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Automatic Recognition Algorithm for Digitally Modulated Signals

D. Le Guen
Laboratoire E^3I^2 - ENSIETA
2, rue Franois Verny
29806 BREST CEDEX 9
FRANCE
leguende@ensieta.fr

A. Mansour
Laboratoire E^3I^2 - ENSIETA
2, rue Franois Verny
29806 BREST CEDEX 9
FRANCE
mansour@ieee.org

ABSTRACT

Since the end of the eighties, many researchers have been investigating the automatic identification and recognition of modulated communication signals. Recently, many algorithms have been proposed to automatically identify and recognize the digitally modulated signals. Such types of signals have been used in many applications such as: Electronic warfare, surveillance and threat analysis, control of communication quality *etc*.

In this paper we outline the major problems, approaches and some algorithms to recognize automatically the type of the modulated signals. First of all, some algorithms to estimate some important features of the modulated signals, as the wave carrier frequency, have been discussed and simulated. At the second part, we propose a modified version of the well-known algorithm DMRA (Digital Modulation Recognition Algorithm) proposed by Azzouz and Nandi. Finally, many experiments and simulations have been conducted and presented.

KEY WORDS

Digital Modulations (ASK, PSK, FSK), Classification, Recognition, Statistical Methods.

1 Introduction

Nowadays digitally modulated signals such as ASK (Amplitude Shift Keying), PSK (Phase Shift Keying) among others are very important for telecommunication systems. Such signals can be founded in many civil as well as military applications such as: interference identification and spectrum management, identification of non-licensed transmitters, electronic warfare, surveillance and threat analysis, control of communication quality *etc*.

In COMmunication INTelligence (COMINT) applications, the modulation types are considered as signal signatures. Therefore, the modulation recognition is an essential key to demodulate as well as to decode and understand the transmitted message.

In the last two decades, many researchers were interested by automatic recognition and identification algorithms for communication signals. In fact, since 1990 many algorithms have been proposed [1, 2, 3, 4]. The main differences among these algorithms are their sensitivity to Signal to Noise Ratio (SNR), the type of modulation that they can deal with, and the applications where they can be used.

Generally, modulation algorithms consist of various steps depending on the field of interest. First of all, if we are only interested in modulation types, a simple modulation classifier can deal with this case. Once the modulation type has been classified, then one may seek other features and modulation parameters which allow us to better classify and recognize the transmitted signals. The latter step is the modulation recognition step. On the other hand, in order to perform the demodulation of transmitted signals, a necessary step of identification should be performed: at this stage, many characteristic features of the modulated and received signal must be recovered.

In this paper, a complete scheme to classify and recognize a noisy modulated received signals has been presented. Some parameter modulations have been estimated using different methods. Others have been obtained using modified and new features. All of the presented, modified and proposed features have been simulated using many signals and SNR levels.

2 Digital Modulations

Here, we introduce the general model for modulation signals and the different type of modulations. Let $s(t)$ denotes the received signal. In this case, the channel model can be represented as follow:

$$s(t) = m(t) + n(t) \tag{1}$$

where $n(t)$ is considered as an Additive White Gaussian Noise (AWGN) and $m(t)$ is the modulated signal. The latter signal can be obtained using a digital signal, called the modulating signal $x_n(t)$, to modulate a carrier wave (CW) signal $c(t)$:

$$c(t) = A\cos(2\pi f_c t + \psi_c) \tag{2}$$

here f_c is the carrier wave frequency. By considering the channel properties (capacity, signal to noise ratio, noise model, etc) and in order to transmit the information carried by $x_n(t)$ in the best way, many techniques of modulation have been developed [5]. Each of them satisfies some required performance criteria with respect to some constraints depending on the applications.

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2.1 Carrier Wave Signal

To simplify the notations, let us consider, in equation(2), that $A = 1$ and $\psi_c = 0$. Normally, the information (or the modulating signal $x_n(t)$) is carried by the amplitude, the phase, the frequency or a combined modulation. On the other hand, the modulated signal $m(t)$ can be written in a generic form, using two carrier waves in quadrature from each other:

$$m(t) = p_n(t) cos(2\pi f_c t) - q_n(t) sin(2\pi f_c t) + n(t) \quad (3)$$

The modulating signals, $p_n(t)$ and $q_n(t)$ are the "in phase" and the "in quadrature" components of $m(t)$ respectively. Moreover by introducing the complex envelope notation $m_e(t)$ of the modulated signal, one can write:

$$m_e(t) = p_n(t) + j\ q_n(t)$$

here j is the complex number. It is clear that:

$$m(t) = \Re\{m_e(t) \exp(2\pi j f_c t)\}$$

On the other hand, one can easily verify that the complex envelope is the based-band analytic signal given by:

$$m_e(t) = \{m(t) + j\mathcal{H}(m(t))\} \exp(-2j\pi f_c t)) \quad (4)$$

here $\mathcal{H}$ denotes the Hilbert transform [6]. The complex envelope signal is an important representation of the modulated signal since it gives us the constellation of the signal. Using the constellation, i.e. the representation of the modulated signal shifted in base-band, a lot of signal features can be extracted [7]. Based on the above definition (4), it is clear that the carrier frequency f_c is an important feature of the received and modulated signals.

2.2 Major Digital Modulation Types

As it was said before, many modulation techniques and types can be found in the literature. In this section, we outline the major modulation types of interest to our project. Firstly, we consider linear modulations as: ASK (Amplitude Shift Keying), PSK (Phase Shift Keying), QAM (Quadrature Amplitude Modulation). Later on, we discuss non linear modulation techniques such as FSK (Frequency Shift Keying). To reach our goal, the properties of each modulation and the mathematical model of the modulated signal $m(t)$ have been developed and discussed hereafter.

2.2.1 Linear Digital Modulations: QAM, PSK & ASK

For such type of modulations, linear ones, the modulating signal $x_n(t)$ can be written:

$$x_n(t) = \sum_k \gamma_k\ \Omega(t - kT) \quad (5)$$

where γ_k represents the symbol values at time k, T the symbol duration[1] and $\Omega(t)$ is a simple rectangular shaped window of width T.

[1]The symbol duration is the inverse of the symbol rate r_s.

Assuming that each symbol can be written using n bits, one can write $T = nT_b$, where T_b is the bit duration. Let M be the number of states for each symbol. Based on information theory [8], one can write: $T = T_b \log_2(M)$.

From equations (3) and (5), one can develop the needed signals $p_n(t)$ and $q_n(t)$ to obtain the expression of a QAM modulation, where:

$$m_{QAM}(t) = p_n(t) cos(2\pi f_c t) - q_n(t) sin(2\pi f_c t)$$

$$\text{with} \begin{cases} p_n(t) = \sum_k \alpha_k\ \Omega(t - kT) \\ q_n(t) = \sum_k \beta_k\ \Omega(t - kT) \end{cases} \quad (6)$$

For QAM modulation, the total number of possible states can be evaluated by $N = 2^{(m+n)}$, here α_k and β_k contains m and n bits respectively. The different states of each symbol can be written as: $\{\pm d, \pm 3d, \cdots \pm (M-1)d\}$ with d is a digital non-zero number and $M = 2^m$ or 2^n, depending on the considered axes. The last equation (6) can be written as well as:

$$m_{QAM}(t) = \sum_k \Gamma_k \cos(2\pi f_c t + \psi_k) \quad (7)$$

$$\text{with } \Gamma_k = \sqrt{{\alpha_k}^2 + {\beta_k}^2} \text{ and } \psi_k = \arctan(\frac{\beta_k}{\alpha_k})$$

It is clear from the above expression (7), that QAM modulations can be considered as two different modulations: in amplitude and in phase. This kind of modulations has been widely used in different applications, especially in fast modem (MOdulation-DEModulation) connection to increase bit rate without affecting the bandwidth of the modulated signal.

Equation (6) can also be used to represent other linear modulations. Indeed, ASK modulations can be considered as QAM ones which quadrature components are zeros (and $\{\alpha_k = \pm 1, \pm 3, \cdots \pm (M-1)\}$:

$$m_{ASK}(t) = \sum_k \alpha_k\ \Omega(t - kT) \cos(2\pi f_c t + \psi_c)$$

In the case of one bit symbol, ASK modulations are said "On-Off Keying" ($\alpha_k \in \{0, 1\}$). A major inconvenient of ASK modulations is the non optimal use of the channel bandwidth.

As in the case of ASK, PSK modulation can be considered as well as a QAM with a constant amplitude, that is $\Gamma_k = cte$. But, the "in phase" and the "in quadrature" components are generally dependent for a PSK, except for a QPSK "Quadrature Phase Shift Keying". QPSK s a particular case of PSK, where $M = 4$. PSK modulation is given by:

$$m_{PSK}(t) = \sum_k \Omega(t - kT) \cos(2\pi f_c t + \psi_k)$$

Here, the symbol ψ_k takes the values $(\psi_0 + (2m+1)\frac{\pi}{M})$ with $0 \leq m \leq (M-1)$. At the beginning, ψ_0 will often be set to zero. Such a modulation is applied in the framework of long distance spatial communications.

2.2.2 Frequency modulation: FSK

Two types of FSK modulations can be considered, with continuous and non continuous phase :

$$m_{FSK}(t) = \cos(2\pi f_c t + \psi(t))$$

$\psi(t)$ depends on the integral over time of the modulating signal $x_n(t)$. Due to an important spectral overcrowding, more than the ASK case, such a modulation is not suitable to transmit digital information on a limited channel. On the other hand, its good performances against interference make it useful for modem with medium rate as Minitel (A special French Communication System, which is widely used in France).

3 Features extraction

3.1 Introduction

Depending on applications and users, many features can be considered as interesting. For example, one can seek for a state number, a symbol duration among others.
To distinguish the different versions of modulation, algorithms often enclose the computing of states number. For instance, a lot of studies aim to distinguish the different MPSK or the different MFSK versions [2, 3, 4]. With regard to the symbol duration, we can quote the methods based on the level crossing, the derivation or a wavelet transform [9].
On the other hand, it seems that the carrier frequency is a main feature in many applications. Therefore, in the next subsection, we focus on the carrier frequency recovery.

3.2 Carrier frequency

Many classifying methods are based on constellation shapes [7, 10]. Therefore, one should estimated precisely the carrier frequency. Indeed, even a small estimation error on the frequency (cf Fig. 3) can generate some important artifacts over the constellation. Such artifacts are due to the rotation matrix, employed to recover the based-band signal and they are very sensitive to estimation error as well as the sample number.For carrier frequency, many estimators, in the time domain or in the frequency one, have been proposed.

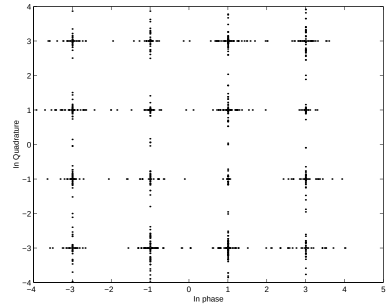
3.2.1 Time-Domain Estimation

In [11], the authors propose a zero-crossing estimator. Let $L = N * T = N/f$ denotes the segment length and N denotes the number of the complete periods. N can be evaluated using the zero-crossing number Nb_{zero} of the signals (in each of the signal period, the signal should twice cross the zero axe. It contains therefore two zero-crossing points):

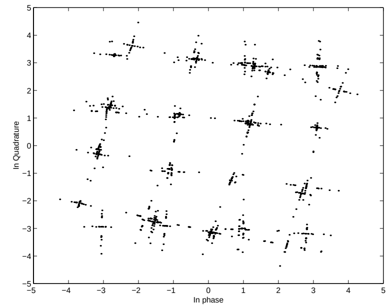
$$N = \frac{Nb_{zero} - 1}{2}$$

Finally, we can write that

$$f_c = \frac{Nb_{zero} - 1}{2 * L}$$



(a) 16QAM and $f_c = 0.25 f_s$



(b) 16QAM and $f_c = 0.25005 f_s$

Figure 3. Constellations of a 16QAM signal with the correct and estimated carrier frequency with a relative error of 0.02%

Obviously, the last equation is sensitive to the SNR. Depending on noise type and SNR, one can make mistakes in finding the zero-crossing positions or number. On the other hand, the performance results of this method depend also on the value of carrier frequency (the higher the frequency is the lower the noise impact is). Thus, one should only consider the zero-crossing sequence in the non-weak signal intervals. Unfortunately, the experimental studies show that a threshold value can not be easily determined. Fig. 1 shows the average over 100 random experimental results using Monte-Carlo approaches.

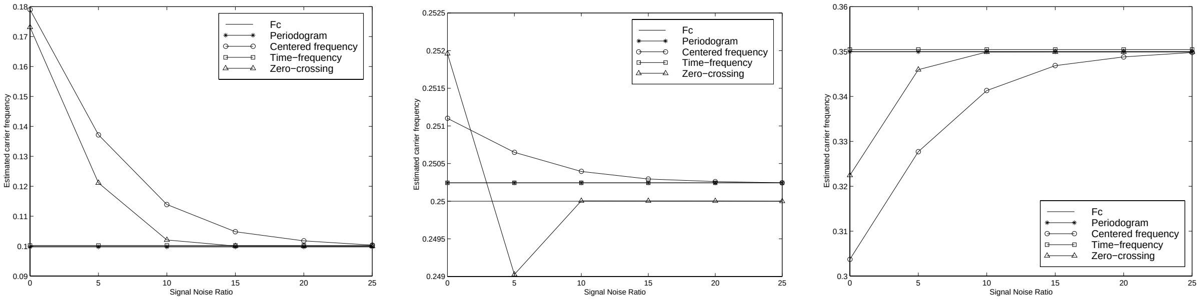
3.2.2 Frequency-domain estimation

Most of the Frequency-domain estimation methods are based on the signal spectrum. The performances of such methods depend on the used estimation techniques (FFT, Welch, ...) and the chosen estimation window (such as Haming, Hanning, ...).

In this section, we emphasize two main frequency methods:

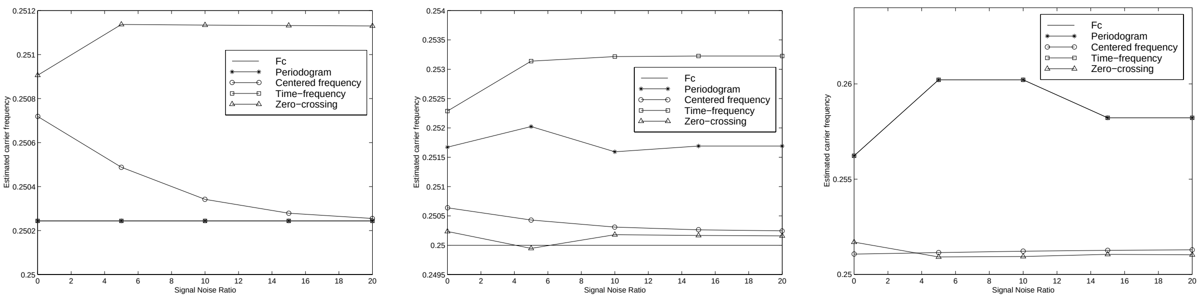
- A frequency-centered method: it is can be considered as a weighted mean of frequency using the spectrum as an histogram. The performances of this method are similar to the zero-crossing ones (cf: 3.2.1). Indeed, the experimental studies show that this technique is sensitive to noise.

- A periodogam method: The spectral representation carry the frequency information. In fact, a peak ap-



(a) Carrier Wave with $f_c = 0.1 f_s$ (b) CW with $f_c = 0.25005 f_s$ (c) CW with $f_c = 0.35005 f_s$

Figure 1. Four methods of frequency recovery for three different frequencies with different SNR.



(a) ASK2 with $f_c = 0.25 f_s$ (b) PSK2 with $f_c = 0.25 f_s$ (c) FSK2 with $f_c = 0.25 f_s$

Figure 2. Four methods of frequency recovery, three different types of modulation and different SNR.

pears for the carrier frequency. Therefore, the maximum of the peridogram allows us to estimate the carrier frequency.

Finally, we tested some new methods based on recent developments: using Wigner-Ville representation [12] to estimate the carrier frequency, one can notice that time-frequency representations are less sensitive to noise. In fact, every point of frequency axe of Fourier Transform can be considered as a line in time-frequency domain.

Fig. 2 shows the performance results of the different presented methods for different type of modulations. Based on the experimental results, we can conclude that zero-crossing method is not suitable for an OOK modulation (cf Fig. 2 (a)) due to the loss of signal on many intervals. Besides, since the spectral representation of an OOK in not symmetric for a low Signal Noise Ratio, the frequency-centered method cannot be considered as a good estimation method.

With regard to PSK (cf Fig. 2 (b)), we can notice the bad performance results for frequency-domain estimation due to the relatively flat shape of the spectrum. This flat shape is due to the successive add of noisy data and it can lead to an important estimation error.

Since FSK spectral representation is multi-modal (cf Fig. 2 (c)), frequency method can be sensitive to noise (for the same SNR, the signal power has been divided on different peaks). In addition, the maximum of the spectrum doesn't correspond to the f_c value. On the other hand, the frequency-centered method is less sensitive to such shape because of the weight average that is considered.

4 Classification

In this section, a modulation classification scheme for ASK2, ASK4, PSK2, PSK4, FSK2 and FSK4 is proposed. Many previous papers can be found in the literature [13, 11, 14, 15, 16]. One of the most recent and the most quoted method is the one developed by Azzouz and Nandi [1]. The latter algorithm has been emphasized, studied and modified in this manuscript.

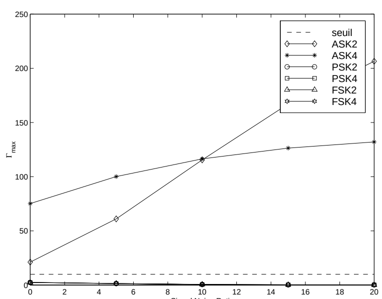
The algorithm of Azzouz and Nandi is based on statistical features. Five discriminated parameters are set up in order to built a decision tree. These parameters are based on the instantaneous amplitude, non linear phase and frequency. The decision is taking by determining heuristic thresholds.

The first parameter, Γ_{max}, is used to divide the modulated signal into two subsets. The first group contains ASK and PSK whereas the second one keeps FSK. Such a classification is realized by computing the maximum value of the spectral power density of the normalized-centered instantaneous amplitude. Because it depends on instantaneous am-

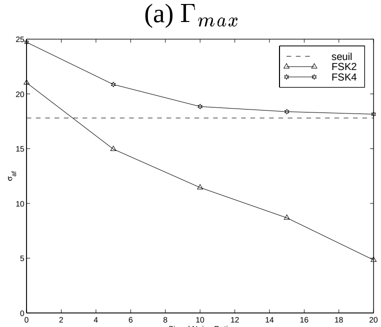
plitude, Γ_{max} contains information (i.e. it is not equal to zero) for an ASK and also for a PSK modulation (for example, in the case of PSK2, the change of the phase from 0 to π can be replaced by 1 and -1 amplitude effects). However, since this information comes from changes of phase for a PSK modulation, the contribution is somehow weak.
The experimental studies conducted separately by Azzouz and other researchers as well as our experimental studies show that for a small SNR (less than 10)[1], Γ_{max} can not be used any more to distinguish between the FSK and the PSK. These reasons lead us to change the threshold and therefore the prior subsets. Thus, we find that Γ_{max} can be used to separated ASK modulations from PSK and FSK. For the last modulations, Γ_{max} is close to zero (cf Fig. 4 (a)). In this case, Γ_{max} can separate ASK even with a SNR = 0dB (instead of the usual 10db proposed by the previous algorithms).

As a second step, one should distinguish PSK and FSK. Unfortunately, Azzouz parameters' can not be used to establish this goal. Here we propose a new feature that can distinguish between FSK and PSK modulations.

The five parameters of Azzouz algorithm are based on the mean and the variance of different parameters. It is clear, that such features are statistical parameters and they are time difference free (relatively difference frequency free), i.e. these parameters don't use the difference in time of the different parameters. To better achieve the separation among the different MFSK and MPSK, we developed and tested a new feature.

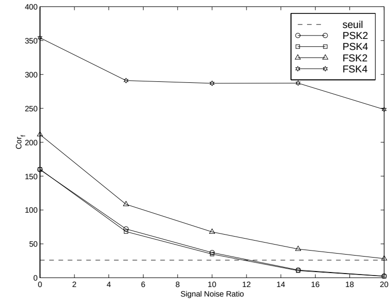


(a) Γ_{max}

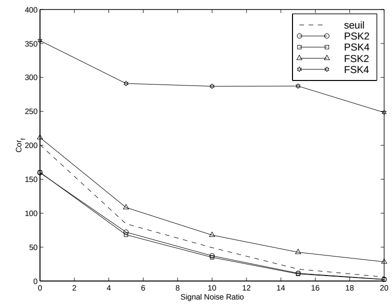


(b) σ_{af}

Figure 4. Azzouz parameters' for modulation classification. The curves are computing by Monte-Carlo approaches over 100 random simulations of each signal.



(a) Constant threshold



(b) Evolutive threshold

Figure 5. New parameter for modulations classification: Cor_f

This new proposed feature is based on the following properties: it is well known that PSK modulations are characterized by discontinues instantaneous phases (due to the modulating signal $x_n(t)$). Such phase can generate a constant instantaneous frequency, except on the time intervals of the phase transition one should find some dirac impulse in the instantaneous frequency. On the other hand, the instantaneous frequency of FSK can be considered as succession of rectangular shaped windows.

To exploit the above properties and by generalizing the correlation concept in the frequency domain, the new proposed feature Cor_f can be considered as the correlation over time of the absolute value of the centered instantaneous frequency.

$$Cor_f = E[|f(t)||f(t-\tau)|] \tag{8}$$

Theoretically, the Cor_f of PSK signals can be equal to zero when $\tau > 0$, using the fact that the noise is a gaussian and i.i.d (independent and identically distributed) signal. In real world applications, the various diracs, in the instantaneous frequency of PSK, mentioned before are replaced by some narrow peaks. Experimental studies show that τ should be around 10 percent of the symbol duration (cf Fig. 5 (a)). Finally, the symbol duration can be estimated using different methods as described in [9].

To achieve our goal of modulation classification, some features proposed by Azzouz [1] can be used for separating ASK2 from ASK4, PSK2 from PSK4 and FSK2 from FSK4. These parameters are σ_{aa}, σ_{ap} and σ_{af} respectively. The latter 3 parameters are the standard deviations of the absolute values of, the normalized-centered instantaneous amplitude, the centered non linear component of the phase and the normalized-centered instantaneous frequency, respectively. For two states of modulation, the signal does not carry information in terms of absolute value. So they allow us to separate the case $M = 2$ and the case $M = 4$. For ASK and PSK modulation the classification is accurate even if SNR =0. For FSK ones, the separation is efficient for SNR higher than 3dB (cf Fig. 4 (b)). We should mention here that in our experiment, many thresholds have been estimated using our data, and some intermediate parameters have been slightly modified.

Finally, we can resume the new proposed algorithm as following: the mentioned modulations can be distinguished using the various above features till a SNR of 12 db. The limitation to 12dB is mainly due to the constant threshold used in our new feature (the Cor_f). For this reason, we investigated different thresholds which depend on the noise level. The selection of these thresholds is not an easy task. Many experimental studies should therefore be performed to better select the threshold depending on noise model, SNR and our major applications. As it was mentioned before: the Cor_f is theoretically zero for PSK signals and the only possible values are due to the noise. Therefore, the Cor_f of noisy carrier wave signals have been used to compute a threshold depending on the noise level. To achieve that gaol we used Monte-Carlo simulations on noisy carrier wave signals. we find a threshold that depends on the noise level. Such threshold improves the performance of our proposed algorithm which can be now used even with a SNR less then 3dB. The obtained results can clearly appear in fig 5 (b).

5 Conclusion

In this paper, a complete scheme of identification, classification and recognition of modulation signals has been developed. Different methods to estimate the carrier frequency have been evaluated and compared. Some previous features for automatic recognition algorithm have been presented and discussed. A new feature to discriminate MPSK and MFSK, has been introduced and tested.

Most of the previous features presented in this manuscript are based on statistical method and they used time or frequency information separately. Nowadays, some researchers [17, 18] are investigating the used of the two dimension spaces (time-frequency or time scale representations) in the field of modulation recognition. Such methods will be objectives in our future works.

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