GENERALIZED WAVELET-BASED SYMBOL RATE ESTIMATION FOR LINEAR SINGLE-CARRIER MODULATION IN BLIND ENVIRONMENT

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Abstract

In non-cooperative communication, signal parameters are unknown at the receiver front-end. This environment is considered as blind. Hence, estimation algorithms become very important for efficient and automatic real-time services. Indeed, knowing the fundamental signal parameters is necessary for data recovering correctness and demodulation reliability. In this paper, we address a symbol period estimation approach generalized for all linear modulation schemes. This approach is based on the wavelet transform due to its high capacity to detect discontinuity structures and zoom on the signal abrupt changes. A pre-estimation of the carrier frequency is introduced, allowing the operating in the totally blind environment. From simulations we conclude that this approach presents high estimation accuracy and high efficiency for very low SNR levels and it is applied for all types of linear modulations in practical Rayleigh channel case.

Keywords: Symbol period estimation, linear modulation, wavelet transform, discontinuities detection

1. Introduction

Recent wireless communication systems provide real-time applications requiring a high flexibility and accuracy techniques. Intelligent receiver is the basic component achieving these issues.

The modulation type is the signature that characterizes received signals (Trees, 2001). It is classified to analog and digital modulations. Modulation order (binary or M-ary order) is an important factor that proportionally affects transmission data rate. Modern communication systems widely introduce digital modulation schemes that are divided to linear modulation schemes, Amplitude Shift Keying (ASK), Phase Shift Keying (PSK) and Quadrature Amplitude Modulation (QAM); and to non-linear modulation schemes, Frequency Shift Keying (FSK).

In blind environment, where no information exchange exists between the transmitter and the receiver, intelligent receiver is based on the signal processing algorithms in order to estimate unknown signal parameters such as carrier frequency, symbol period, and signal bandwidth and so on (Dayoub, Okassa-Mfoubat, Mvone & Rouvaen, 2007; Yu & Bai, 2010). In order to correctly recover transmitted data and demodulate received signal, receiver requires an accurate and efficient estimation of the symbol period.

Relevant researches have paid their attention to the symbol period estimation issue. Symbol period can be estimated by filtering process when the received signal pass through a filter bank and then through a nonlinear unit (Yu, Shi & Su, 2005). This approach treats a baseband signal assuming knowing carrier frequency in priori and suffers from high complexity.

Originally, a mathematical tool is widely used to image processing and compression, it is the Wavelet Transform (WT). With the introduction of this transformation in the telecommunication fields, some authors benefit from this tool for the estimation objectives. In (Chan, Piews & Ho, 1997), authors use the Haar wavelet transform to estimate the symbol rate of the M-ary PSK signal. In (Deng & Liu, 2008), they estimate the symbol rate according to the relation between the signal bandwidth and the symbol rate. The method is based on the Haar wavelet when the scale value is optimized by a Monte Carlo simulation. Therefore, in (Xu, Wang & Wang, 2005) authors proposed an improvement of the symbol rate estimation based on the wavelet transform of the baseband signal. This proposal is very sensitive to frequency errors and so, it is not stable. Authors in (Gao, Li, Huang & LU, 2009) overcome the stability problem of such algorithms and estimate the symbol rate of the M-ary PSK signal taking into account Doppler frequency effect. The choice of wavelet scale is critical and it depends on the carrier frequency. Thus, the environment is considered as pseudo-blind since the signal carrier frequency that is necessary to choose the most appropriate scale value, is assumed known.

Therefore, a pre-estimation of the carrier frequency becomes an important task in totally blind environment (Xu, Yu, Liu, Zhang & Guobing, 2009, Yu, Shi & Su, 2004). However, the estimation fails if the frequency estimated from the interval search is not included in the signal's bandwidth. This indicates that the search taking place in a wrong medium (Hatoum, Ghaith & Pujolle, 2012). Thus, we must accurately determine the spectrum occupancy boundaries of the signal. To achieve this, we are based on the spectrum sensing techniques to search the occupied spaces (unlike the CR context), then to detect their boundaries; giving ease to the search of significant signal parameters.

In this paper, we present a generalized symbol period estimation for all types of digital and linear modulation (ASK, PSK and QAM) and all modulation order (binary and M-ary). In addition, we pre-estimate the signal carrier frequency, and then the estimation of the symbol rate of the linear modulations becomes totally blind unlike in the case of (Gao, Li, Huang & LU, 2009) where they operate in pseudo blind environment and restrict the estimation for M-PSK schemes only.

The sequel of the paper is organized as follows: in section 2, we present and describe the wavelet transform tool. In section 3 we present the system model. Then, we explain the pre-estimation task of the carrier frequency in section 4. In section 5 we present and describe the blind symbol period estimation for the linear modulations. Simulation results are shown and analyzed in section 6. Finally we conclude in section 7.

2. Wavelet Transform Overview

Wavelet Transform is a mathematical tool that has been dominating in the field of signal processing and analyzing. It has the excellent capability identifying, in terms of time and frequency, the local characteristics of a signal (Malat, 2009). Unlike Fourier Transform, that globally characterizes a signal, wavelet Transform is adopted to analyze non-stationary signals. It reflects the instantaneous behavior of each frequency component with locally characterization (Torrence & Compo, 1998). The wavelet transform is characterized by a variable resolution suitable to the signal variations. Based on the window function, called "wavelet mother" function, we consider different types of the Wavelet Transform function, e.g. Gaussian, Haar, Morlet, Hamming, Hanning, Mexican Hat, etc. The mother wavelet must be scaled and translated to scan the entire signal in multi-resolution way, we obtain a family of wavelet functions represented by Eq. 1 where a and b are the scale and translation factors respectively. Scaling factor must be an integer as a power of 2: $\psi_{a,b}(t) = \frac{1}{\sqrt{a}}\psi(\frac{t-b}{a})$ (1)

This transform is a kind of filtering process represented by the convolution:

$$S_{a,b} = \int_{-\infty}^{+\infty} X(t).\psi^{*}_{a,b}(t)dt \qquad (2)$$

Filters coefficients are based and determined by the wavelet family functions. The applications field is very large, for image processing and compression; also it applied for discontinuities detection, de-noising, smoothing function, features extraction, data analysis, distribution estimation, etc.

3. System Model

Our aim is to estimate the symbol period T_s in a blind environment we consider the wireless Rayleigh channel. A pre-estimation of the carrier frequency is necessary. The processing tool is the wavelet transform; particularly the mother wavelet function used is the Morlet one due to its high flexibility and high precision.

At the transmitter, digitally and linearly modulated data symbols "s_n" pass through a pulse shaping filter g (t). The passband transmitted signal s (t) is given in Eq. 3: $s(t) = \sum_n s_n g(t - nT_s) e^{j\omega_c t + \theta}$ (3)

In this case we consider the root raised cosine (RRC) filter as pulse shaping filter. ‘‘f_c’’ is the carrier frequency and θ is the carrier phase. To simplify, $\theta = 0rd$. This filtering gives the rectangular shape for the signal in the frequency domain. Thus, the spectrum is clearly characterizes by its discontinuity structure and abrupt changes.

Conveyed signal is intercepted by the receiver with no prior information about transmitted signal characteristics and it given by the following Eq. 4: $y(t) = \sum_k \alpha_k s(t - \tau_k) + w(t)$ (4)

where α_k and τ_k are the gain and delay kth path characteristics respectively due to the Rayleigh channel effect. w(t) is the Additive White Gaussian Noise (AWGN). The linear modulation type is unknown by the receiver. It may be ASK, PSK or QAM modulation, binary or M-ary order. For ASK signal, we consider the case of the continuous phase signal; as constellation, the ASK symbols are real values. Therefore, in the linear modulated signal, changes can appear at each symbol period (Ts and its multiple values). Thus, this time domain signal is characterized by an abrupt variations and discontinuity structure.

Mainly, our objective is, to pick clearly the positions of these discontinuities (singularities) in frequency domain signal for the carrier frequency estimation and time domain signal for the symbol period estimation.

Continuous Wavelet Transform (CWT) is considered in order to reflect this discontinuity characteristic and the chosen Morlet wavelet function has the following form: $\varphi(t) = e^{-t^2/2} e^{j\omega_\varphi t}$(5)

where ω_φ is the central angular frequency that characterizes the Morlet function. This parameter is adjustable which offers high processing flexibility. Choice of this frequency value is much critical since Smooth signal features produce relatively large wavelet coefficients at scales where the oscillation in the wavelet correlates best with the signal feature. In time domain, the Morlet function scans the entire signal in order to identify the abrupt changes, if exist, at each symbol period.

As first step, we estimate the signal carrier frequency that is the basic to the symbol period estimation. In particular, these holes may be licensed spectrum bands, not currently in an exploited state. In addition, these holes may be guard bands to avoid interference between user transmissions. Bandwidth edges are accurately detected; then, we determine by filtering a part of the received large band where we decide to paid an attention and find the carrier frequency. Once this carrier frequency is estimated, we begin searching of the symbol period.

4. Carrier Frequency Estimation

Carrier frequency knowledge has an essential role in signal processing, down-conversion and demodulation of the received wireless communication signal. The carrier frequency estimation is the basic task allowing estimating other signal parameters. We have introduced a new method to estimate the carrier frequency in totally blind environment based on the high wavelet transform capability to detect discontinuities edges. Morlet wavelet is used and no restraint on the choice of the scale value but the scaling factor must be an integer as a power of 2.

For our purpose, basing on the spectrum sensing approach, we examine the presence of an intercepted signal through a particular bandwidth which may contain several signals of different systems.

The processed signal to be concerned is the Power Spectral Density (PSD) of the received signal. Indeed, this spectral structure supports discontinuities represented by edges of each sub-band, we mean the frequencies f_n and f_{n-1} where *n* is the occupied bandwidth number in the considered spectrum. The estimation steps are as follow:

- First, we sense the presence of signal energy inside a determined frequency range with respect to a determined energy threshold.
- Then, the detected signal is auto-correlated in order to reduce the white noise effect.
- The basic domain is the frequency one. Thus, we obtain the auto-correlated signal spectrum through the Fourier Transform: $S_{corr}(f)$.
- For spectrum edges detection purpose, we introduce the Wavelet Transform (WT) of the autocorrelation spectrum: we apply the convolution product between the autocorrelation $S_{corr}(f)$ and the

scaled Morlet function $\varphi_a(f)$: $WT(f) = S_{corr}(f) * \varphi_a(f)$ (6)

The convolution in frequency is equivalent to the product in the time domain. The Wavelet Transform can be obtained in an alternative way by the Fourier Transform of the multiplication of: the signal autocorrelation (in time domain) and inverse Fourier Transform (FT) of the wavelet function. Indeed, it is considerably faster to do the wavelet transform calculation based on the multiplication way. Therefore, the wavelet transform can be obtained by the Eq. 7: $WT(f) = F.T\{S_{corr}(\tau).\phi(a\tau)\}$ (7)

- The important transitions in the signal are reflected by a high modulus level of the wavelet transform, Fig. 1. Hence, we detect the bandwidths boundaries by picking the local maxima of the wavelet transform PSD modulus.

In real-time applications, manually identification of the local maxima is not satisfied; the results are not expected to be accurate, especially in noisily conditions. Thus, we introduce an automatic method to accurately detect frequency edges from the wavelet transform local maxima. The basic idea is that a maximum is searched within a window with a fixe size ‘’L’’. This window scans the entire considered spectrum. Each modulus value inside the window is compared to the average of all modulus values in the window. If the comparison ratio is greater than a pre-defined decision threshold “g”, the corresponding modulus is considered as a local maximum and the corresponding frequency is identified as a bandwidth edge. The following equations resume the local maxima selection conditions:

- $\dfrac{(2L-2).|WT(f_i)|}{\sum_{k=2}^{L}\left(|WT(f_i)|+|WT(f_i)|\right)} > g$
- $|WT(f_{i-1})| < |WT(f_i)| \; and \quad |WT(f_{i+1})| < |WT(f_i)|$

‘L’ and ‘g’ are the robustness parameters, their choice is very critical:

- Increasing ‘L’ gives more method accuracy

- High value of level ‘g’ may not show the existence of a significant peak. Low value of ‘g’, may lead to a false decision when considering low peak levels, which are a noise peaks, as local maxima (bands boundaries).

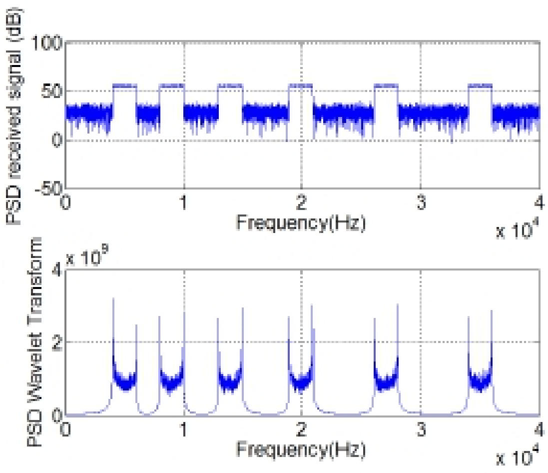

Fig. 1 Received signal PSD (top) and wavelet transform modulus (bottom).

Due to this search, frequency band edges are automatically identified with very high precision. These edges allow us to clearly locate spectrum occupancy of a desired signal in a totally blind environment. We remind that the communication signals are symmetric signals where the carrier frequency is the center of the bandwidth occupation. Thus, once the bandwidth edges are accurately determined, the carrier frequency is automatically found by the center of the determined and surely band (Hatoum, Ghaith & Pujolle, 2012).

5. Symbol Period Estimation

We develop a method to estimate the symbol period of a linear modulated signal. Such signal is characterized by a discontinuous structure. Indeed, the information data is carried by the amplitude and/or the phase of a sinusoidal oscillation at each symbol period. The "Ts" estimation is based on the wavelet transform, since this analysis tool has excellent capability to reflect the discontinuities in the signal oscillation. These discontinuities are translated to the abrupt changes of the wavelet transform. This wavelet behavior depends on the relation between the wavelet function and the studied signal: at scales where the wavelet oscillation correlates best with the signal feature, largest are the wavelet coefficients.

For sinusoidal oscillations, the CWT coefficients display an oscillatory pattern at scales where the oscillation in the wavelet approximates the period of the sine wave (Torrence & Compo, 1998). Thus, the choice of scale is very important for the symbol period estimation. For Morlet function, at scale equal to: $a = \dfrac{\omega_\varphi}{\omega_c}$ (8)

The wavelet coefficients change abruptly and present high level modulus at the amplitude and/or phase change position of the signal, where $\omega_c = 2\pi f_c$ represents the carrier frequency. This motivates us to pre-estimate the carrier frequency as presented in section above. After obtaining the carrier frequency, the scale value is calculated in order to having better estimation performance. Locally characterization analysis of the wavelet function allows a clear detection of the instantaneous signal feature. Morlet Wavelet function makes zooming on the abrupt signal changes.

- ASK signal is given by the equation below:

$$s_{ASK}(t) = A_n \sum_n g(t - nTs)e^{j\omega_c t} \qquad (9)$$

$$A_n \in A_0 + \{0,1,...,M-1\}.A_{step} \qquad (10)$$

where A_n is the amplitude value during the period $n.T_s$, A_0 is the reference amplitude value and A_{step} is the amplitude separation in the ASK constellation and M is the modulation order. At each symbol period, only the amplitude may change; let consider $\Delta A = A_{n+1} - A_n$ the difference amplitude between two consecutive symbols; thus, the wavelet transform can be expressed as follow:

$$WT_{ASK}(a,\tau) = \frac{1}{\sqrt{a}} \left(\begin{array}{l} \int_{-\infty}^{b} A_n e^{j\omega_c t} e^{-(\frac{t-\tau}{\sqrt{2a}})^2} e^{-j\omega_\varphi(\frac{t-\tau}{a})} dt \\ + \\ \int_{b}^{+\infty} (A_n + \Delta A) e^{j\omega_c t} e^{-(\frac{t-\tau}{\sqrt{2a}})^2} e^{-j\omega_\varphi(\frac{t-\tau}{a})} dt \end{array} \right) \qquad (11)$$

“b” is the time difference that determines the relative distance between the Morlet function and the transition position in the modulated signal at the multiple of symbol period.

Now, let introduce the scale value calculated from the Eq. 8. We consider two cases: 1) if $\Delta A = 0$, no amplitude change between two consecutive symbols: $WT_{ASK}(a,\tau) = A_0\sqrt{2\pi a}\,e^{j\omega_c \tau}$ (12)

and the wavelet modulus is considered as constant with respect to the amplitude and it equal to: $|WT_{ASK}(a,\tau)| = A_0\sqrt{2\pi a}$ (13)

2) If $\Delta A \neq 0$, we obtain the equation below:

$$WT_{ASK}(a,\tau)=\frac{A_0 e^{j\omega_c\tau}}{\sqrt{a}}\begin{pmatrix}\int_{-\infty}^{b} e^{-(\frac{t-\tau}{\sqrt{2a}})^2}dt \\ + \\ (1+\frac{\Delta A}{A_0}).\int_{b}^{+\infty} e^{-(\frac{t-\tau}{\sqrt{2a}})^2}dt\end{pmatrix} \quad (14)$$

For expression simplicity, let consider the variable change: $B = 1+\frac{\Delta A}{A_0}$. With integral calculation and with referred to the error function complement below

$$erfc(x)=\frac{2}{\sqrt{\pi}}\int_{x}^{\infty} e^{-t^2}dt$$

Let us consider $\rho_a(b)=0.5erfc(b/a)$, then we obtain the following expression: $WT_{ASK}(a,\tau)=A_0\sqrt{\pi a}\big(1+\rho_a(b)(B-1)\big)e^{j\omega_c\tau}$ (15)

Now, we search the points that maximize the modulus function of the wavelet transform in order to pick the amplitude transitions position in the ASK modulated signal with respect to the follow derivation. $\frac{\partial\left|WT\ (a,\tau)\right|}{\partial\rho_a(b)}=0$

Therefore, for $a=\frac{\omega_\varphi}{\omega_c}$, the modulus of this wavelet transform is as follow:

$$\left|WT_{ASK}(a,nT_S)\right| = A_0\sqrt{\pi a}\left|(1+\frac{A_0}{\Delta A})\right| \quad (16)$$

- For the PSK signal, the expression is: $s_{PSK}(t)=A_0\sum_n g(t-nTs).e^{j\varphi_n}.e^{j\omega_c t}$ (17)

  $\varphi_n\in\left\{0,\frac{1}{M}2\pi,\frac{2}{M}2\pi,....\frac{M-1}{M}2\pi\right\}$ (18)

Similarly, we consider $\Delta\varphi=\varphi_{n+1}-\varphi_n$ the difference phase between two consecutive symbols. Thus, the wavelet transform is given by:

$$WT_{PSK}(a,\tau)=\frac{A_0 e^{j\varphi_0}}{\sqrt{a}}\begin{pmatrix}\int_{-\infty}^{b} e^{-(\frac{t-\tau}{\sqrt{2a}})^2}dt \\ + \\ e^{j\Delta\varphi}\int_{b}^{+\infty} e^{-(\frac{t-\tau}{\sqrt{2a}})^2}dt\end{pmatrix}.e^{j\omega_c\tau} \quad (19)$$

After calculation, we obtain the following expression:

$$WT_{PSK}(a,\tau) = A_0\sqrt{a\pi}\left[1+(e^{j\Delta\varphi}-1)\rho_a(b)\right]e^{j(\omega_c t+\varphi_0)} \quad (20)$$

Hence, the maximized modulus is obtained when $\rho_a(b) = 0.5$ for all values of $\Delta\varphi \neq 0$. By analyzing this value, we conclude that it is achieved when b=0, thus, when the central of the Morlet wavelet coincides with the abrupt change in the signal. We obtain the Eq.21:

$$\left|WT_{PSK}(a,nT_s)\right| = \frac{A_0\sqrt{a\pi}}{2}\left|1+e^{j\Delta\varphi}\right| \quad (21)$$

- For QAM signal where amplitude and/or phase can change:

$$s_{QAM}(t) = A_n\sum_n g(t-nTs).e^{j\varphi_n}.e^{j\omega_c t} \quad (22)$$

A_n and φ_n are as shown in Eqs. 10 and 18. Wavelet transform becomes as:

$$WT_{QAM}(a,\tau) = \frac{A_0 e^{j\varphi_0}}{\sqrt{a}}\left(\begin{array}{c}\int_{-\infty}^{b} e^{-(\frac{t-\tau}{\sqrt{2a}})^2}dt \\ + \\ B.e^{j\Delta\varphi}\int_{b}^{+\infty} e^{-(\frac{t-\tau}{\sqrt{2a}})^2}dt\end{array}\right).e^{j\omega_c\tau} \quad (23)$$

And the modulus is maximized and presented below:

$$\left|WT_{QAM}(a,nT_S)\right| = A_0\sqrt{\pi a}\left|1+\rho.B.e^{j\Delta\varphi}-1)\right| \quad (24)$$

Where ρ is the maximization factor: $\rho = \dfrac{1-(B.\cos(\Delta\varphi))}{B^2+1-2.B.\cos(\Delta\varphi)}$ (25)

For $\Delta A \neq 0$ and $\Delta\varphi = 0$ we return to the ASK case Eq. 16; and if $\Delta A = 0$ and $\Delta\varphi \neq 0$ we return to the PSK case Eq. 21.

After calculating and maximizing the modulus of the Morlet wavelet transform for the modulated signal in time domain, we detect the local maxima points. They reflect variations of the modulated signal, thus the minimum value of the difference between the peaks is considered as the symbol period. Due to the noise, peaks' searching is not efficient since small changes are introduced. This effect can be overcome by computing the cyclo-autocorrelation function of the $\left|WT(a,\tau)\right|$. This function reduces effectively the noise level and clearly shows maximum changes; in addition, it presents a periodicity that makes easier the calculation of the difference between peaks positions Fig. 2.

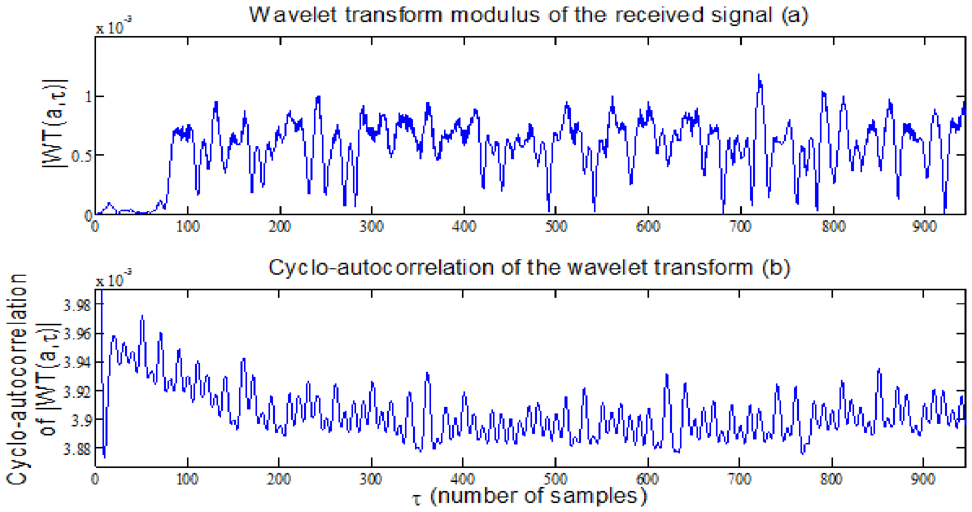

Fig. 2 The wavelet transform (a) and its cyclo-autocorrelation (b)

However, we find that the search in the frequency domain is more robust. Therefore, we analyze the autocorrelation spectrum obtained through the Fourier transform calculation. For PSK and QAM modulated signals, the first peak after the central frequency (for baseband signal, the central frequency is equal to zero) represents the symbol rate. As known, this frequency is the inverse value of the symbol period $R_s = 1/T_s$. In other hand, For the ASK modulated signals, first peak after the central frequency is equal to the twice of the symbol rate. In time domain, difference between peaks in ASK autocorrelation function is equal to half of the symbol period.

6. Simulation Results and Analysis

The performance of the proposed scheme is studied and evaluated by Matlab simulation. Two performance criteria are considered:

1) The probability of the estimation errors
2) The Normalized Root Mean Square Error (NRMSE)

These values are calculated over 2500 Monte Carlo iterations and presented in function of Signal to Noise Ratio (SNR). At the transmitter, the considered signal parameters are as follows: the carrier frequency is fc=1.5MHz and the symbol rate is Rs=0.5MHz (symbol period is 1/Rs). The sampling rate is fs=5MHz. The central angular frequency of Morlet wavelet transform is $\omega_\varphi = 5rd$ with respect to efficient range considered as: $\omega_\varphi{}^2 \geq 25$. We assume 1000 symbols as data length and SNR range is -10→14 dB. The value of the symbol period to be estimated is obtained by the minimum difference between the peaks of the time domain corresponding function, it is the wavelet transform cyclo-autocorrelation of the received signal (Fig. 2b). This minimum is explained by the fact that the data information carried by the signal features (amplitude and/or phase) can change at least once at each symbol period. However, due to the noise effect, this calculation for symbol period is unclear, thus we propose to introduce the *'histogram'* of the peaks difference and choose its maximum value corresponding to the most repeated difference value, as the estimated symbol period value.

Nevertheless, in the frequency domain the search is more robust. Thus, the estimated symbol period is calculated from the estimated symbol rate which is equivalent to the first peak unless the central frequency in the PSD spectrum. In order to make more obvious the peak search, we introduce a '*smoothing function*' to avoid appearing undesired peaks. By a simple way, this peak value can be found, because it is the globally maximum. The performance of the symbol period estimation is studied for both ideal channel (AWGN) and Rayleigh channel with Doppler frequency fd=130 Hz.

Fig. 3 shows the estimation errors probability for the 16-PSK, 16-ASK and 16-QAM, in the AWGN channel. By comparing, we observe that this estimation algorithm is optimal after -2 dB in an ideal channel (AWGN channel) and presents an excellent performance.

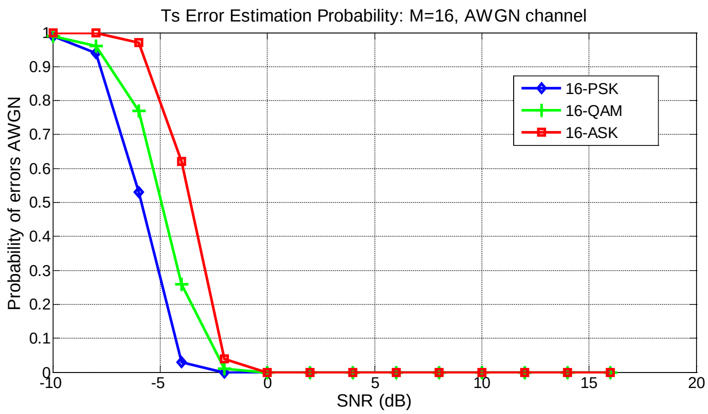

Fig. 3 Symbol Period estimation probability in AWGN channel, M=16.

Thus, this algorithm is very suitable for very low SNR. As shown, it is more efficient for the PSK modulation then for the QAM modulation. For Rayleigh channel, Fig. 4 shows the probability of the estimation error for all modulation when M=16. Similarly, this estimation algorithm outperforms for the PSK modulation then for QAM modulation. Since the ASK modulation is more sensitive to noise that affects directly the amplitude value, it shows less performance by comparing with others linear modulations.

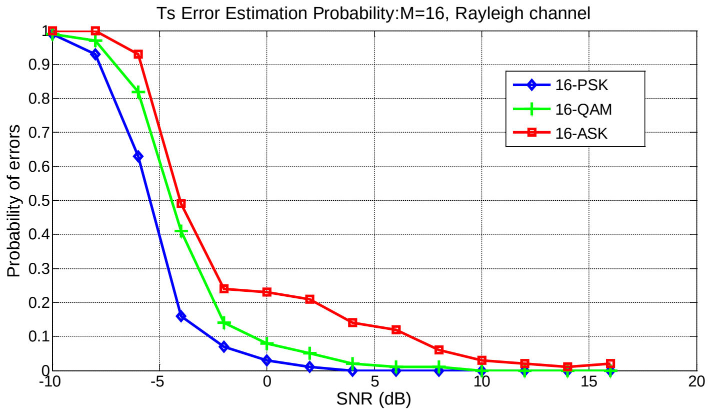

Fig. 4 Symbol Period estimation probability in Rayleigh channel, M=16.

As it is clear, due to the fading effect of the Rayleigh channel, the performance is not optimal by comparing with the AWGN channel. But for practical Rayleigh channel, this method is very efficient for low SNR values, above 2dB. In other hand, with respect to the NRMSE criterion, results are shown in Figs. 5 and 6 for AWGN and Rayleigh channels respectively. In addition, the NRMSE shows a high deviation of the estimated symbol period value in a Rayleigh channel with respect to the AWGN channel, especially for SNR > 0dB Fig. 6. We have compared with the results shown in (Xu, Wang & Wang, 2005) and from the NRMSE values in the Fig. 7, we observe that our new method outperforms the method based on the multi-scale Haar wavelet and presented in (Xu, Wang & Wang, 2005). With respect to the modulation order M, the performance of this estimation algorithm is the same (show Fig. 8). This is due to the fact that the algorithm estimates the symbol period instead of the bit duration $(T_b = T_s / \log_2(M))$.

7. Conclusion

In this paper, a symbol period estimation method is generalized for all linear modulation schemes. Non-cooperative environment is considered where the signal parameters are unknown by the receiver. The processing tool is the “wavelet transform” that shows an excellent capability to detect discontinuities.

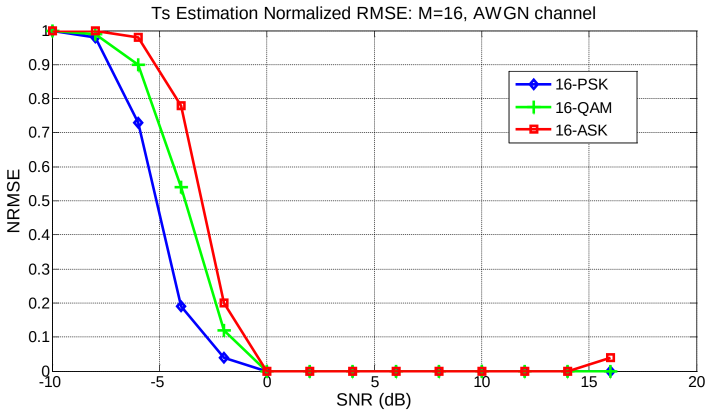

Fig. 5 Symbol Period estimation NRMSE in AWGN channel, M=16.

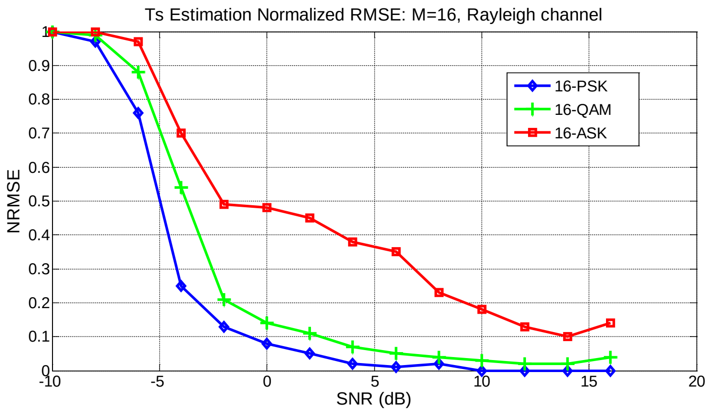

Fig. 6 Symbol Period estimation NRMSE in Rayleigh channel, M=16.

These abrupt changes appear in the original signal at the symbol period and/or at its multiple values. A pre-estimation of the carrier frequency is introduced. In order to overcome the effect of the white noise, we introduce the autocorrelation function. The local maximum position of the autocorrelation wavelet transform in the frequency domain corresponds to the estimated symbol period value. This method shows a significant performance and a very high accuracy at very low SNR values. It has a low computation complexity and it is suitable and robust for a practical Rayleigh channel.

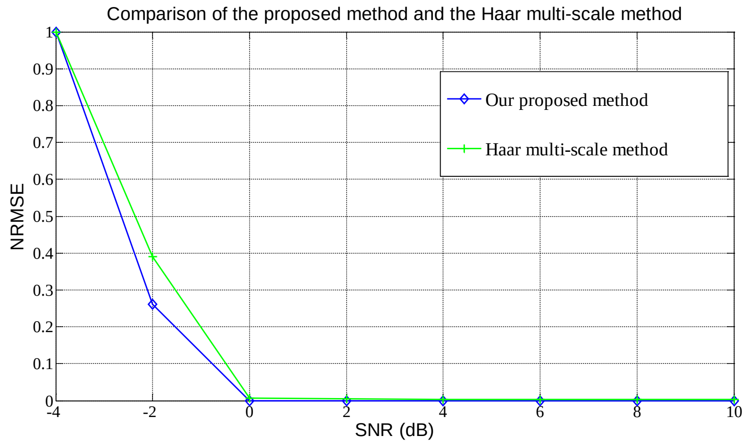

Fig. 7 Comparison of our proposed method and the HAAR multi-scale method in (Xu, Wang & Wang, 2005):16-PSK, AWGN channel.

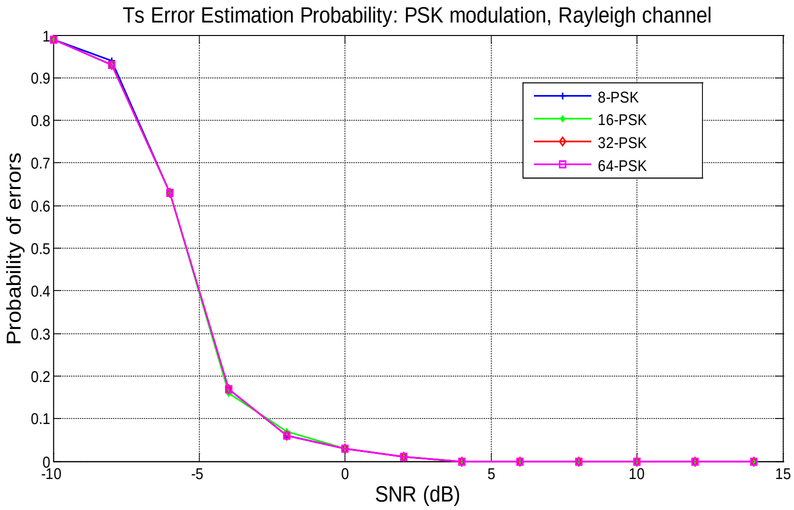

Fig. 8 Probability of error estimation in function of the modulation order M.

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