NEW TECHNIQUES FOR THE BAUD DURATION ESTIMATION

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ABSTRACT

The aim of this paper is to introduce fast and reliable baud duration estimators. This work is concerned with the symbols transitions sequence extraction and the baud duration estimation. The symbols transitions sequence is extracted using one of three methods - the level-crossing method, the derivative method and the wavelet method. Subsequently, the baud duration is estimated by applying the greatest common divisor principles on the symbols transitions difference sequence.

1 Introduction

Automatic estimation of baud duration is very essential for automatic digital modulation recognition and digital symbol sequence extraction. By integrating the automatic baud duration estimator into an electronic support measurement receiver, including an energy detector, a directional finder and a digital modulation identifier will increase the ability of information extraction. Several techniques used for baud duration estimation are introduced in [1].

There are many practical techniques for baud duration estimations. One of these techniques utilizes the averaged spectrum of the digitally modulated signals. It is well known that all digitally modulated signals have $\{(\sin x)/x\}^2$ spectrum shape with main lobe width equal to twice the baud rate (reciprocal of the baud duration), except the binary FSK signal spectrum consists of two $\{(\sin x)/x\}^2$ centered at the mark and space frequencies [2]. Thus, by observing the averaged spectrum one can measure the baud duration. This method requires long signal duration. Hence, this method is used in the off-line analysis.

In automatic signal classification systems, no priori information about the exact signal parameters as well as the signal nature is available. Sometimes, ranges for some parameters such as carrier frequencies and baud durations are specified. Indeed, there are three system categories according to the amount of the available priori baud duration information. These are: 1) systems with no priori information, 2) systems with defined range of baud durations and 3) systems with defined a list of baud durations. This work is concerned with the second category (range of baud durations).

In [1] Wegener introduced a review about the different methods used for baud duration estimations. He mentioned that, the most simple baud duration estimation method assumes that there is at least one duration -1 baud was received in the observed sequence, which requires long signal duration to achieve, and sort the sequence of transitions difference in an ascending order. Then consider the first element as the baud duration and compare the rest of the transition difference sequence with that element. However, this method requires a priori information about the lower limit of the baud rate estimation. In [1] it is mentioned that Gaby and McMillan [3] introduced an method for baud duration estimation based on the pattern analysis, but this method requires long signal duration. There are some other methods based on baud features extraction. In [1] it is mentioned that all these methods are mainly used in the off-line analysis.

In the following section, three new and fast methods for baud duration estimations is introduced. In section 3 computer simulations for test signals used in performance evaluations are presented. In section 4 a comparison between the developed methods is introduced. The paper is concluded in section 5.

2 Baud duration estimation methods

In this paper three methods for the on-line baud duration estimation are introduced. The functional flowchart for these is shown in Fig. 1. Once the correct modulation type of digitally modulated signals is determined, the baud duration estimation can be achieved easily. If the input signal is ASK, the interested sequence is the instantaneous amplitude, $a(t)$. If the input signal is PSK, the interested sequence is the instantaneous phase, $\phi(t)$. Finally, if the input signal is FSK, the interested sequence is the instantaneous frequency, $f(t)$. For the mathematical expressions of the instantaneous amplitude, phase and frequency [see 4].

The only difference between the developed methods is in the way for extracting the transition sequence. In the first method, the transition sequence extraction is based on the level-crossing of the input sequence. Note that, in binary modulations, the level-crossing is equivalent to the zero-crossings. In the second method, the extraction of the transition sequence is based on the the determination of the spikes in the derivative of the input sequence. The differentiation of the input sequence may be achieved in one of two ways: in time domain using the numerical difference and in frequency domain using the Fourier transform property [5] as follows:

$$Y(f) = (-j2\pi f)X(f) \tag{1}$$

where X(f) is the Fourier transform of the input sequence, $x(t)$, and Y(f) is the Fourier transform of the derivative of $x(t)$. Thus, $y(t)$ can be obtained through the second use of the Fourier transform as

$$y(t) = IFT\{Y(f)\} \tag{2}$$

Due to the numerical problems associated with the numerical difference, the authors use the frequency domain method, which gives more smoothing in the derivative sequence. In this method, the symbol transitions sequence is identified as the set of spikes in the derivative sequence. Fig. 2 shows a band-limited binary sequence and its derivative using (1) and (2). The third method is based on the use of the wavelet transform as a method for edge detection. In wavelet transform [6], signals are decomposed into multi-scale details. As signals are decomposed into elementary frequencies, the wavelet transform can measure the local regularity of a signal such as the periodicity in digitally modulated signals. In this method, the symbol transitions sequence is identified as a set of the spikes that occurs at the same position at several adjacent scales. Direct correlation of the wavelet transform at different scales are used to identify the symbol transitions sequence. In wavelet transform there are many types of filter for the different signal processing applications. In this work we use the filter introduced by *Mallat* [7] for spikes detection. The first six scales are computed using *Mallat* filter, then the direct spatial correlations between the first six scales of the wavelet transform are calculated as [8]

$$Corr(L) = \prod_{i=1}^{6} W(i, L), L = 1, 2, ..., N \tag{3}$$

where $W(i, .)$ are the scales of wavelet transform using *Mallat* filter, i is the scale number of the wavelet transform and N is number of samples of a signal under consideration. Fig. 3 demonstrates the first six scales of the wavelet transform for a noisy band-limited binary sequence, instantaneous amplitude for an ASK2 signal. Also, the first five direct correlation, defined by (3), between the extracted scales are shown in Fig. 4. After determining the symbols transitions sequence by one of these two methods, the durations between successive transitions are obtained. To the list of these estimated durations, the greatest common divisor principle (GCD) is applied to measure the common baud duration of the received signal.

3 Computer Simulations

The carrier frequency f_c , the sampling rate f_s, and the symbol rate r_s were assigned the values 150 kHz, 1200 kHz, and 12.5 kHz respectively. The generation of the modulating symbol sequence comprised the following steps:

1. The average value x_{av} of a simulated speech signal sequence $\{x(i)\}$ was calculated.

2. The number of samples per symbol duration, $N_b = 96$, was determined from the assumed symbol and sampling rates.

3. The simulated speech signal sequence $\{x(i)\}$ was divided into adjacent sets of $N_b = 96$ samples. Then in every set if the number of samples exceeding x_{av} was larger than 48 samples, the set was represented by binary bit "1", otherwise, the set was represented by a binary "0".

ASK2, PSK2, and FSK 2 signals were derived from

$$s_\theta(i) = a_\theta \cos\left(\frac{2\pi f_\theta i}{f_s} + \phi_\theta\right); \quad N_s \geq i \geq 1, \quad \theta = 0, 1 \tag{4}$$

The selection of the parameters a_θ, f_θ, and ϕ_θ were made as shown in [4; Table 1] to simulate the above mentioned digitally modulated signals.

Every communication transmitter has a finite transmission bandwidth. Consequently, the transmitted signal is band-limited. Therefore, the simulated modulated signals were band-limited to make them represent more realistic test signals. The band-limitation of digitally modulated signals was exercised after generation. Note that digital modulation systems are usually implemented in practice as shift-keying systems and hence cannot be regarded as versions of analogue modulation systems. In this case the simulated digitally modulated signals were band-limited to bandwidth containing 97.5% of the total average power according to [9].

$$\int_{f_c-B2}^{f_c+B2} G_s(f)df = 0.975 \int_{-\infty}^{\infty} G_s(f)df \tag{5}$$

where $G_s(f)$ is the power spectral density of the modulated signal $s_\theta(t)$. For the analytic expressions of the 97.5 % bandwidth for different types of digital modulation, see [4, Appendix C]. In our simulations, the bandwidth for ASK2, PSK2, and FSK2 are chosen to be 4 r_s, 6 r_s , and 8 r_s respectively.

4 Performance Evaluations

Simulations of three band-limited binary digitally modulated signals (ASK2, PSK2 and FSK2), corrupted with a band-limited Gaussian noise, have been carried out at different SNR to evaluate the performance of the proposed methods. Sample results are presented in the following tables at the SNR of 15, 20, 30 and 40 dB. It is worth noting that all these results are derived from 100 realizations for each modulation types of interest. The performance of these methods is measured at two estimation errors values ($\pm 1\%$ and $\pm 4\%$). For the method I (level-crossing), it is clear that at SNR $\geq$ 20 dB the probability of correct estimation of the baud duration is $\geq$ 98% except PSK2 (= 84%), if the accuracy of estimation is within $\pm 1\%$ of the true value. Meanwhile, if the accuracy of baud duration estimation is $\pm 4\%$, the probability of correct estimation is 100%. For the method II (derivative) and at SNR $\geq$ 20 dB, the probability of correct estimation is $\geq$ 89%, if the accuracy of estimation is within $\pm 1\%$ of the true value. Furthermore, if the accuracy of baud duration estimation is $\pm 4\%$, the probability of correct estimation is $\geq$ 95%. For the method III (Wavelet) and at SNR $\geq$ 20 dB, the probability of correct estimation is $\geq$ 99% except PSK2 (=88%) when the accuracy of estimation is within $\pm 1\%$ of the true value. If the accuracy of baud duration estimation is $\pm 4\%$, the probability of correct estimation is 100% for ASK2 and FSK2 but for PSK2 is $\geq$ 98%.

5 Conclusions

In this paper fast and reliable baud duration estimators have been introduced. Three methods - the level-crossing method, the spikes determination method and the wavelet transform principles. Sample results have been presented at the SNR of 10 dB, 20 and 40 dB only. It is found that the threshold SNR for successful baud duration estimation (at a success rate greater than 90%) is about 20 dB. The most interesting observation is that these methods can be extended to larger number of levels ($M > 2$). Currently, the work is under way in implementing and testing these methods for $M > 2$ as well as in radar applications such as pulse width and pulse repetition period estimations.

References

[1] A. W. Wegener, " Practical techniques for baud rate estimation," IEEE, pp. IV 681-684., 1992.

[2] L. W. Couch II, " Digital and analogue communication systems; fourth edition," Maxwell Macmillan Canda, Inc., 1993.

[3] G. Gaby and W. McMillan, "Automatic bit pattern analysis of communication signals," Proceedings ICASSP-90, pp. 1715-1718, April 1990.

[4] E. E. Azzouz and A. K. Nandi, "Automatic identification of digital modulations," Signal Processing, Vol. 47, No. 1, November 1995, pp. 55-69.

[5] H. Urkowitz, "Signal theory and random processes," Artech House, Inc. 1981.

[6] O. Rioul, and M. Vetterli, "Wavelets and signal processing," IEEE Signal processing Magazine, Vol. 8, No. 4, pp. 14-37, Oct. 1991.

[7] S. Mallat and W. L. Hwang, "Singularity detection and processing with wavelets," IEEE Trans. Information Theory, Vol. 38, No. 2, pp. 617-643, March 1992.

[8] Y. Xu and J. B. Weaver, D.M.Healy, Jr.Lu, and Jian Lu, "Wavelet transform domain filters: A spatially selective noise filtration technique," IEEE Trans. Image Processing, Vol. 3, No. 6, pp. 747-757, Nov. 1994.

[9] K. S. Shanmugam, "Digital and analogue communication systems," John wiley and sons, Inc., 1985.

SNR	Method I		Method II		Method III	
	±1%	±4%	±1%	±4%	±1%	±4%
15	91%	99%	82%	95%	87%	100%
20	98%	100%	90%	95%	99%	100%
30	100%	100%	93%	98%	100%	100%
40	100%	100%	95%	98%	100%	100%

Table 1: Baud duration estimation accuracy (ASK2).

SNR	Method I		Method II		Method III	
	±1%	±4%	±1%	±4%	±1%	±4%
15	34%	75%	53%	89%	74%	95%
20	84%	100%	89%	99%	88%	98%
30	100%	100%	96%	97%	94%	100%
40	100%	100%	97%	97%	99%	100%

Table 2: Baud duration estimation accuracy (PSK2).

SNR	Method I		Method II		Method III	
	±1%	±4%	±1%	±4%	±1%	±4%
15	100%	100%	86%	100%	99%	100 %
20	100%	100%	89%	100%	100%	100%
30	100%	100%	94%	100%	100%	100%
40	100%	100%	94%	100%	100%	100%

Table 3: Baud duration estimation accuracy (FSK2).

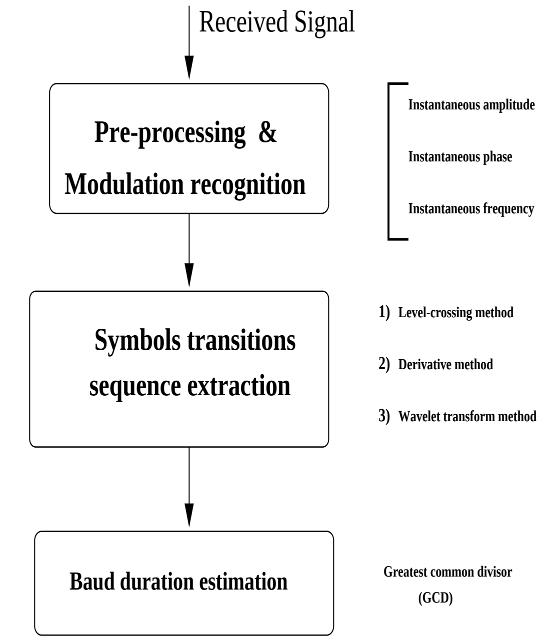

Figure 1: Block diagram for the proposed methods

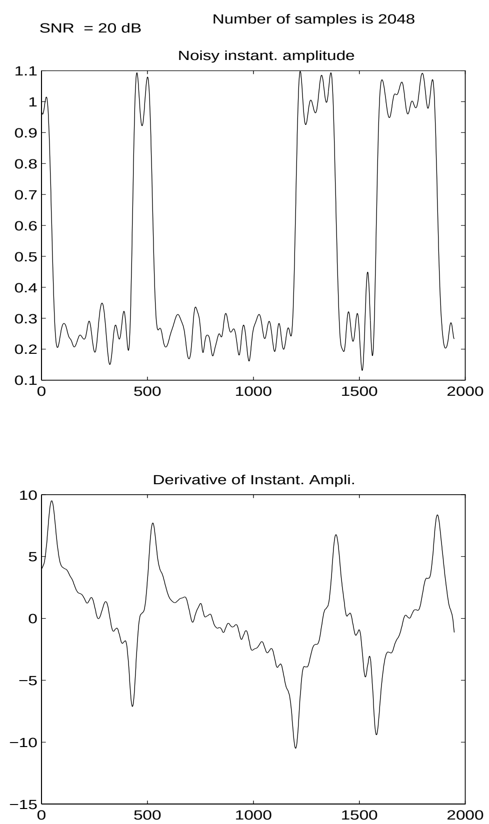

Figure 2: Instant. amplitude and its derivative

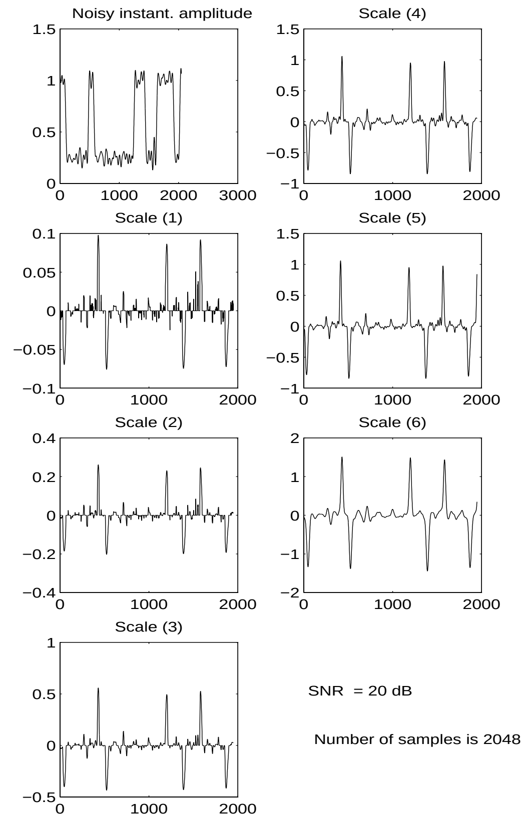

Figure 3: First six scales of the instant. amplitude for ASK2

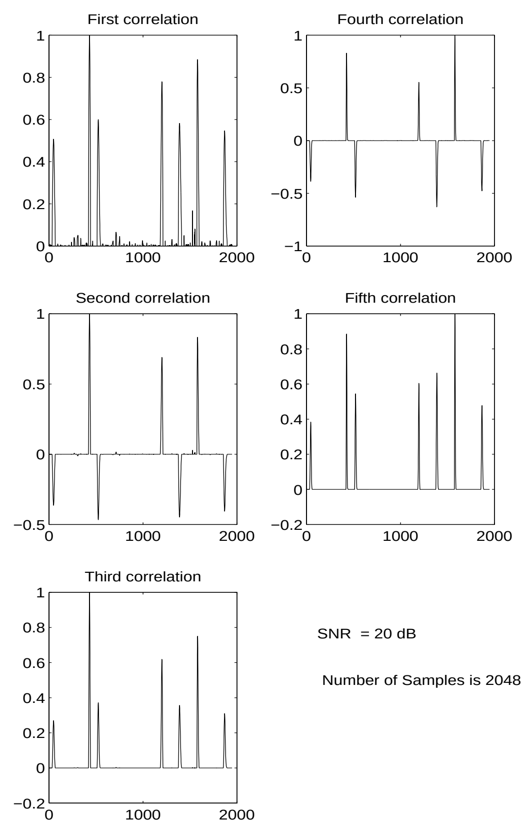

Figure 4: First five correlation sequences