sample autocorrelations of lag k are given by

$$\hat{r}_k = \frac{\hat{g}_n(k)}{\hat{s}_n^2} \qquad (3.4)$$

(Equations (3.1), (3.2), (3.3) and (3.4) denote the sample mean, the sample covariance, the sample variance and the sample autocorrelation, respectively). A second-order stationary process is said to be exactly second-order self-similar with Hurst exponent $1/2 < H < 1$ if

$$r_k = 0.5\,[(k+1)^{2H} - 2k^{2H} + (k-1)^{2H}] \qquad (3.5)$$

From equation (3.5), Kettani and Gubner suggest a moment estimator of H. They consider the case where k =1 and replace r_1 by its sample estimate $\hat{r}_1$, as defined in equation (3.4). This gives an estimate for H of the form

$$\hat{H} = \frac{1}{2} + \frac{1}{2 \log_e 2} \log_e(1 + \hat{r}_1) \qquad (3.6)$$

Clearly, this estimate is straightforward to evaluate, requiring no iterative calculations. For more details of the properties of this estimator, see Kettani and Gubner [**27**].

An alternative estimator of H is proposed based upon equation (3.5), by considering the cases where $k>1$. Note that the sample equivalent of equation (3.5) can be expressed as

$$f(H) = \hat{r}_k - 0.5\{(k+1)^{2H} - 2k^{2H} + (k-1)^{2H}\} = 0. \qquad (3.7)$$

Thus, for a given observed $\hat{r}_k$, $k>1$, a suitable numerical procedure can be used to solve this equation, and find an estimate of H. This is denoted as a HEAF(k) estimate of H.

To solve equation (3.7) for H the well-known Newton-Raphson (N-R) method is used. This requires the derivative of $f(H)$. Here note that k ? 1,

$$f'(H) = -0.5 \left\{ \begin{array}{l} (2\log(k+1))(k+1)^{2H} \\ -(4\log(k))(k)^{2H} + \\ (2\log(k-1))(k-1)^{2H} \end{array} \right\} \qquad (3.8)$$

Hence, the algorithm to estimate HEAF(k), for any lag k, consists of the following steps:

1. Compute the sample autocorrelations for lag k of a given data set by equation (3.4). (Note that X_i can be denoted as the number of bits, bytes, packets or bit rates observed during the i th interval. If X_i is a Gaussian process, it is known as fractional Gaussian noise).
2. Make an initial guess of H, e.g. H_1 = 0.6, then calculate H_2, H_3, H_4,…., successively using $H_{r+1} = H_r - f(H_r)/f'(H_r)$, until convergence, to find the estimate $\hat{H}$ for the given lag k. An initial consideration is of the case where k = 2 in equation (3.2); i.e. HEAF(2) is considered first.

One of the major advantages of the HEAF estimator is speed, as the NR-method converges very quickly to a root. There is no general convergence criterion for NR. Its convergence depends on the nature of the function and on the accuracy of the initial guess. Fortunately the form of the function (i.e., equation (3.7)) appears to converge quickly (within at most four iterations) for any initial guess in the range of interest, namely H in *(0.2, 1)*. If an iteration value, H_r is such that $f'(H_r) \cong 0$, then one can face "division by zero" or a near-zero number. This will give a large magnitude for the next value, H_{r+1} which in turn stops the iteration. This problem can be resolved by increasing the tolerance parameter in the N-R program. A HEAF(k), for $k = 2, \ldots, 11$, have been considered and no difficulty in finding the root in (0.5, 1) have been encountered.

IV. Robust Autocorrelation funct ion

The forecasting of network traffic and Quality of Service (QoS) can be affected by the additive outliers. The sample ACF that was used in HEAF (2) is sometimes controversy. In this research we test the performance of HEAF (2) by using three robust ACF such as Trimmed ACF [28], variance-ratio of differences and sums which is known as D/S variance estimator [29, 30], weighted sample autocorrelation function (shorten as WACF) [31]. Polasek [32] showed in his paper how to eliminate these additive outliers by different robust acf. According to his findings the sample acf (i.e. moment based) was surprisingly ranked as 2 after TACF for eliminating additive outliers. Due to space limitation we only present the results from Trimmed ACF.

The Trimmed ACF can be calculated by the following procedure:

Let $z_{(1)} \le z_{(2)} \le .... \le z_{(n)}$ be the ordered observations of the given time series z1, z2, …., and zn. Chan and Wei [28] introduced the α -trimmed sample autocorrelation function (shorten as TACF) defined by

$$\hat{r}_T(k) = \frac{\hat{g}_T(k)}{\hat{g}_T(0)}$$

where

$$\hat{g}_T(k) = \frac{\sum_{t=k+1}^{n} (z_{t-k} - \bar{z}^{(\alpha)})\,(z_t - \bar{z}^{(\alpha)})\,L_{t-k}^{(\alpha)}\,L_t^{(\alpha)}}{\sum_{t=k+1}^{n} L_{t-k}^{(\alpha)}\,L_t^{(\alpha)}}$$

$$\bar{z}^{(\alpha)} = \sum_{t=1}^{n} z_t L_t^{(\alpha)} \Big/ \sum_{t=1}^{n} L_t^{(\alpha)}$$ and

$$L_t^{(\alpha)} = \begin{cases} 0, & if \quad z_t \le z_{(g)} \;\; or \;\; z_t \ge z_{(n-g+1)} \\ 1, & otherwise \end{cases}$$

where $g = [\alpha\, n]$ is the integer part of $\alpha\, n$ and $0 \le \alpha \le 0.05$. Chan and Wei showed that TACF is, in general, very successful in removing the adverse effect of outliers on the estimation of ACF. The parameter called, automatic alpha can be estimated by trimmean filter (TMF) [33, 34].

The procedure for estimating alpha by TMF is as follows:

1. Sort the data in ascending order.
2. Calculate the parameter Q according to the equation below

$$Q = \frac{[U(20\%) - L(20\%)]}{U(50\%) - L(50\%)]}$$

- where U(x%) is the average of the upper x% of the ordered sample and L(x%) is the average of the lower x% of the ordered sample.
- Q is a measure of the departure of the distribution contained in the sample from a normal distribution.
- Trim off each tail of the ordered distribution according to the value of the trimmean parameter alpha.

$$\alpha(Q) = \begin{cases} 0.04 & Q \le 1.75 \\ 0.04 + 0.01 * \dfrac{(Q-1.75)}{0.25} & 1.75 < Q < 2.0 \\ 0.05 & Q \ge 2.0 \end{cases}$$

Note that the alpha parameter given in [33, 34] is modified here for estimating a good degree of accuracy when considering network traffic data. The TMF assumes the distribution to be symmetric, but not necessarily Gaussian. For a pure Gaussian distribution of data, 4 percent of the data is trimmed from each tail of the original sorted distribution. For a given segment of time, a maximum of 5 percent of the data is trimmed off each tail.

V. Results and Discussion

In [1, 35, 36], the results show that HEAF(2) is an estimator of *H* with relatively good bias and mse, when estimating fractional Gaussian noise or FARIMA processes. Because of its simplicity and reliability it is believed that HEAF (2) can be used for real time network traffic control. Of course, a real process will be unlikely to be exactly an fGn process or even FARIMA process. Indeed, a real process may suffer from a 'noise', discrepant values or other outliers. This section presents the robustness of the proposed estimator, HEAF(2), against departures from ideal assumptions.

In order to test the robustness of HEAF (2) we generate some noisy sequences by mixing with the data sequences generated by FARIMA (0, d, 0) and fGn processes for a particular Hurst parameter (H). Obviously H will be changed when making noisy data, meaning that the process (FARIMA or fGN) no longer exists as it holds additive outliers. Figure 1 shows a pictorial view of noisy data to be analysed in order to explore the robustness of the HEAF(2).

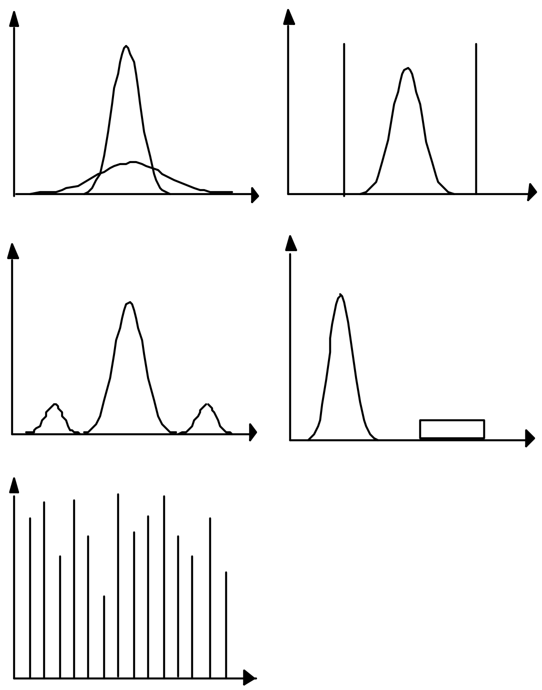

Fig. 1. Pictorial view of noisy samples (i.e. data with additive outliers)

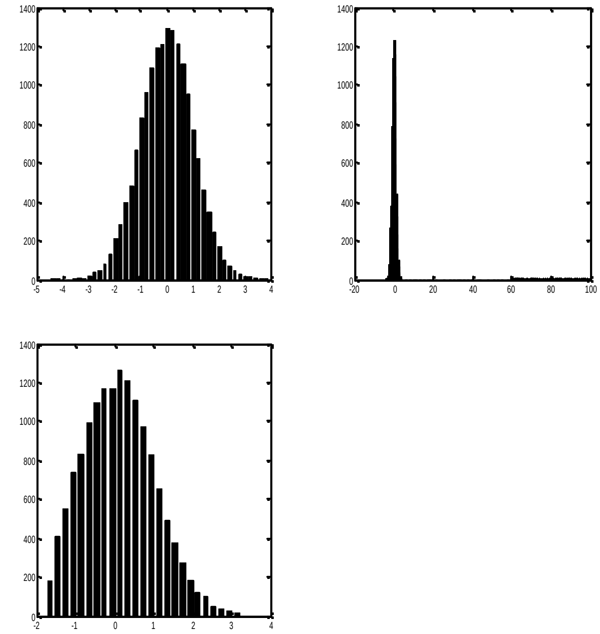

Fig. 2. Top left figure - Data generated by FARIMA (0,d, 0) process for H =0.6 (H measured by HEAF (2) = 0.585), N = 16384. Top right figure – generated Noisy sample (measured H = 0.8993). Bottom figure - H = 0.576 (after elimination of the outliers) where alpha = 0.048

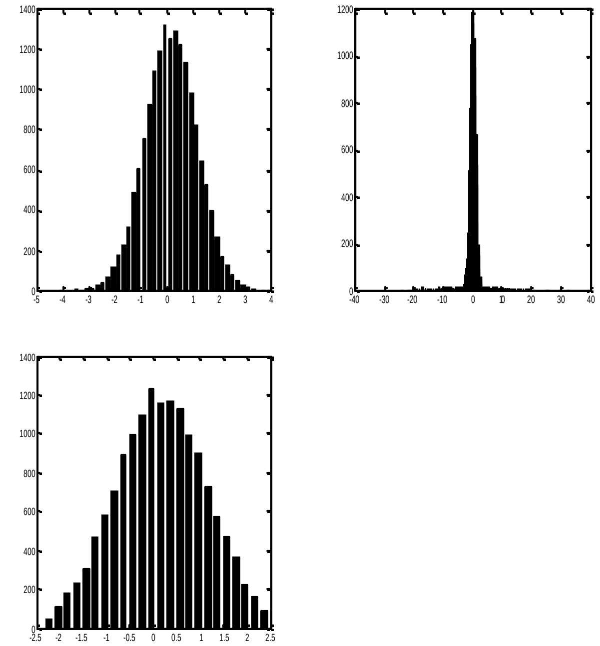

Fig. 3. Top left figure - Data generated by fGN process for H =0.6 (H measured by HEAF (2) = 0.795), N = 16384. Top right figure – generated Noisy sample (measured H = 0.556). Bottom figure - H = 0.77 (after elimination of the outliers) where alpha = 0.048

In Figure 2, the top left figure shows a histogram of FARIMA (0, d, 0) process with H = 0.6. The estimated H by HEAF(2) is 0.585. The top right figure represents a histogram for a noisy samples generated by mixing with FARIMA (0,d, 0) process for H = 0.6 having the sample length, N = 16384. The histogram at the bottom of Figure 2 is plotted after elimination of the outliers shown in the top right figure. The estimated H for noisy samples (top right figure) and samples after elimination are 0.8993 and 0.576 respectively. The outliers from noisy samples are eliminated by automatic alpha and then the alpha value is used in TACF which in turn applied in HEAF(2).

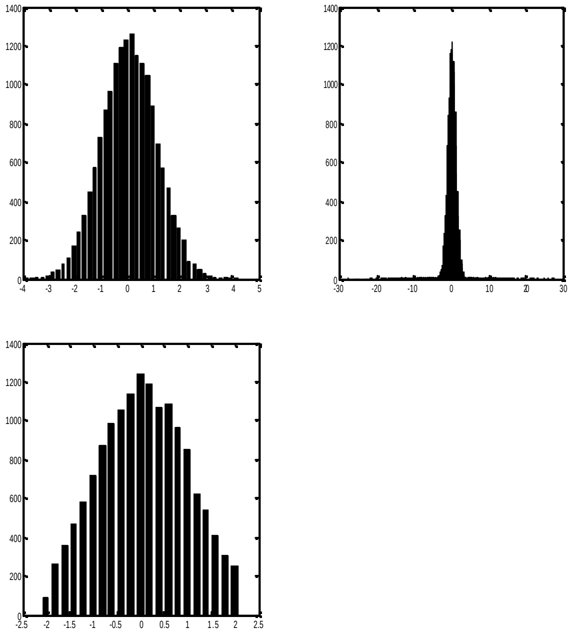

Fig. 4. Top left figure - Data generated by FARIMA (0,d, 0) process for H =0.7 (H measured by HEAF (2) = 0.683), N = 16384. Top right figure – generated Noisy sample (measured H = 0.573). Bottom figure - H = 0.65 (after elimination of the outliers) where alpha = 0.041

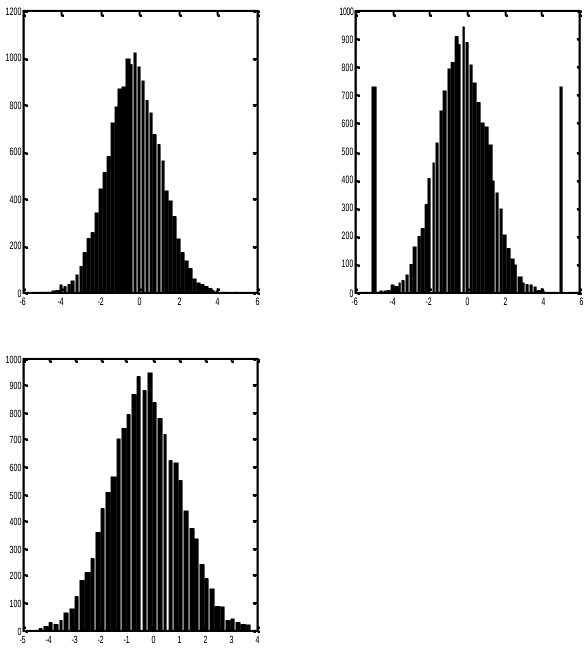

Fig. 5. Top left figure - Data generated by FARIMA (0,d, 0) process for H =0.9 (H measured by HEAF (2) = 0.858), N = 16384. Top right figure – generated Noisy sample (measured H = 0.701). Bottom figure - H = 0.857 (after elimination of the outliers) where alpha = 0.045

In Figure 6, uniform random numbers are chosen to generate FARIMA (0,d,0) sequences for various Hurst parameters. Due to uniform random function used in the process, FARIMA (0,d,0) generates only positive sequences, which can imitate real Internet packet sequences. It is clear from the results presented in this research that additive outliers can be removed by applying robust ACF and after elimination of these outliers from different case study, it is evident that HEAF(2) yields a reliable value of H.

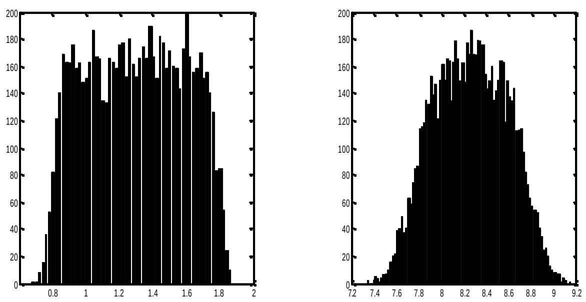

Fig. 6. Left figure - FARIMA (0,d,0) for H = 0.6 (measured H by HEAF(2) = 0.579), N = 8192. Right figure – FARIMA (0, d, 0) for H = 0.8 (measured H by HEAF(2) = 0.774), N = 8192.

VI. CONCLUSION

It is possible to end up with wrong conclusions and wrong models when measuring the intensity of the LRD with unreliable estimators. In this research we have shown that the plausible H for given data can be overestimated or underestimated due to additive outliers possessing in the data. These outliers can be removed by applying robust ACF in HEAF(2) and in this case HEAF(2) yields a consistent and reliable results. Because of the simplicity, robustness and reliability, we believe that HEAF(2) can be used to estimate the intensity of LRD in real time network traffic.

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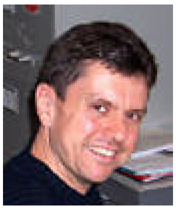

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