International Journal of Electrical, Electronic and Communication Sciences
ISSN: 2517-9438
Vol:3, No:10, 2009

A Methodological Approach for Detecting Burst Noise in the Time Domain

Liu Dan, Wang Xue, Wang Guiqin and Qian Zhihong

***Abstract*—**The burst noise is a kind of noises that are destructive and frequently found in semiconductor devices and ICs, yet detecting and removing the noise has proved challenging for IC designers or users. According to the properties of burst noise, a methodological approach is presented (proposed) in the paper, by which the burst noise can be analysed and detected in time domain. In this paper, principles and properties of burst noise are expounded first, Afterwards, feasibility (viable) of burst noise detection by means of wavelet transform in the time domain is corroborated in the paper, and the multi-resolution characters of Gaussian noise, burst noise and blurred burst noise are discussed in details by computer emulation. Furthermore, the practical method to decide parameters of wavelet transform is acquired through a great deal of experiment and data statistics. The methodology may yield an expectation in a wide variety of applications.

***Keywords*—**Burst noise, detection, wavelet transform

I. Introduction

WITH the rapid development of contemporary electronic, electrical and computer techniques, there are more and more rigorous demands to electronic circuits and devices. It is inevitable to have some defects in electronic circuits or devices due to inherent factors like fabrication workmanship. What we are focusing on is detecting those devices with defects from electronic devices or circuits.

When bipolar transistors have severe g-r noise, a series of random jumps like rectangle pulses, with different width and similar amplitudes, may be found, which is so called Burst Noise, or Popcorn Noise. In addition, there are some other burst noise phenomena like sporadic burst noise generated from arc discharge [1], but burst noise generated from fault devices proves to be the most involved.

The earliest model describing burst noise was proposed by Hsu at al [2]. According to this model, metal impurities precipitate in the space-charge region of an emitter-base junction and compose a metal-semiconductor point contact with semiconductor. If there is a dislocation-like g-r center in the space-charge region formed by a point contact, the center occupied by carriers may give rise to fluctuating voltage to control the current flowing through metal-semiconductor junction so as to contribute noise. The pulse amplitude and pulse width of the noise behaves as an abrupt style.

A further interpretation to the origin of burst noise is presented in the literature [3], in which the author found it may bring about burst noise if there is a high density of impurity levels in a barrier potential section with forward bias of a p-n junction, and the defects just locate adjacent to the cross of defective levels and Fermi levels. The explanation implies that metal impurities are dispensable for burst noise. The occurrence of burst noise is particularly troublesome for an electronic component or a system because its amplitude in radio frequency range is much higher than the thermal or 1/f noise normally observed in the device or system. As a summary of above-mentioned, the author believe:

1. Burst noise is substantially ascribed to g-r noise. When semiconductor device have severe defects, that is the density of the impurity levels is high, burst noise may come up.
2. The device with burst noise implies that the device may have severe defects, probably in the p-n junction, hence the device is unreliable.
3. The burst noise comes primarily up in forward-biased p-n junctions of bipolar transistors and in bipolar VLSI circuits as well.

Our lab has ever carried out the testing and analyzing 60 model GO103 optic couplers made in a factory, as a result, of the 60 couplers, 19 showed burst noise to some extent, forming a large portion of the products by 31.7%. If those devices with burst noise were applied into circuits, the reliability of the circuit system would be declined or even fail to work [3].

There is no effective and practicable method to detect burst noise so far. The traditional methods used to detect burst noise should be viewed as approaches for detection within the frequency domain. The methods demonstrate the utility only if the amplitude of burst noise is distinctly high to be identified, and the methods prove to be time consuming, computation cumbersome; therefore, approaches for detection within the frequency domain are not applicable for non-stationary process. Furthermore the weakness of the Fourier domain is that it does not economically represent signals with singularities[4].

Most detection techniques rely on prior knowledge of either

Liu Dan is with 1. College of Communication Engineering, Jilin University, Changchun 2.College of Electric and Information, Changchun Institute of Technology, Changchun,China; (e-mail: lldd2001@gmail.com.)
Wang Xue is with the College of Communication Engineering, Jilin University, Changchun,China(e-mail: yeti_1019@yahoo.com.cn)
Wang Guiqin is with the College of Communication Engineering, Jilin University, Changchun,China (e-mail: wangguiqin2005@163.com)
Qian Zhihong is with the College of Communication Engineering, Jilin University, Changchun,China (phone:+8613504415955e-mail: dr.qzh@163.com).

the signal or the noise performance or both. But a correlator may fail to detect time-varying signals since the waveforms of those kinds of signals may be significantly discrepant sometimes. In other words, the validity of the approach may be questioned on the premise of no more prior knowledge about the signals to be detected[5]. Traditional work, in addition, aimed at reconstructing the power spectral density of random signals using infinitely long sequences of non uniformly distributed signal samples or tackled deterministic signals and estimate the Fourier transform using finite numbers of signal samples, which proves to be accurate[6], however, proves to be hugetime-consuming as well.

Considering the limitations of traditional approaches, we restrict attention signal analyzing in the 2-D plane by wavelet transforms[7]. The wavelet transform can be viewed as a time-frequency representation that has good identifying properties. The analysis of singularity of the signals to be detected tells us that signals and noises have different modulus maxima of wavelet transform in multiscale space so that endowed with advantages beyond debate.

II. Detection Theorem for Transient Signal

Burst noise looks a sequence of random pulses with non-uniform waveform width and comparatively large variation of amplitude. Those random pulses overlap each other sometimes, or far away each other. Observing waveform of burst noise, a transient character can be found whatever on the leading edge or trailing edge of the pulse mode noise, which proves to be an important information for investigation to burst noise. It should be mentioned that it is necessary for us to regard one of them, burst noise, as a "signal" when we study two or more types of noise submerged together.

Burst noise, known to be endowed with singularity of function, can be analyzed by Fourier transforms, investigating decay of the function in the Fourier transform domain so as to deduce whether the function bears singularity or not, and magnitude of the singularity as well. Fourier transforms, however, lack localizing properties, and can only carry the frequency information, whereas, wavelet transforms are endowed with space localizing properties, and can localize the signal in both time and frequency domain simultaneously. It proves to be practicable by exploiting wavelet transforms to estimate and detect nonstationary or time-varying signals [8-11].

The previous work of Mallat indicates: let n be positive integer and n≤α≤n+1, a signal x□t□ is said to be Lipschitz exponentα, at moment t_0 , if and only if there exists two constants A, and a polynomial of order n, P_n□h□, such that for 0<h<h_0 [12].

$$|x(t_0+h)-P_n(h)| \le A|h|^{\alpha} \tag{1}$$

The signal x□t□is said to be uniformly Lipschitz exponentα over an open interval]a□b[, if equation (1) holds for any t_0 □]a□b[□and t_0 +h□]a□b[.

The Lipschitz exponentαof the signal x□t□at t_0 is the magnitude of the local regularity for x(t) at t_0 . The larger value of α, the stronger the local regularity of x(t) at the moment. x(t) is called singularity at t_0 , if the local regularity for x(t) at t_0 is not 1. The classical for measuring the Lipschitz regularity of a function x(t) is to investigate the asymptotic decay of its Fourier transform decay, but one can not determine whether the function is locally more regular at a particular point. This can be interpreted as the Fourier transform unlocalizes the information along the spatial variable. The Fourier transform is therefore not well adapted to measure the local Lipschitz regularity of functions[12].

According to the initial definition of continuous wavelet transform first introduced by Morlet and Grossmann [13], the continuous wavelet transform of a signal x(t) is defined as

$$WT_a x(t) = \frac{1}{a}\int x(\tau)\,\psi\left(\frac{t-\tau}{a}\right)d\tau \tag{2}$$

or it may be written as

$$WT_a x(t) = x(t) \otimes \psi_a(t) \tag{3}$$

here, $\psi_a(t) = \frac{1}{a}\,\psi\left(\frac{t}{a}\right)$ denotes the dilation of basic wavelet functionψ(t) by scale. The following theorem may be exploited to procure the relationship between the uniform Lipschitz exponentαof x(t) in the neighborhood of singularity and the modulus maxima of $WT_a x(t)$ at multiscale.

Theorem 1

Let 0<α<1, and let t□(a,b), x(t) is uniformly Lipschitzαat all points of an open interval if and only if there exists a constant K such that for all t in this interval

$$|WT_{2^j} x(t)| \le K (2^j)^{\alpha} \tag{4}$$

here, 2^j is a discretized scale[14].

Let basic wavelet function be viewed as first-order derivative of Gaussian low-pass function, θ(t), that is

$$\psi(t) = \frac{d\theta(t)}{dt} = -\frac{1}{\sqrt{2\pi}}\, t\, e^{-\frac{t^2}{2}} \tag{5}$$

here,

$$\theta(t) = \frac{1}{\sqrt{2\pi}}\, e^{-\frac{t^2}{2}} \tag{6}$$

If let

$$\theta_a(t) = \frac{1}{a}\,\theta\left(\frac{t}{a}\right) \tag{7}$$

it is not difficult to obtain

$$WT_a x(t) = a\; x(t) \otimes \frac{d\theta_a(t)}{dt} = a\,\frac{d}{dt}\left[x(t) \otimes \theta_a(t)\right] \tag{8}$$

The above formula implies that the continuous wavelet transform of x(t) performs imposing x(t) upon low-pass filtering by the low-pass functions, $\theta_a(t)$ and $\theta(t)$, then procuring derivation calculus. The maxima of $WT_a x(t)$ corresponds to the inflexion of the smoothed signal. The Lipschitz exponent corresponds to transient edges of the signal to be detected is larger or equal to zero, here so called signal to be detected is burst noise in fact, whereas the Lipschitz exponent corresponds to noise is much smaller than zero, therefore, the modulus maxima corresponding to transient edges of the signal to be detected enhances or remains relatively unchanged with larger scales, but the modulus maxima corresponding to wavelet transform of noise decays remarkably with larger scales. Those analysis indicate that both the transient edges of the signal to be detected and the background noise be endowed with singularity, but their modulus maxima of continuous wavelet transform wear quite different character. Hence, it is reasonable to exploit maxima of $WT_a x(t)$ to detect singularity out from signal x(t) and locate precisely.

It is easy to find out from the power spectral density of burst noise that low-frequency components of burst noise without other background noise are abundant, but the energy of the high-frequency components is typical small relative to that of low-frequency. The energy of the high-frequency components and the low-frequency components of burst noise must be retained while background noise is filtered out by decomposition of burst noise in terms of wavelets. Concerning above factors and the waveform features of burst noise, Haar wavelet is to be used to decompose and reconstruct burst noise when burst noise in terms of wavelets, as a signal to be detected here, is carried out. The Haar Wavelet gives a slightly faster decomposition speed compare to the other Wavelets at the same decomposition level[15]. The operation of Haar wavelet is

$$f(t) = \begin{cases} 1, & 0 \le t \le 0.5 \\ -1, & 0.5 < t \le 1 \\ 0, & otherwise \end{cases} \tag{9}$$

Considering the waveform of Haar wavelet, burst noise to be detected is described as

$$s(t) = u(t - t_1) - u(t - t_2) \quad (t_1 < t_2) \tag{10}$$

Here, $u(t)$ denote unit-step function.

Assume that the signal to be detected, burst noise in fact, is not interfered by background noise, that is

$$f(t) = s(t) \tag{11}$$

$f(t)$ is 1 over the interval $t_1 \le t \le t_2$,and it is 0 over other arbitrary interval. When *t* is over the interval $t_1 \le t < t_1 + 2\sigma$ and in the neighborhood of t_1,

$$W_\sigma(t) = \int_{t-2\sigma}^{t} \psi_{a,\sigma}(\tau - t) u(\tau - t_1) d\tau$$

$$= \Psi_{a,\sigma}(\tau - t) u(\tau - t_1)\Big|_{\tau=t-2\sigma}^{\tau=t} - \int_{t-2\sigma}^{t} \Psi_a(\tau - t)\delta(\tau - t_1) d\tau$$

$$= \Psi_a(\sigma) - \Psi_a(t_1 - t + \sigma) \tag{12}$$

Here, $\delta(t)$ denotes unit-impulse function, and $\Psi_a(t)$ is primitive function of $\psi_a(t)$.

By the same token, when *t* is over the interval $t_2 \le t < t_2 + 2\sigma$ and in the neighborhood of t_2 ,

$$W_\sigma(t) = -\Psi_a(-\sigma) + \Psi_a(t_2 - t + \sigma) \tag{13}$$

Whereas when *t* is over the interval $t_1 + 2\sigma \le t < t_2$,

$$W_a(t) = \Psi_a(-\sigma) - \Psi_a(-\sigma) \tag{14}$$

Obviously, $\Psi_\sigma(t) \equiv 0$ keeps on the rest arbitrary interval of the abscissa axis. It is easy to be obtained since $\psi_a(t)$ is restricted, mentioned above, that

$$\Psi_\sigma(\sigma) = \Psi_\sigma(-\sigma) = 0 \tag{15}$$

Based upon the above, it is obtained that

$$W_\sigma(t) = \begin{cases} -\Psi_a(t_1 - t + \sigma), & t_1 \le t < t_1 + 2\sigma \\ \Psi_a(t_2 - t + \sigma), & t_2 \le t < t_2 + 2\sigma \\ 0, & \text{otherwise} \end{cases} \tag{16}$$

The formula indicates the singularity at the positive-edge or negative-edge of burst noise.

The local Lipschitz exponents of a signal can be estimated by tracing the evolution of its wavelet transform modulus maxima. With the assumption that "noiseless" signals have singularities with positive Lipscliitz exponents while the noise creates singularities whose Lipschitz exponents are negative, the detection of signals in noise can be effectively solved [15]. It can be proved that Gaussian noise is a random distribution endowed with singularities at any point along the abscissa axis, with negative singular exponent $\alpha = -\frac{1}{2} - \varepsilon$, $\forall \varepsilon > 0$, while singular exponent of a unit-step function is $\alpha = 0$. By means of algorithms for singularity and modulus maxima of wavelet transform coefficients, one can estimate that the singularity at some point is brought about by burst noise or background noise so as to estimate the turning-up moment and impulse width of the burst noise.

Here, we regard burst noise as a generic signal to be analyzed. The high frequency of a one-dimensional discrete signal influences on the first level of the high frequency based on the decomposition of the signal in terms of wavelets, whereas the low frequency of the signal influences on the last level and low frequency based on the decomposition[16]. If the decomposition of Gaussian noise in terms of wavelets is carried out, it can be found that the amplitude of the high frequency coefficients decays associated with augmenting of decomposition levels, and the variances of the high frequency coefficients decay quickly as well.

III. Simulation and Analysis on Burst Noise Detection

Regarding probability distribution functions of noise, noise can be divided into Gaussian noise, following a normal distribution, and non-Gaussian noise. In linear two-port analogous circuits, Gaussian noise is predominant noise, and color noise occurs primarily at fairly high or fairly low frequency [17].

Let's focus on a prototype version, to study the characteristics of additive Gaussian noise by multi-resolution analysis. Fig. 1 presents the emulation experiment results of multi-resolution analysis on each step in terms of Gaussian noise. In Fig. 1, A3 denotes the 3rd -step-up reconstruction signals gotten from low-frequency wavelet decomposition coefficients of decomposed Gaussian noise; D3 denotes the 3rd -step-up reconstruction signals gotten from scale high-frequency wavelet decomposition coefficients of decomposed Gaussian noise; D2 denotes the 2nd -step-up reconstruction signals gotten from scale high-frequency wavelet decomposition coefficients of decomposed Gaussian noise; and D1 denotes the reconstruction signals through the process of 1st up decomposition. Fig. 1 indicates that high-frequency wavelet decomposition coefficients gradually decrease associated with larger scales, which corresponds with the previous analysis.

Burst noise in an electronic device generally has a series of pulses with approximate amplitudes and varied pulse-widths, but pulse amplitudes of different electronic device defer each other. Computer emulation is carried out in our experiment to generate burst noise waveforms, which is shown in Fig. 2. Here, we assume that the signals to be observed are two rectangle pulses to represent burst noise waveforms, which have the same amplitudes and different pulse-widths. The burst noise waveforms obtained by measuring in reality are not highly desirable as we assumed due to background noise interfused, but it does not impact our study consequence because there is fair agreement between real burst noise and the burst noise we made, the rectangle pulses with background noise.

It is intractable to detect burst noise immerged in the background noise. The threshold strategy has to be taken into account because those two noise mix together. In terms of the model of the noise to be detected, 4 ways may be considered to determine thresholds as follows:

- Universal Thresholding Rule [18], the simplest threshold selection rule.
- A wavelet threshold selection based on Stein's unbiased risk estimator theory, or SURE. One can obtain risk estimation for a defined threshold and selected threshold by means of minimize the non-likelihood threshold.
- A heuristic variant of SURE, by mixing the two previous rules [19].
- Another threshold rule realizes the minimum of the maximum mean square error in a given set of functions, and this rule is named the Minimax Threshold Selection Rule.

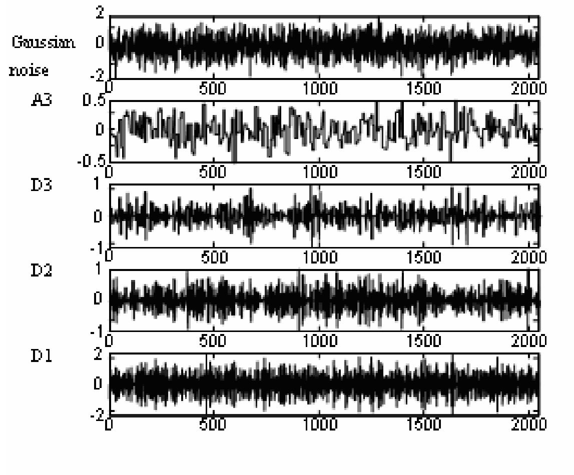

Fig.1 Wavelet mult-resolution analysis additive Gaussian noise

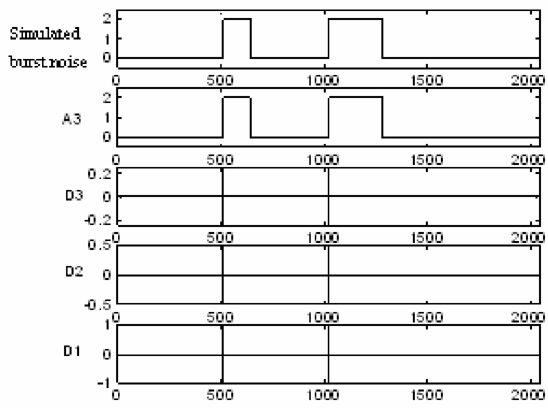

Fig. 2 Wavelet Mult-resolution analysis for burst noise

It should be mentioned in the process of thresholding that intensity of the noise must be estimated on each wavelet level to transform threshold scale if the ground noise is known as non-Gaussian noise. We take advantage of plotting levels to determine threshold scale together with the threshold selection criteria described in [20], and carry out burst noise simulations by the Heuristic thresholding. The simulation results are obtained through just 3 levels of decomposition as shown in Fig. 3, where A3 denotes the 3rd -step-up reconstruction signals gotten from low-frequency wavelet decomposition coefficients of decomposed burst noise; D3, D2 and D1 denotes the 3rd -step-up, 2nd -step-up, and 1st-step-up reconstruction signals, respectively, gotten from scale high-frequency wavelet decomposition coefficients of decomposed burst noise. It is easy to find that the reconstruction signals the 1st, 2nd, and 3rd-step-up reconstruction signals gotten from scale high-frequency wavelet decomposition coefficients of blurred burst noise is pretty similar with early analysis on reconstruction signals gotten from low-frequency wavelet decomposition coefficients of decomposed Gaussian noise, and the difference between those reconstruction signals are no more than that the 3rd -step-up reconstruction signals gotten from low-frequency wavelet decomposition coefficients of decomposed blurred-burst-noise retain the signal features of burst noise very well. By exploiting multi-resolution analysis, approximation, thresholding and signal reconstruction, most of background noise will be filtered out after wavelet transform, whereas the energy of the burst noise to be detected does not lose, which proves it is practicable to detect burst noise in time domain by wavelet transform.

IV. Conclusion

In contrast to traditional approaches for detecting burst noise in frequency domain, the approaches for detecting burst noise in time domain appear to have more advantages. Traditional approaches investigate frequency spectrums of noise in frequency domain, by which lots of data need to be acquired so that real-time performance is not good, and furthermore, labor, resource and time cost is considerably high, or even makes devices breakdown. Traditional approaches obtain statistic analysis consequences by batches; therefore, it is impracticable to valuate the reliability of a device specifically. Wavelet transform, however, creates a new concept for us. Wavelet transform provides us with good local performance in both the time and frequency domains. The use of the wavelet transform appeared to be the most relevant to transient detection due to its inherent localization properties in both time and frequency domains. The simulation we implemented indicates that wavelet transform is endowed with perfect adaptation properties, depending upon prior knowledge scarcely, computing fast, being able to be reconstructed completely (having inverse transformation), leading to a higher signal-to-noise ratio, preferably retaining the desired information and properties in the signal wave, and so forth, but those are what traditional approaches cannot do. Exploring of multi-resolution analysis and implement based on wavelet transform yields a new scheme for weak signal detection, and the approach is able to detect signals with low signal-noise-rate, or even burst noise merged in background noise.

References

[1] Yasuo Ebara, Hideaki Sone and Yoshiaki Nemoto. Correlation between arcing phenomena and electromagnetic noise of opening electric contacts. Proceedings of the Forty-Sixth IEEE Holm Conference on 25-27 Sept. 2000 Page(s):191 – 197.
[2] S T Hsu, R J Whitter, C A Mead. Physical model for burst noise in semiconductor devices. Solid-state Electronics,1970,13:1055-1071.
[3] Dai Yisong. Electronics in Noise. Shang Dong: ShangDong Science&Technology Press, 1997..3..
[4] R. Neelamani, Choi Hyeokho, R. Baraniuk. ForWaRD: Fourier-wavelet regularized deconvolution for ill-conditioned systems. IEEE Transactions on Signal Processing, Feb. 2004, 52 (2): 418 – 433.
[5] Yang Zongkai. Noise Elimination by Wavelet and Its Application to Signal Detection. Journal of Huazhong University of Science and Technology, Feb., 1997, 25(2):1-4.
[6] A. Tarczynski, N. Allay. Spectral analysis of randomly sampled signals: suppression of aliasing and sampler jitter. IEEE Transactions on Signal Processing, Dec. 2004, 52 (12): 3324 – 3334.
[7] Dakai Wang, Jinye Wang. Wavelet analysis and the application of signal processing. Beijing: Publishing House of Electronic Industry, 2006.
[8] Rao A. and Jones D. Nonstationary array signal detection using time-frequency and time –scale representations. Proc. ICASSP 1998: 1989-1992.
[9] Colonnese S. and Scarano G. Transient signal detection using higher order moments. IEEE Trans. on SP, 1999, 45(2): 515-521.
[10] Kulkarni S., et. al. Nonuniform M-Band wavepackets for transient signal detection. IEEE Trans. on SP, 2000, 48(6): 1803-1807.
[11] Chen Xiaojuan Zhao Rui. Detection of Burst Noise Based on Wavelet. Proceedings of the Second International Symposium on Test Automation & Instrumentation(Vol.3), 2008.
[12] S. Mallat, and Liang Hwang W. Singularity detection and processing with wavelets. IEEE Trans. IT., 1992, 38(2):617-643..
[13] A. Grossmann and J. Morlet. Decomposition of hardy functions into square integrable wavelets of constant shape. SIAM J. Math. Anal., Jul. 1984, 15(4): 723–736.
[14] L. Hwang, S. Mallat. Singularities and noise discrimination with wavelets. Acoustics, Speech, and Signal Processing, 1992. ICASSP-92., 1992 IEEE International Conference, 23-26 March 1992, 4: 377 – 380.
[15] K. Usman, , H. Juzoji, , I. Nakajima, M.A. Sadiq. A study of increasing the speed of the independent component analysis (IA) using wavelet technique. Proceedings. 6th International Workshop on Enterprise Networking and Computing in Healthcare Industry, HEALTHCOM 2004, 28-29 June 2004: 73 – 75.
[16] Chen Fengshi. The Wavelet Transform Theory and Its Applications in Signal Processing. Beijing: National Defense Industry Press, 1998.
[17] Dai Yisong. Investigation of G-R Noise Induced by Defects in P-N Junetion of Bipolar Transistor. Chinese Journal of Semiconductors,1989,10(1) : 47-54.
[18] David L. Donoho. De-noising by soft-thresholding. IEEE Transactions on Information Theory, May 1995, 41(3): 613-627.
[19] Pantelis D. Agoris, Sander Meijer, Edward Gulski, Johan J. Smit. Threshold selection for wavelet de-noising of partial discharge data. Conference Record of the 2004 EEE International Symposium on Electrical Insulation, Indianapolis, USA, Sep. 19-22, 2004, 62-65.
[20] Agoris, P.D. Meijer, S. Gulski, E. Smit, J.J. Threshold selection for wavelet denoising of partial discharge data. Conference Record of the 2004 IEEE International Symposium on E lectrical Insulation, 19-22 Sept. 2004: 62- 65.