**Procedings of the Sixth Baiona Workshop on Signal Processing in Communications
September 2003, Baiona, Spain**

Automatic Recognition Algorithm for Digitally Modulated Signals based on Statistical Approach in Time-Frequency Domain

D. Le Guen and A. Mansour *
ENSIETA - E^3I^2 Lab
2, rue François Verny
29806 Brest cedex 9
FRANCE
leguende@ensieta.fr & mansour@ieee.org

Abstract

This paper deals with a new modulation recognition algorithm based on an analysis of time-frequency representations of different modulated signals (PSK, QAM and FSK). At first, we conduct experimental studies over a range of time-frequency representations (TFR) in order to choose the more appropriated one. Once, an appropriated TFR has been chosen, some statistical functions applied on that TFR are used in order to extract the desired information included in the representation. The desired information could be used to estimate the symbol duration estimation. Otherwise a classification scheme that allows to distinguish PSK, FSK and QAM. Finally, many experiments and simulations have been conducted and we present the obtained results.

1 Introduction

For the last three decades, digitally modulated signals such as QAM (Quadrature Amplitude Modulation), PSK (Phase Shift Keying), FSK (Frequency Shift Keying), TCM (Trellis Coded Modulations), CDMA (Code Division Multiple Access), as well as OFDM (Orthogonal Frequency Division Multiplexing) have been used in many important applications such as satellite communications, mobile phone, military communications, *etc.* Therefore, automatic recognition algorithms for these signals are very attractive especially for electronic warfare, control of civilian authorities over the radio-band frequency as well as for control of communication quality. In [1], the authors developed a statistical recognition algorithm and they cited and discussed many other algorithms proposed by different other researchers [2, 3]. Almost all of these algorithms are based on statistical approaches.

Recently, Time-Frequency Representations (TFR) have been developed by many researchers [4, 5, 6] and they are considered as very powerful signal processing tools. In our previous work [7], we proposed a statistical algorithm to estimate carrier frequency and to distinguish the different type of modulation (especially PSK versus FSK). However, the classification process didn't include QAM modulation and many importing features as symbol duration couldn't be estimated. To complete our previous algorithm, we develop here a complete process of classification of QAM, PSK and FSK. Moreover, we propose a new algorithm of symbol duration estimation based on modified statistical functions which have been applied to different TFR. Finally, many experiments and simulations have been conducted and are presented.

2 Time-Frequency field

Obviously, the choice of an adequate TFR is very important to reach our goal [8, 9]. For this reason, experimental studies have been conducted. An adequate TFR must be the simplest function that keeps all the desired information (symbol changes for instance). Assuming these requirements, we found that a Pseudo-Wigner-Ville transform, denoted $\mathrm{TFR}(t, f)$, can be considered as a good can-

*Thanks to **CELAR** (Centre d'Electronique de l'Armement) (i.e. The French Armament Center of Electronics) who has supported the work.

didate TFR among many other tested TFR such as Wigner-Ville, Smooth Pseudo-Wigner-Ville, Cho-Willims, Born-Jordan, Zao-Atlas-Mark as well as spectrogram representations. The major drawback of a Wigner-Ville TFR is its strong awkward interference terms. Among filtered version, we have found that Pseudo-Wigner-Ville is a best trade-off between simplicity and efficiency (cf Figure 1). Let $s(t)$ to be a modulated signal, in this case, one can write:

$$\mathrm{TFR}(t,f) = \int_\tau s\left(t+\frac{\tau}{2}\right) s^*\left(t-\frac{\tau}{2}\right) h(\tau) e^{-2j\pi f\tau} d\tau \tag{1}$$

where $h(\tau)$ is an applied filter. Without loss of generality, one can assume that the observed modulated signals contain at least 100 symbols. Using this assumption, one can adjust the size l_h of the previous filter $h(\tau)$. However, this value in not critical but it can justify or not the appropriateness of the Pseudo-Wigner-Ville.

Hereinafter, we consider that the time-frequency domain as a succession of time slots $TFR_t(f)$ or spectral slots $TFR_f(t)$ and we define:

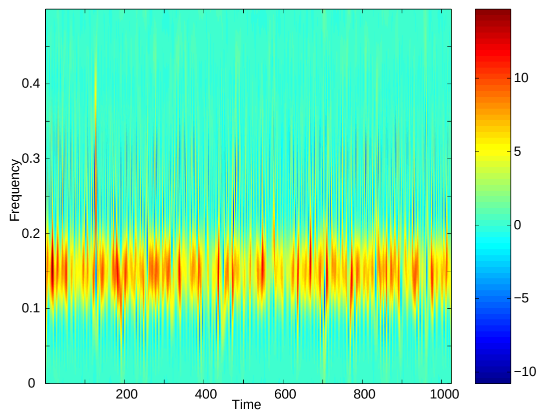
$$\begin{aligned} N_t &= \sqrt{\sum_{f=1}^{M} \mathrm{TFR}_t(f)^2} \\ \overline{\mathrm{TFR}}_t(f) &= \frac{\mid \mathrm{TFR}_t(f) \mid}{\sum_{f=1}^{M} \mid \mathrm{TFR}_t(f) \mid} \end{aligned} \tag{2}$$

where M is the number of frequency bins, N_t is the modulus of a time slot and $\overline{\mathrm{TFR}}_t(f)$ the normalized time slot which values are between 0 and 1.

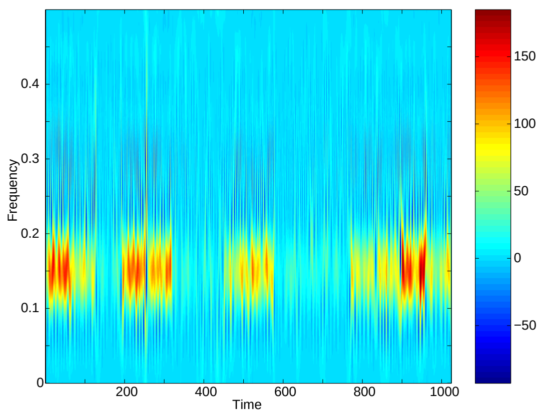
3 Type of modulation

The modulation recognition procedure consists on the estimation of different modulation parameters. In order to reach this goal, one should firstly process observed signals to classified them into divers modulation types such as QAM, PSK *etc.*

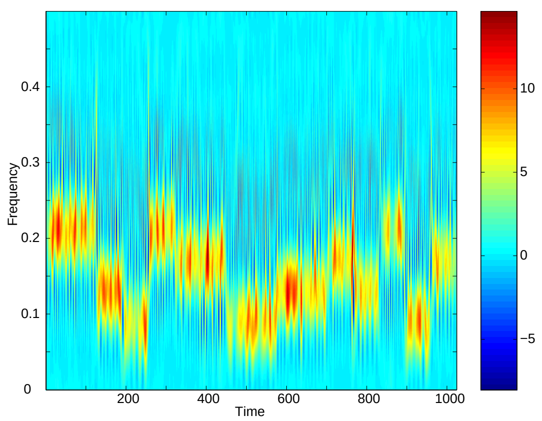
A first approach toward the classification task could be a classification based on the frequency components existence in the modulations (i.e. FSK, OFDM contain multi frequency components instead of mono-frequency for the other modulations). To detect the multi-frequencies of a modulated signal, one can use many techniques. In our experimental study, we found that a simple Power Spectral Density (PSD) of the signal is sufficiently enough to achieve this task.



(a) PSK 4



(b) QAM 16



(c) FSK 4

Figure 1: Pseudo-Wigner-Ville representations of modulated signals with $l_h = 11$, $N = 1024$ samples, $f_c = 0.15$ relative carrier frequency, $d = 64$ symbol duration and a SNR = 5dB.

Obviously, the number of PSD picks gives a first approximation of the type of the modulated signal. As the PSD has been estimated using samples of noisy data, the estimated PSD function suffers from spurious extrema. A technique has been developed in order to give all the local maxima. When the estimated PSD becomes a mono-modal function, one can be sure that the observed signal isn't a FSK neither an OFDM modulation. Unfortunately, in the opposite case i.e. when the obtained PSD becomes a multi-modal function, no decision can be considered. In fact, for noisy data, spurious picks can take place on the estimated PSD and they can be considered as composite frequencies. Therefore, QAM and PSK modulations can be taken for FSK or OFDM modulation. To deal with this specific problem, an energetic analysis of the PSD function has been set up. The main idea is to estimated the mean energy of the signal, E_{mean}, over a growing window centered on f_c:

$$E_{mean} = \frac{1}{W_{size}} \sum_{f=f_c-Wf_{size}}^{f=f_c+Wf_{size}} \mathrm{PSD}(f)^2$$

where $Wf_{size} = \frac{W_{size}}{2} < M - fc$ is the half width of the estimation window and f_c stands for the index of the carrier frequency.

For FSK modulations, the obtained curves present several maxima whereas PSQ and QAM modulations give strictly decreasing energy curves. Thus, the sign of the derivative curves can be used to classify the modulation. Once FSK is considered, PSD curve gives other information such as the number of states which can be simply the number efficient maxima in the PSD.

Spectral analysis can not be used to distinguish between PSK and QAM signals. Indeed, the main difference between QAM and PSK can be the energy changes of the signal over time. The previous statement can be useful to emphasize the difference between the two mentioned modulations. Indeed, by making a threshold on maximum normalized amplitude of a fixed size slippery window energy on a TFR, we found the right type of modulation.

4 Symbol duration extraction

We should mention that the symbol transitions affect the modulated signal and they generate some discontinuities in the time-frequency domain (cf Figure 1). These discontinuities characterize perfectly the symbol rate and the symbol duration. To extract symbol rate using the TFR discontinuities, some statistical functions have been modified and applied to TFR.

4.1 Functions' definitions

At first, a simple derivative function is considered:

$$Der(t) = \sum_{f=1}^{M} \mid TFR_{t+1}(f) - TFR_t(f) \mid$$

The previous function presents some picks whenever two successive vectors are different. Unfortunately $Der(t)$ is quite sensitive to noise.
To be more robust to noise, we considered another function based on vectorial product, $VP(t)$:

$$VP(t) = N_t \; N_{t+1} \; sin(\alpha_{t,t+1})$$

It is clear that this function is sensitive to a frequency transition. In fact, in this case the two successive vectors are orthogonal and $VP(t)$ has a maximum. This function is especially adapted to analyze a FSK modulation.

Based on information theory [10], a normalized version of the entropy, $Ent(t)$, is proposed. It is known that the entropy function is based on probability density functions (pdf). Therefore, a normalization should be considered in the first stage. A normalized vector, $\overline{\mathrm{TFR}}_t(f)$ should be used and the $Ent(t)$ becomes:

$$Ent(t) = \frac{-1}{log_{10}M} \sum_{f=1}^{M} \overline{\mathrm{TFR}}_t(f) \quad log_{10}\overline{\mathrm{TFR}}_t(f)$$

Such a function will be equal to 1 if the studied vector is uniformly spread. Symbol transition is characterized by an important energetic spread and it gives a pick on $Ent(t)$.

On the other hand Kullback-Leibner divergence, $Div(t)$, is a nice criterion to compare two pdf and it can be considered as the generalization of mutual-information:

$$Div(t) = \sum_{f=1}^{M} \overline{\mathrm{TFR}}_t(f) \quad log_{10}\left(\frac{\overline{\mathrm{TFR}}_t(f)}{\overline{\mathrm{TFR}}_{t+1}(f)}\right) \quad (3)$$

In our case, $Div(t)$ becomes a measure of an asymmetric distance between two successive normalized vectors. Therefore it is suitable for most of modulated signal and especially for a PSK, see Figure 2.

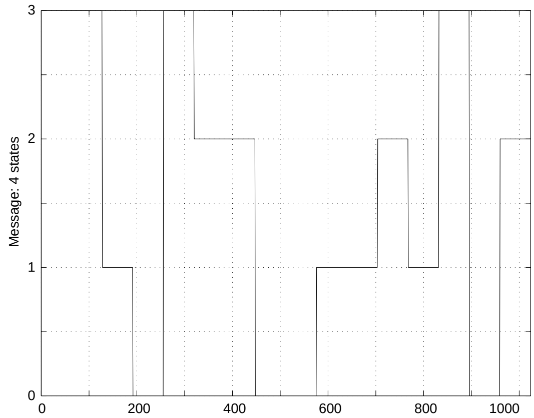
Finally, we consider a function based on time variations of the representation at $f = f_c$. The latter function is named "Carrier Variations" and it is given by:

$$CV(t) = \mathrm{TFR}(t, f_c) = \mathrm{TFR}_{f_c}(t)$$

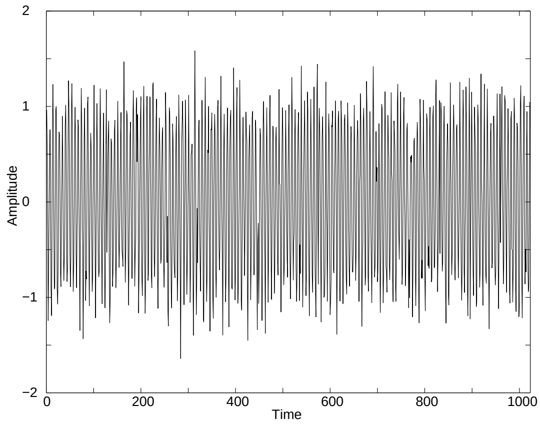
As PSK and QAM modulations are carried by using only one frequency $f = f_c$, all the related information is present in $CV(t)$. Thus, symbol transitions generate local minimum in $CV(t)$. Unfortunately, $CV(t)$ can't be used to deal with FSK signals.

4.2 Pulse Repetition Interval Estimation

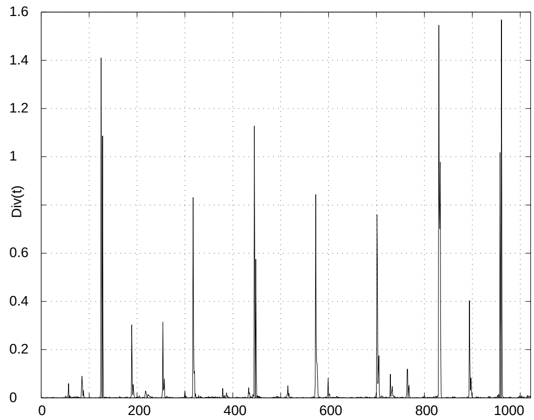
Once the modulation has been recognized, and an extraction function has been applied, an estimation algorithm should be used to estimate the distance among the picks. Similar problem is well-known in ELectronic INTelligence (ELINT) field to estimate the Pulse Repetition Interval (PRI). The difficulties for the estimation of the PRI are of various origins: temporal jitters on measurements, missing pulses and parasite pulses. Solutions based on optimal filtering [11, 12] need a complete model of perturbations. Many experiments have been conducted and we found that Kalman or recursive filtering algorithms don't achieve better performances than a simple periodogram since our model is less noisy than the ones considered in ELINT.



(a) Modulating message with 4 states



(b) Related PSK 4 with SNR = 10dB



(c) Divergence of the modulated signal

Figure 2: Divergence for a PSK modulation based on a PWV with TFR-trunc.=15%, TFR thres.=0.177, $l_h = 11$, $N = 1024$ samples, $f_c = 0.15$ relative carrier frequency, $d = 64$ symbol duration and a SNR = 10dB.

5 Experimental Results

The experimental results have been obtained for PSK, QAM and FSK simulated signals of $N = 4096$ points and different number of states as 2, 4 and 8 for PSK and FSK signals and 16, 32 and 64 for QAM. The noise is "AWG", Additive White and Gaussian.

5.1 Type of modulation

As far as the type of modulation is concerned, good experimental results have been observed (cf Table 1). Indeed, for many modulation types, the detection rates are very significant (greater than 90%) even for a SNR near 0dB. We can peculiarly notice the good results for FSK and QAM modulation.

	PSK	QAM	FSK
$5dB$	91.66%	98.02%	99.03%
$0dB$	90.62%	97.03%	99.03%

Table 1: Detection of modulation type for some modulated signals.

5.2 Symbol duration

Concerning the estimation of symbol duration, we found that the experimental results are less attractive than the results presented in the previous subsection. Indeed, we found that the performances are quite depending on the modulation type i.e. none of the previous cited functions can give satisfactory results for all type of modulation. Besides, according to the duration value, extraction is more or less difficult. Thus the shorter the duration is the more difficult the PRI estimation is. However, if the duration is very long, some states can disappear and therefore yield to a wrong estimation. These disadvantages have been considered in our simulations.

	CV	Der	Ent	Div
$10dB$	**100%**	**82.69%**	57.05%	58.97%
$5dB$	**100%**	**84.43%**	29.94%	8.98%

Table 2: Estimation of symbol duration for 160 realizations of a QAM signal.

For QAM modulation type (cf Table 2), Carrier Variations, $CV(t)$ seems to be the best solution. On the other hand, the performances of Carrier Variations depend on the accuracy of the carrier frequency estimation. For this inconvenient, we can not suggest $CV(t)$ to be used alone. However, it can be mixed with other functions to improve the global results. Consequently, the choice of $Der(t)$ can be made even for a QAM.

	CV	Der	Ent	Div
$10dB$	**100%**	**100%**	54.49%	**98.20%**
$5dB$	**100%**	**98.80%**	36%	**94.86%**

Table 3: Estimation of symbol duration for 160 realizations of a PSK signal.

Concerning PSK modulations, we can mention that the techniques of Derivative $Der(t)$ and Divergence $Div(t)$ (cf Table 3) give good results even for a small SNR.

	CV	Der	Div
$10dB$	**100%**	**100%**	**100%**
$5dB$	**100%**	**100%**	**100%**

Table 4: Estimation of symbol duration for 160 realizations of a PSK signal with $d = 39$.

We should mention that all conducted experiments take into account 3 symbol durations: $d = 17$, 39 and 63. $N = 4096$ and $d = 39$ satisfy the constraint concerning that 100 symbols at least must be present in the signal. $d = 17$ and $d = 63$ concern some extreme cases. On the other hand, we must stress on the fact that results are done with $d = 17$ and 63. Such durations lead a decreasing of the general performance. It is due to the non adaptation of time-frequency representation to such signals: the chosen value for the filter length, l_h, is not enough accurate. To illustrate this effect, let show the results obtained for a PSK with $d = 39$ (cf Table 4). There are really better than before, namely for $Div(t)$. We must therefore go on in order to find a less constrained time-frequency representation.

	VP	Der	Ent	Div
$10dB$	**97.48%**	**100%**	**100%**	**97.47%**
$5dB$	2.02%	**88.89%**	**81.82%**	33.33%

Table 5: Estimation of symbol duration for 100 realizations of a FSK2 modulation.

For FSK modulation, the choice of the adequate function is less obvious because it depends on the number of states. Since we can estimate this parameter, we have distinguished different cases: FSK2, FSK4 and FSK8. The results are presented for simulated signals with $d = 39$.

	VP	Der	Ent	Div
$10dB$	**100%**	**100%**	**100%**	**100%**
$5dB$	23.86%	**100%**	**100%**	**81.82%**

Table 6: Estimation of symbol duration for 100 realizations of a FSK4 modulation.

For FSK2, the estimation is less robust than for the other FSK modulations (cf Table 5). In this case, one can consider two functions Derivative or Entropy.

	VP	Der	Ent	Div
$10dB$	**100%**	**100%**	**100%**	0%
$5dB$	**96.63%**	**100%**	**94.38%**	0%

Table 7: Estimation of symbol duration for 100 realizations of a FSK8 modulation.

In the case of FSK4, the duration extraction is very efficient (cf Table 6). To reach that, one can use Derivative $Der(t)$, Entropy $Ent(t)$ as well as Divergence $Div(t)$. There are some specific characteristics for $Div(t)$. This function is very interesting. In fact, we obtained 100% of success at 10 db and for all tested durations.

Unfortunately, $Div(t)$ function gives bad results for FSK8 (cf Table 7). An extraction method based on Vectorial Product, Entropy or Derivative could be envisaged. In addition, we should mention that the Derivative gave good results (over 96% of good extraction) at 10dB and over all tested durations ($d = 39$, 63 or 17).

6 conclusion

This paper deals with a main step of modulation recognition process: the symbol duration estimation. This parameter has been estimated by using some modified standard statistical functions applied to optimized Pseudo-Wigner-Ville representation. We should mention that good experimental results have been obtained even with noisy signals. Moreover we have also proposed a classification technique that distinguishes PSK, FSK and QAM from each others. We should mention here that the results of the previous section encourage us to suggest a method which mix several functions.

Now, we are working on the recognition of the states number of PSK and QAM modulations. It seems that such a problem can be solved by complex time-frequency representations or complex wavelets. The last two theories will be the main subject of our future work.

References

[1] E. E. Azzouz and A. K. Nandi, *Automatic Modulation Recognition of Communication Signals*, Kluwer Academic Publishers, 1996.

[2] S.S. Soliman and Z.S. Hsue, "Signal classification using statistical moments," *IEEE Trans. Comm.*, vol. 40, no. 5, pp. 908–916, May 1992.

[3] B.F. Beidas and C.L. Weber, "Higher-order correlation-based approach to modulation classification of digitally modulated signals," *IEEE Journal on Selected Areas in Communications*, vol. 13, no. 1, pp. 89–101, January 1995.

[4] F. Hlawatsch and G. F. Boudreaux-Bartels, "Linear and quadratic time-frequency signal representations," *IEEE signal processing magazine*, pp. 21–67, April 1992.

[5] S. Qian and D. Chen, *Joint time-frequency analysis - methods and applications*, Prentice Hall, 1996.

[6] P. Flandrin, *Time-Frequency / Time-Scale analysis*, Academic Press, 1999.

[7] D. Le Guen and A. Mansour, "Automatic recognition algorithm for digitally modulated signals," in *SPPRA*, Crete, pp. 32–37, June 2002.

[8] H. Ketterer, F. Jondral, and A. H. Costa, "Classification of modulation modes using time-frequency methods," in *ICASSP*, Arizona, vol. 5, pp. 2471–2474, March 1999.

[9] L. Hong and K. C. Ho, "Identification of digital modulation types using the wavelet transform," in *MILCOM*, New Jersey, October 1999.

[10] T. M. Cover and J. A. Thomas, *Elements of Information Theory*, Wiely Series in Telecommunications, 1991.

[11] S. D. Elton and B. J. Slocumb, "A robust kalman filter for estimation and tracking of periodic discrete processes," in *ISSPA'96*, pp. 184–187, October 1996.

[12] S. Sirinumpiboon, G. Noone and S. Howard, "Robust and recursive radar pulse train parameter estimators," in *ISSPA'96*, October 1996.