Level-Shift detection in communication network traffic traces

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Fecha de recepción: 21 de febrero de 2011 – Fecha de aprobación: 11 de julio de 2011

ABSTRACT
A method for the accurate detection of level-shifts in $1/f^{\alpha}$ communication network traffic traces is presented in this article. The method is based on the definition of the concept of physical information in the time-scale domain. It is shown that wavelet physical information describes the complexities associated to fractal $1/f^{\alpha}$ signals and shows robustness in detecting weak level-shifts embedded in these signals. Experimental results using synthesized signals mimicking signals with level-shifts validate our results. Applications of wavelet physical information to real $1/f^{\alpha}$ traces, particularly in detecting route-changes in delay time series and jumps in VBR video traffic are discussed.

Keyword: Communication network, Wavelets, fractal $1/f^{\alpha}$; signals.

Detección de cambios de niveles en trazas de tráfico de redes de comunicación

RESUMEN
Este artículo presenta un método para la detección eficiente de cambios de nivel en trazas de tráfico en redes de comunicaciones. El método se basa en la aplicación del concepto de información física en el dominio tiempo-escala. Se muestra que la información física en el dominio de las ondoletas describe las complejidades asociadas a las señales fractales del tipo $1/f^{\alpha}$ y se muestra que es robusta en la detección de cambios de nivel de baja amplitud añadidos a estas señales. Resultados experimentales usando señales simuladas con cambios de nivel muestran la validez de nuestras afirmaciones. Se discuten de igual manera aplicaciones de la información física en el dominio de las ondoletas en la detección de cambio de rutas en trazas de retardos y saltos en trazas de video VBR.

Palabras Clave: Redes de comunicaciones, Ondoletas, señales fractales $1/f^{\alpha}$

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Nota: El período de discusión está abierto hasta el 1º de marzo de 2012. Este artículo de investigación es parte de **Ingeniería–Revista Académica de la Facultad de Ingeniería, Universidad Autónoma de Yucatán**, Vol. 15, No. 2, 2011, ISSN 1665-529X.

INTRODUCTION

Fractal processes describe a large number of phenomena appearing in diverse fields of science. The voltage fluctuations in resistors, semiconductors and vacuum tubes (Frieden and Hughes, 1994); aggregated traffic in communications networks (Leland *et al.* 1994); wireless communications tra-ffic (Lee and Fapojuwo 2005) and laser propaga-tion through turbulent media (Zunino *et al.* 2004) represent just a partial list of such phenomena. Fractal processes are characterized among other properties by self-similarity and $1/f$ power spectrum. Parameter estimation has been recognized as an important issue in characterizing such signals (Taqqu *et al.* 1995) and many estimators have claimed to provide efficient and accurate estimation under the assumption of pure fractal behaviour. Estimation of parameters of fractal processes, however, remains a field of active research due to the absence of a robust estimator capable of dealing with the many features encountered in recorded data (Serinaldi 2010). Periodicities, missing values and level-shifts impact significantly the estimated parameters giving rise to biased estimates and consequently misinterpretation of the phenomena. Motivated by this, the paper defines the notion of physical information in a dyadic time-scale representation of the data (Wavelet Physical Information, WPI) and explores the possibility to use its properties for the detection of level-shifts embedded in stationary and non-stationary fractal processes of parameter $\alpha, \alpha \in R$. The proper detection of such level-shifts will improve the overall estimation process. As a matter of fact, the paper shows that WPI detects level shifts in stationary and non-stationary contexts using synthesized signals mimicking fractal-like properties. The application of WPI in several real communication network traffic trace is presented. In particular, it is shown that WPI can detect route-change in delay times series traces and also jumps in Variable-Bit-Rate (VBR). The organization of the paper is as follows. Methodology section reviews fractal processes and its wavelet analysis. It also constructs probability mass functions (pmfs) using the wavelet spectrum of fractal signals. The notion of physical information based on Fisher information measure (FIM) is briefly described and the wavelet physical information (WPI) is defined. Finally, this section provides description of the procedure used for detecting level-shifts in fractal signals using WPI and synthetic fractal processes with known parameter α. Results and discuccion section presents experimental results of the WPI as level-shift detection by using synthesized signals with fractal-like behaviour and evaluates its ability to detect routing changes in real traces and jumps in VBR video traces. Finally, the conclusion of the paper is given.

METHODOLOGY

Fractal Signals

Fractal random processes have been found in numerous fields of science and technology. They are characterized by *self-similarity* and $1/f^{\alpha}$ power spectrum. *Self-similarity* is defined as invariance of statistical properties under proper scaling of time and space, i.e.,

$$X(at) \stackrel{d}{=} a^{-H}X(t), \qquad (1)$$

for a process $X(t), t \in \mathbb{R}$ and $\alpha \in \mathbb{R}$. $1/f^{\alpha}$ spectra, on the other hand, dictates the form of the spectral density function (SDF) as a power-law in a range of frequencies, formally $X(t)$ presents a $1/f^{\alpha}$ spectra if

$$S_x(f) \backsim c_f|f|^{-\alpha}, f \epsilon (f_a, f_b) \qquad (2)$$

and c_f is a constant where f_a and f_b represent the lower and upper frequencies upon which the power-law holds. Depending upon α, these processes exhibit time-dependent and time-independent moments. When $\alpha \in (-1,1)$, the process is stationary while for $\alpha \in (1,3)$, process is regarded as non-stationary. Many stochastic models satisfy the conditions of *self-similarity* and $1/f^{\alpha}$ spectra. The most popular, by far, are fractional Brownian motions (fBm), fractional Gaussian noises (fGn), pure-power-law models and fractional ARIMA signals. For more details on the definition, properties and estimators of *self-similar signals* please refer to (Beran 1994, Percival 2003 Lee and Fapojuwo 2005).

Wavelet Analysis of Fractal Signals

Wavelets and wavelet transforms have played an important role in the analysis, estimation and modeling of signals with fractal-like structure (Abry and Veitch 1998, Veitch and Abry 1999, Soltani, *et al.* 2004, Pesquet-Popescu 1999). In-deed, estimators based on orthonormal wavelet transforms (OWT) are recognized as the more efficient non-parametric estimators of α, by far, the principal parameter characterizing scaling or fractal signals. Although these estimators are efficient they tend to overestimate stationary fractal signals in the presence of level-shifts of amplitude (1) (Stoev *et al.* 2005). Let $X(t)$ be a fractal process with SDF satisfying equation (2), the discrete wavelet transform (DWT) of $X(t)$, at time $k \in \mathbb{Z}$ and scale $j \in \mathbb{Z}$ is defined as $d_x(j,k) \triangleq 2^{-j/2} \int X(t)\psi(2^{-j}t-k)dt$ for some dilated and translated mother or analyzing wavelet $\psi(t)$.

The family of functions $\psi_{j,k}(t) \triangleq 2^{-j/2}\psi(2^{-j}t-k)$ form an orthonormal set and thus any function $X(t) \in \mathcal{L}_2(\mathbb{R})$ (of finite energy) can be represented as $X(t) = \sum_j \sum_k X(t) d_X(j,k)$. For fractal processes the variance of such DWT or wavelet coefficients, $\mathbb{E}d_X^2(j,k)$, called the wavelet apectrum or wavelet variance is of primary importance since for fractal singnals they satisfy

$$\mathbb{E}d_X^2(j,k) \backsim 2^{j\alpha}C(\psi,\alpha), \qquad (3)$$

where $C(\psi,\alpha) = c_\gamma \int |f|^{-\alpha}|\Psi(\mathrm{f})|^2 df$ and $\Psi(f)$ is the Fourier Transform of the mother wavelet $\psi(t)$ at Fourier frequency f. The importance of the wavelet spectrum resides in its ability to estimate α (Abry *et al.* 2009, Stoev *et al.* 2005, Flandrin 1992) and to construct form such a representation probability mass functions (pmf) which would allow a deeper understanding of their dynamics and nature (Zunino *et al.* 2007, Perez *et al.* 2007, Kowalski 2009). Indeed, estimation from such wavelet spectrum representation has been shown to be robust to periodicities and trends of polynomial nature. Probability mass functions derived from the wavelet spectrum allowed to define quantifiers such as wavelet entropy (Zunino *et al.* 2007), wavelet q-entropies (Kowalski 2009) among others. The pmf derived from the wavelet spectrum takes the form

$$p_j = \frac{(N_j)^{-1}\sum_k \mathbb{E}d_X^2(j,k)}{\sum_{i=1}^{\log 2(N)}(N_i)^{-1}\sum_k \mathbb{E}d_X^2(j,k)} \qquad (4)$$

where N_j representss the number of wavelet coefficients at scale j. The pmf for a $1/f^\alpha$ signal of length N is determined by direct application of equation (3) to equation (4) which results in

$$p_j = 2^{(j-1)\alpha}\frac{1-2^\alpha}{1-2^{\alpha M}}, \qquad (5)$$

where $M = \log 2(N)$. As indicate above numerous information theory quantifiers can be determined by the use of such a pmf. The paper defines a novel quantifier based on Fisher's information measure and the DWT representation of fractal signals.

Fisher's information measure

Fisher's information measure (FIM) has recently been applied to several problems of physics and engineering (Martin *et al.* 2001) (Martin *et al.* 1999) (Telesca 2005). Actually, FIM has been employed for the detection of changes in non-linear dynamical systems (Martin *et al.* 2001), detection of epileptic seizures in EEG signals (Martin et al 1999) and for the analysis of geoelectrical signals (Telesca 2005). Let $X(t)$ be a signal with associated probability density function (PDF) $f_X(x)$. The Fisher's information of $X(t)$ is defined as

$$I_X = \int \left(\frac{\partial}{\partial x} f_X(x)\right)^2 \frac{dx}{f_X(x)}. \qquad (6)$$

Fisher's information, I_X is a non-negative quantity that yields large (possibly infinite) values for smooth (ordered) signals and small (~ 0) values for random (disordered) signals. In a similar manner, Fisher's information is large for narrow PDFs and small for wide (or flat) PDFs. For instance, Fisher's information is expected to be small for Gaussian white noise and large for fBm. Fisher's information has been applied in a time-domain context in the framework of the analysis of stationary signals. Actually, Fisher's information has been applied to non-linear time series using a discretized version of equation (6) as

$$I_X = \sum_{l=1}^{L}\left\{\frac{(p_{l+1}-p_l)^2}{p_l}\right\} \qquad (7)$$

that is suitable for discretized random data with associated pmf p_l. Equation (7), when computed in sliding windows is called Fisher's information measure (FIM).

Wavelet Physical Information

Since $1/f^{\alpha}$ signals have a well-defined pmf in the time-scale domain (as given by equation (5)), a Fisher's information quantifier can be associated to these signals. The Fisher's information (represented by equation (6)) applied to equation (5) is referred in this work to as *wavelet physical information* (WPI). WPI is thus a dyadic time-scale version of Fisher's information computed with the aid of orthonormal DWTs. With the Fisher's information computed in this way, WPI is expected to inherit all the properties associated to both wavelet transforms and Fisher's information. Actually, by defining FIM in the time-scale domain, WPI is expected to detect changes in stationary and non-stationary $1/f^{\alpha}$ signals even in the presence of polynomials trends embedded in these signals. Fisher's information of $1/f^{\alpha}$ signals take the particular form

$$I_{1/f} = \frac{(2^{\alpha}-1)^2\left(1-2^{\alpha(M-1)}\right)}{1-2^{\alpha M}}, \qquad (8)$$

which is a non-negative quantity nearly independent of length $M = \log 2(N)$. The WPI corresponding to $1/f^{\alpha}$ signals is thus dependent upon α as is expected since this parameter determines their ordered and disordered character. WPI is expected to be low in the interval $\alpha \in (-1,1)$ and higher in the interval $\alpha \in (1,3)$. Accordingly, WPI is lower for stationary $1/f$ signals and higher for non-stationary ones. WPI, thus characterizes the complexities associated to $1/f^{\alpha}$ signals in the same way as wavelet entropies and q-entropies (Kowalski 2009) do. Note, however that unlike wavelet q-entropies, WPI, associates high values to ordered signals and small values to disordered ones. Based on this behavior and the fact that for signals with embedded level-shifts the estimated $\hat{\alpha} = 1$, the paper attempts to use WPI as a level-shift detector and studies its robustness for synthesized stationary and non-stationary fractal signals of pure-power-law type. The appropriateness of WPI as a shift-level detector will greatly enhance the overall estimation process and will be expected to be useful in areas such as electronics, communications networks, wireless communications, physics among others.

Computation of WPI

There is several ways in which WPI can be computed. The most common are to compute WPI in the whole signal and in sliding windows of size w, simulating a real-time computation. The latter is more robust and more suitable to our purposes since it allows to follow the temporal evolution of the WPI. Formally, let $X(t_k)$ be a signal of length N, a subset of $X(t_k)$ at time $m\Delta < t_k < \omega + m\Delta$ for $t_k, \Delta \in \mathbb{Z}$ can be determined as

$$X(m;\omega,\Delta) = X(t_k)\Pi\left(\frac{[t-m\Delta]}{\omega} - 1/2\right) \qquad (9)$$

where $m = 0,1,2,\ldots$; Δ is a sliding factor, ω is the size of the window and $\Pi(t)$ is the well-known rectangular function. To every subset $X(m;\omega,\Delta)$ of $X(t_k)$ a WPI is computed to obtain $I_X(m)$. $I_X(m)$ represents the degree of disorder of the segment of $X(t_k)$ at $(m\Delta, \omega + m\Delta)$. Finally, the evolution in time of WPI for $X(t_k)$ is archived by plotting the relation

$$I_X = \{(\omega + m\Delta, I_X(m))\}_{m=0}^{m_{max}} \qquad (10)$$

where m_{max} is the number of window computed. For $\Delta = \omega, m_{max} = N/\omega$. Figure 1 illustrates the WPI for a fractal signal of type fGn with $\alpha = 2H - 1 = 0, \Delta = 50$ and $\omega = 1024$. Note that WPI is always non-negative and the evolution of the WPI displays small peaks as expected since fGn with H=0.5 is totally disordered. The small peaks can be associated to small changes in the structure of the signal and not to the presence of a non-stationarity. Figure 2 displays the WPI evolution for a smooth signal representing a more ordered behaviour than that observed in figure 1. Figure 2 portrays the time evolution of WPI for a non-stationary fBm of index $\alpha = 2H + 1 = 2$ and analyzed using $\Delta = 50$ and $\omega = 1024$. Note that WPI evolution displays peaks with higher amplitude than the WPI of fGn. These peaks are also associated to small changes in the structure of the fBm signal. The above-observed behaviour was expected since for fractal signals the higher the α the smoother the signal (Eke *et al.* 2000). In the case of fractal signals, when $\alpha > 0$, as α increases, the WPI is expected to increase. Thus, we have shown that WPI provides a plausible explanation to the complexities associated to fractal signals, in the same way as q-entropies do.

Note that unlike q-entropies (which decrease) WPI quantifies ordered behaviour by high values.

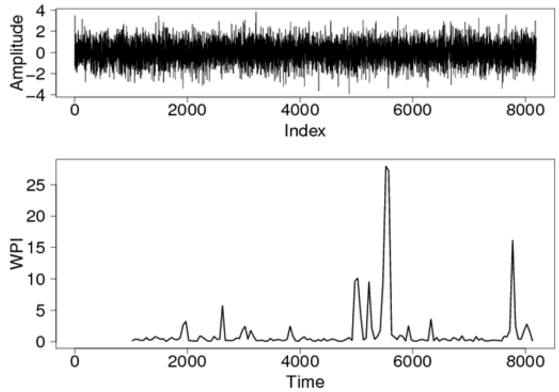

Figure 1. WPI for a fGn signal with $H = 0.5$. Top plot depicts the stationary fractal signal while bot-tom plot illustrates the time evolution of its WPI.

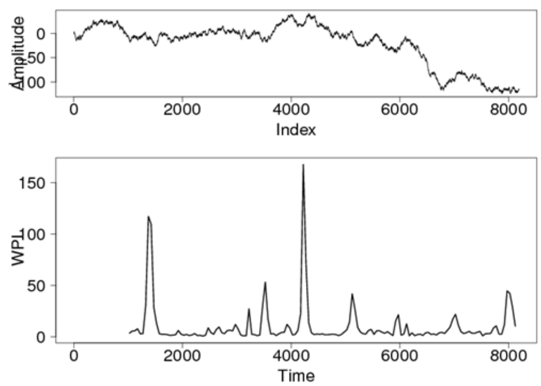

Figure 2. WPI for a fBm signal with $H = 0.5$. Top plot depicts the non-stationary fractal signal and the bottom plot illustrates the time evolution of its WPI.

Level-shift detection with WPI

It has been reported that the presence of level-shifts, periodicities, trends and other types of non-stationarities impact signficantly the estimated index α in recorded stationary fractal signals. Most estimators are subject to biases when the signal under study has these non-stationarities embedded in its structure. Because of this, several approaches have been advanced mainly to improve the overall estimation process. In (Stoev *et al.* 2005), the wavelet spectrum is reported to be a useful tool for detecting these phenomena and the effect of several non-stationarities on the so-called log-scale (LD) diagram (Abry and Veitch 1998) was studied. Additionally in (Shen *et al.* 2007) an algorithm capable of constructing the level-shifts present in the signal was presented. Once the level-shifts were constructed they were eliminated in the analyzed signal. Wavelet spectrum-based shift-level detection has limited applicability due to the fact that it relies in the study of the deformation of LD diagram in the presence of a level-shift. However, such deformation may be caused by other fractal signals, not necessarily a level-shift. The method proposed in (Shen *et al.* 2007) is robust but complex. In addition the above-referred works limited their attention to stationary fractal signals. This article proposes to use the WPI of fractal signals as a means to detect such level-shifts in stationary and non-stationary settings. The detection capabilities of WPI is first studied by using synthesized signals conforming to equation (2) in all the frequency range (pure-power-law). Signals exhibiting this behaviour were generated by the use of the fractal package of the statistical software **R**. Once the fractal signal is synthesized, the next step is to add to this signal level-shifts. In order to synthesize fractal $1/f^{\alpha}$ signals with level-shifts the following operation was performed

$$B(t) = X_{1/f}(t) + \sum_j \mu_j 1_{[t_j,t_j+N]}(t), \qquad (11)$$

where $X_{1/f}(t)$ is the $1/f^{\alpha}$ signal and $1_{[t_j,t_j+N]}(t)$ is the indicator function of amplitude μ_j defined in the interval $(t_j, t_j + N)$. $B(t)$, thus, represents a $1/f^{\alpha}$ signal with level-shift embedded in its structure. We synthesize signals where the level-shifts are not detected by eye. The time evolution of $B(t)$ is then analyzed by WPI and the presence of level-shift searched. The presence or absence of a level-shift is based on the following experimentally observed behaviour.

1. WPI increases when the level-shift is in the window of observation.
2. WPI maintains this high value whenever the level-shift duration is in the window of observation.

It is important to stress that the increase in WPI to the presence of a level-shift is significantly higher than when the level-shift is not present. Based on this, it can be inferred that a level-shift narrows the PDF of the signal plus level-shift and based on this property, accurate detection of level-shifts is accomplished. Note also, that by the use of WPI not only the beginning but also the complete duration of the level-shift can be detected.

RESULTS AND DISCUSSION

Detection in stationary signals

Figure 3, displays the WPI (Bottom plot) of a stationary pure-power-law signal with $\alpha = 0.50$ (Top plot). The length of the signal is 2^{13} points. The fractal signal is analyzed using a sliding window of length $\omega = 1024$ and sliding factor of $\Delta = 50$. Level shifts are added to the fractal signal at time instants $t \in \{1500,2000,4000,4500,6500,700\}$ with alternating amplitudes of $+0.5$ and -0.5. The breaks embedded in the fractal signal are plotted in white in top plot for reference. Note that as long as the level-shift is in the window of observation, WPI increases and preserves this high value. At the time the level-shift is not in the window of observation, WPI decreases to a small value that approaches zero. Same behaviour is observed for signals in the interval $\alpha \in (-1,1)$ (stationary signals). Note that WPI not only detects the beginning but also the complete duration of the level-shift. Thus, for stationary fractal signals, WPI provides a robust detection of level-shifts with amplitudes higher than 0.5 . These amplitudes are by far lower than amplitudes of changes reported in (Martin *et al.* 1999) which in fact are observed by eye. These results demonstrate that level-shifts narrows the PDF of the observable signal, a property which is used by WPI for detecting such non-stationarity.

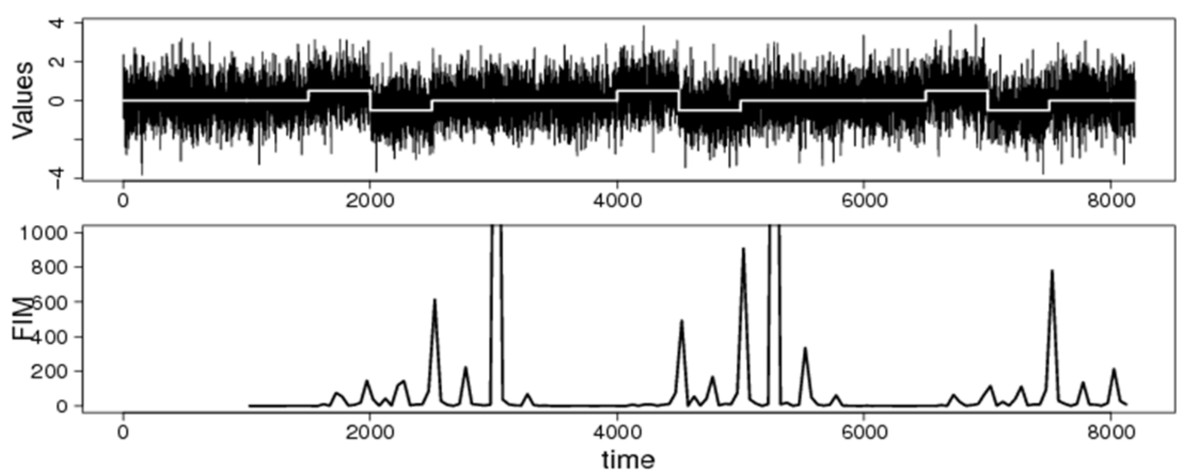

Figure 3. Detection of level-shifts embedded in a stationary fGn signal with $H = 0.50$. Top plot display the fractal signal plus breaks in black. Same plot displays the level shifts added to the fractal signal in white. Bottom plot presents the wavelet physical information of the top plot using $\omega = 1024$ and $\Delta = 50$.

Detection in non-stationary signals

Figure 4 displays the WPI (Bottom plot) of a non-stationary pure-power-law signal of parameter $\alpha = 1.70$. The length of the signal is 2^{13} points and the breaks embedded in this signal are of the same nature of the breaks in stationary signal studied above. It has been reported that level-shift detection is more complex for non-stationary signals since most detectors are based on techniques which require the stationary assumption in the signals to work. WPI displays a high value as long as the window of observation covers the level-shift. When this is not the case, WPI is small. In the same way as the WPI observed in stationary signals, the WPI of non-stationary ones allow to follow the beginning and complete duration of the level shift with high accuracy. Similar results are observed when analyzing non-stationary pure-power-law signals in the range $\alpha \in (1,3)$. Consequently, WPI allows to detect, with high accuracy, level-shifts in stationary as well as non-stationary fractal signals of parameter α. The above results suggest that WPI must be used as part of the estimation process in order to improve the estimation of α. It is expected that by the use of WPI, the biases observed in the presence of a non-stationarity be detected and eliminated. In particular, the procedure for estimating α, in stationary and non-stationary frameworks, reported in (Eke *et al.* 2000) can be greatly improved by the use of WPI.

Applications to Communication network traces

It is known that packets in Internet travel through multiple hops in a route and that a change in routing damages the network Quality of Service (QoS). For instance, outages, loops and instability routes are routing pathologies present in the network (Paxson 1997, Borella et al 1997). The routing instability requires a continuing use of CPU-switching implying an excessive use of resources and the limitation of the World Wide Web (WWW) growth. Also this pathology produces a fast Border Gateway Protocol (BGP) refresh which bounds the communications between Autonomous Systems (AS). Additionally, routing instability can lead to packet loss, increased network latency and time to convergence (Labovitz *et al.* 1997). Stanford Linear Accelerator Center reports routing instability pathologies in its web page (SLAC 2001). The solution to this problem has been boarded from different perspectives: the aggregation of IP prefixes into a set of specific network routers (Labovitz *et al.* 1997) and the off-line analysis of traceroute traces to detect the path with the problem (Paxson 1997b), however, theaccelerated growth of Internet disable a fixed labeling of routers and the guarantee of a constant network performance is only achievable if the instability is detected on-line. Moreover, a non-stationary behavior is presented in network parameters such as delay. Thus, the contribution of this work is a methodology for instability detection through Wavelet-based Physical Information in real traces. Figure 5 display a delay trace affected by a typical instability in a high traffic hour. The instability pathology produces a level-shift in the delay trace which was located at time 5800. Because WPI was computed with $\omega = 1024$, the route change detection was phased but efficiently detected. Delay in Internet presents a high variability behavior that degrades the network performance and can be observed at time 5000; the statistical tool proposed in this paper (WPI) is no perturbed by this kind of outlier. As a final point, the early detection of some network pathologies advances the routing task and improves the QoS. An additional application of WPI is in the analysis of VBR video traces. VBR video traces will represent in the future the major type of traffic transported in communications networks.

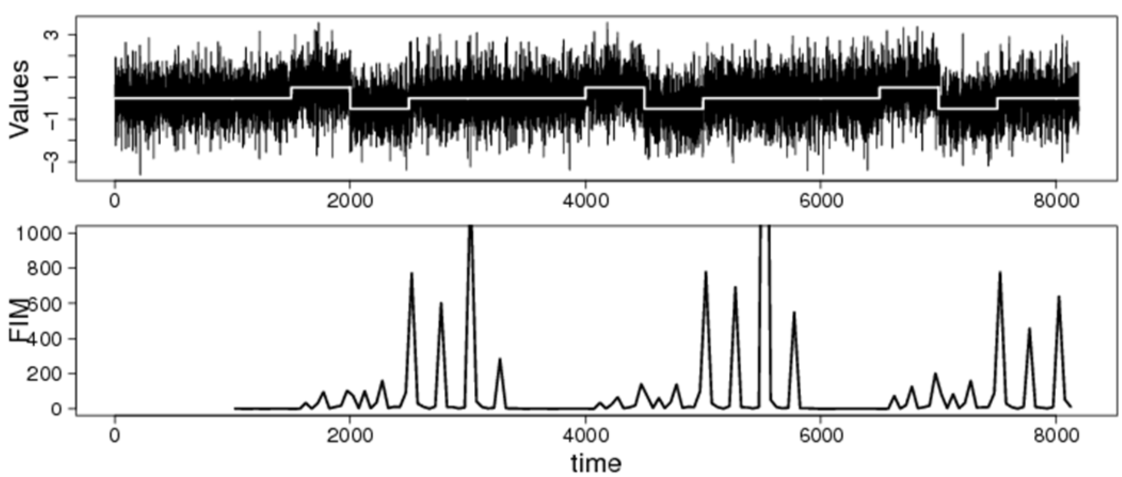

Figure 4. Detection of level-shifts embedded in a non-stationary fBm signal with $H = 0.50$. Top plot display the fractal signal plus breaks in black. Same plot displays the level shifts added to the fractal signal in white. Bottom plot presents the wavelet physical information of the top plot using $\omega = 1024$ and $\Delta = 50$.

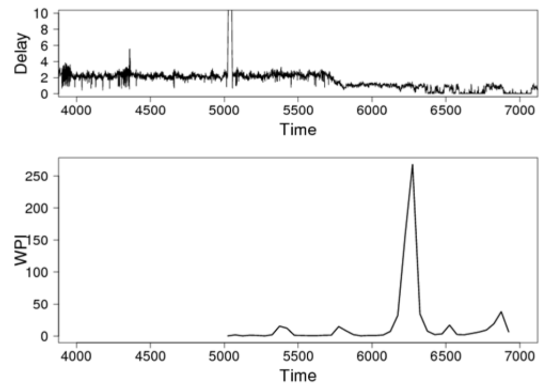

Figure 5. WPI for WWW trace with route-change.
Top plot depicts the real trace while bottom plot illustrates the time evolution of its WPI.

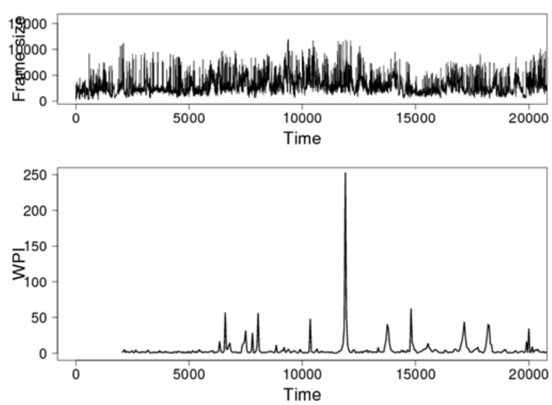

Figure 6. WPI of Mr Bean VBR Video Trace. Y axis represents the number of frames per time.

Thus, an accurate characterization of these signals will aid in the design of future networks. VBR video traffic has been shown to exhibit self-similar behaviour (Beran 1994, Lee and Fapojuwo 2005) and thus standard fractal analysis tools should be employed. Wavelet estimation tools, however, leads to Hurst indices $\hat{H} > 1$ (Stoev *et al.* 2005), an indicator of the presence of a non-stationarity embedded in the signal. Motivated by this, we apply the WPI to various VBR network traffic traces to detect the presence of jumps embedded in the signal under study. Figure 6 displays a VBR video trace and its associated WPI computed in windows of length $\omega = 2048$. Note that the WPI of this signal exhibits peaks, an indicator of the presence of a level shift embedded in the signal. The trace represent the number of frames in the video Mr Bean per unit of time encoded using a VBR codec. Figure 7 displays the trace and its associated WPI for the video Star Wars IV. As in the previous figure, peaks are also encountered in this signal. Again, this signal can be thought of a stationary signal with jumps embedded in its structure. Finally, figure 8 depicts the WPI of VBR video trace Jurassic Park. Note that as in previous traces, the WPI of this signal exhibits peaks with suggest that in general VBR video traces can be modeled as a fractal signal with level shifts. This model explains the biases in the estimated scaling exponents and the estimated $\hat{H} > 1$.

This result is important since future communications network are expected to transport a high percentage of video traffic and thus the design of network algorithms will be based on accurate models of this traffic.

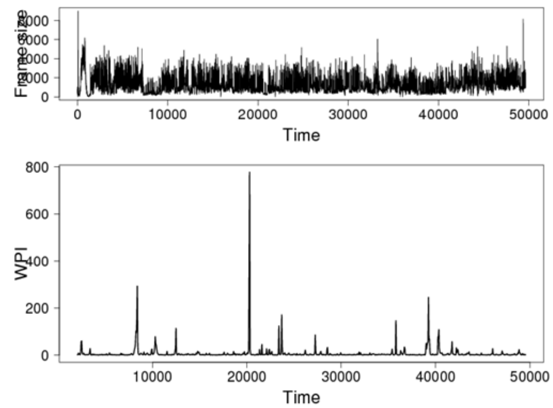

Figure 7. WPI of Star Wars IV VBR Video Trace.
Y axis represents the number of frames per time.

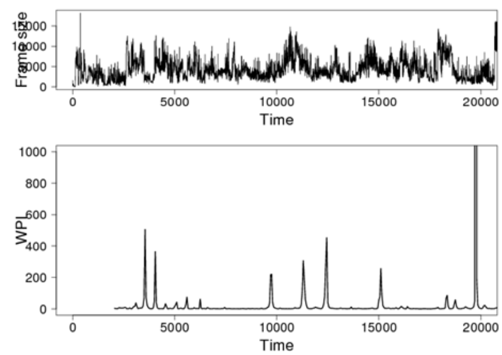

Figure 8. WPI of Jurassic Park VBR Video Trace.
Y axis represents the number of frames per time.

CONCLUSIONS

A novel method for detecting weak level-shifts in stationary and non-stationary $1/f^{\alpha}$ signals with emphasis to fractal communications network traffic traces was presented in this article. Wavelet physical information, basically tantamount to computing Fisher information functional on a dyadic time-scale representation of the data was shown to be robust in the detection of level shifts added to $1/f^{\alpha}$ signals. WPI permits to track both the beginning and total duration of the level-shifts embedded in $1/f$ signals. WPI allowed the description of the complexities associated to fractal signals in the same way as wavelet q-entropies do. A closed form expression for the WPI of $1/f^{\alpha}$ signals was obtained and applications to the analysis of real network traffic traces discussed. WPI detects changes of route in delay time series traces and also jumps in VBR video traffic traces. The results demonstrate that WPI is an excellent alternative tool for characterizing network traces.

Acknowledgments

The authors would like to thank at FOMIX-COQCYT (number 126031), internal funds of Universidad del Caribe and CONACYT for funding this project.

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Este documento debe citarse como:
Ramírez Pacheco, J., Torres Román, D., Rizo Domínguez, L., Trejo Sánchez, J., Manzano Pinzón F. (2011). **Level-Shift Detection in Communication Network Traffic Traces**. Ingeniería, Revista Académica de la FI-UADY, 15-2, pp 81-91, ISSN: 1665-529-X.