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An Improved Method for the Automatic Digital Modulation Classification

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Abstract *– In this paper, a new method for the automatic modulation classification of an unknown signal, working without any knowledge about the modulation parameters, is proposed. The method has been developed in two different versions, such that it can be implemented on both waveform digitizers and vector signal analyzers. The developed method is able to recognize classical single carrier modulations such as M-ary Phase-Shift Keying (PSK), M-ary Frequency Shift Keying (FSK), M-ary Amplitude Shift Keying (ASK), and M-ary Quadrature Amplitude Modulation (QAM), as well as Orthogonal Frequency Division Multiplexing modulations (OFDM) such as the Discrete MultiTone (DMT). Both the versions of the new developed method are able to work with limited-bandwidth signals, too. After the identification of the modulation type, the method automatically estimates some parameters characterizing the modulation. In order to evaluate the method performance, several experimental tests, with simulated and actual signals, have been carried out in different operating conditions by varying the Signal to Noise Ratio and other parameters characterizing the modulation, such as the carrier frequency and the symbol rate.*

Keywords *– Classification, digital modulations, orthogonal frequency-division multiplexing (OFDM).*

I. INTRODUCTION

Digitally modulated signals play an important role in the world of communications and the automatic recognition of a signal's modulation has received international scientific attention in recent years. The modulation detection has acquired, in the last decade, a decisive position in some telecommunication applications belonging to the signal intelligence (SIGINT) field, such as military communications, emitter interception, electronic surveillance systems and electronic warfare. Moreover, it is really important for network management and control applications, to have the capability to detect a communication in progress and to extract information effectively in an automated way.

For all these applications, it could be very interesting to realize a universal classifier that is able to recognize the modulation type with the minimum a priori knowledge about the signals under test [1]-[3].

Modulation classification is a middle step between signal interception and information recovery. When the modulation scheme of an unknown signal is identified, it is possible to demodulate it properly with the right demodulator in order to recover the transmitted information.

In order to get this aim, two different hardware architectures of signal analyzers can be used.

i. The first one adopts Digital Storage Oscilloscopes (DSOs) and Waveform Digitizers (WDs). They act simply by acquiring the signal directly at a Radio Frequency (RF), or, eventually, after a preliminary conversion to an Intermediate Frequency (IF). Such acquisition architecture requires a high sampling speed, especially if the acquisition is operated directly at a RF.
ii. The second hardware solution is based on Vector Signal Analyzers (VSAs). They operate by demodulating the signal and extracting from it a vector representation, in which the carrier has been removed. In this case, a lower sampling rate, than in the previous architecture, is used. However, the knowledge of the

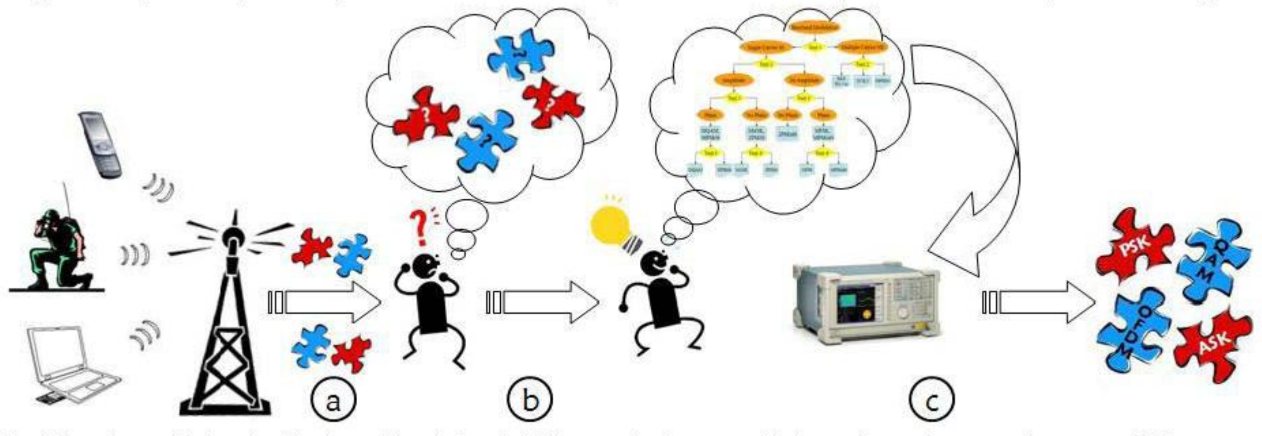

Fig.1. How the modulation classification problem is faced: a) All types of unknown modulations arrives to the operator by antenna; b) The operator do not know how demodulate the incoming signal; c) Adding the classification method inside the acquisition system it is possible to classify different kinds of modulated signals.

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carrier frequency is required, in order to correctly remove it.

Several methods for the modulation classification have been proposed in literature [1], even if the most part of them describes only methods able of identifying a restricted number of modulations, like M-ary Phase Shift Keying (M-PSK) and M-ary Frequency Shift Keying (M-FSK). The methods using a statistical approach [4], [5] are particularly interesting, but they require the knowledge of the symbol rate. Other methods use neural networks [6], [7] or time-frequency representations [8], [9], achieving better results but requiring more processing power.

An interesting classification strategy, reported in [10] and [11], is based on a zero-crossing technique, which allows evaluating the instantaneous frequency of the signal. The instantaneous frequency is, then, used to classify and explore the properties of the modulated signal.

A method for the automatic classification of digital modulations, based on the zero-crossing technique, has been presented in [1]. It is capable of working on a large variety of modulations by means of a hierarchical and modular structure.

The method in [1], however, has some limitations:

i. It has been developed by considering only ideally modulated signals, having rectangular pulses, without taking into account limited-bandwidth (LB) signals. Such limitation reduces the field of application of the method to few modulation schemes. Most of the telecommunications systems, in fact, especially operating at RF, use a raised cosine or a Gaussian filter in order to limit the bandwidth of the modulated signal.
ii. It is thought to be applied on signals acquired using a waveform digitizer. It is not applicable to signals digitized using a different acquisition system such as a VSA.

Starting from the method reported in [1], this paper proposes a reliable method to automatically identify the modulation scheme of an unknown digitally modulated signal (Fig.1), which is able to work also on LB signals. The method has been developed in two different versions, in order to make it applicable to both the above described hardware architectures.

In the following section, a description of the method presented in [1] is given. Subsequently, the first version of the new method, to be used on a WD hardware is described. In the Section IV, the second version of the new method, working on a VSA hardware is presented. For each version, a method validation is presented either with simulated or actual telecommunication signals.

II. METHOD FOR THE AUTOMATIC MODULATION CLASSIFICATION

The method for the recognition of digital modulations proposed in [1] is based on a hierarchical decision tree; the branches of such tree are selected starting from the root, evaluating some parameters, as shown in Fig. 2.

First, the procedure selects the type of modulation between the single-carrier (SC) and multiple-carrier (MC) ones (Step 1). Then, among the SC modulations, it discriminates between the angle-modulated signals and the amplitude modulated ones (Step 2). Finally, a series of specialized classifier modules select the correct modulation type:

- Among the SC amplitude-modulated signals, the method discriminates the M-ary Quadrature Amplitude Modulation (M-QAM) from the M-ary Amplitude Shift Keying (M-ASK) (Step 3).
- Among the SC angle-modulated signals, the previous classifier has been used to select between M-PSK and M-FSK modulated signals (Step 4).
- Among the MC-modulated signals, the method has been developed to identify OFDM modulated signals with cyclic extension and to carry out compliance tests for the Asymmetric Digital Subscriber Line (ADSL) and Very high Speed Digital Subscriber Line (VDSL) standards and Power-Line Carrier (PLC) modulated signals (Step 5).

III. VERSION OF THE NEW METHOD OPERATING ON WAVEFORM DIGITIZERS

A. Method description

In order to overcome the limits of the method proposed in [1], it has been reviewed and extended in order to include also LB signals.

The tree structure of the method presented in the previous section has been changed, as shown in Fig.3. In this new structure, the classification between signals modulated in amplitude and signals modulated in phase can not be used to distinguish PSK signals from ASK and QAM signals. This is due to the fact that the band limitation acts on the signal as an amplitude modulation. Frequency modulation, instead, can be easily identified as the first step of the new tree. Step 2 consists of selecting among signals with just 2 levels of phase modulation and signals with more than 2 levels of phase modulation. The classification between amplitude-modulated and phase-modulated signals has been, instead, used in Steps 3 and 5 of the tree. This is

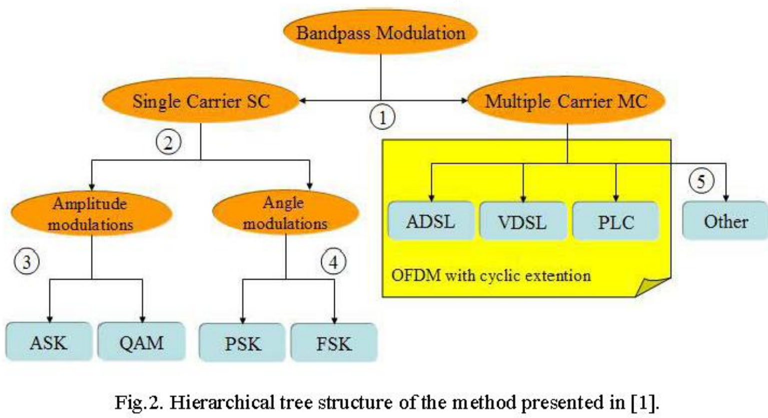

Fig.2. Hierarchical tree structure of the method presented in [1].

done with the aim of distinguishing between unlimited bandwidth (UB) 2PSK and ASK/BL-2PSK on one side (Step 3) and UB PSK with more than 2 levels and PSK BL/QAM signals, on the other side. Finally, if Step 3 has been executed, the only classification remaining is between ASK and BL-2PSK (Step 4). Instead, if Step 5 has been executed, last selection on the decision tree regards the distinction among the BL 4-8PSK or 16-64 QAM.

In the following, the steps of this version of the method are shown in details.

Step 1: Classification between SC and MC signals

The classification between SC and MC has been realized by means of the fourth order cumulants, as in [1]. It is possible to see, in fact, that the norm of the fourth order cumulant, evaluated on specific trajectories, goes to 0, when the number of the carrier of a MC signal increases. Instead, it is non-zero for SC signals.

Step 2: Classification between phase and frequency modulated signals.

The classification between phase and frequency modulated signal is obtained by means the Zero Crossing Sequence Shape (ZCSS), as shown in [1].

Step 3: Classification between signals with 2 or more phase levels.

The classification between signals with 2 or more phase levels is achieved by estimating the distribution of the phase shifts. From the zero crossing sequence, the phase shifts present in the modulated signal, are extracted. The histogram of the phase shifts is compared, then, with the theoretical phase shift histograms of all phase modulations, through the correlation function. Such theoretical histograms are obtained by considering a uniform distribution of the data. If the maximum value of the correlation is obtained by the theoretical histogram of the 2PSK modulation containing only 2 levels phase, the signal is recognized to belong to such modulation; otherwise it is identified as belonging to the class of signals with more than 2 phase levels.

Steps 4 and 5: Classification between signals modulated/ not modulated in amplitude.

The classification between these two modulation schemes is achieved by considering the maximum value of the power spectral density (PSD) γ_{max} of the a_{cn} sequence, defined as in [1].

$$\gamma_{\max} = \frac{\max\left|DFT\left(a_{cn}(i)\right)^2\right|}{N_O} \qquad a_{cn}[k] = \frac{a[k]}{m_a} - 1 \tag{1}$$

where $a[k]$ is the instantaneous amplitude sequence, m_a is its average value and N_O is the number of the acquired samples.

The LB-PSK signals will be recognized as signals modulated in amplitude, as a result of the modulation introduced by the pulse shape filter, while the UB-PSK signals will be recognized as signals not modulated in amplitude, thank to the constant envelope.

Step 6: Classification between signals ASK and 2PSK band limited signals.

In this case, the classification is done using, as discriminating parameter, the standard deviation of a new sequence, obtained discarding the a_{cn} values below a fixed threshold, obtained experimentally, in order to discard the first and last values of each symbol:

$$\sigma_a = \sqrt{\frac{1}{N_O}\left(\sum_{a_{cn}>t_a} a_{cn}^2[i]\right) - \left(\frac{1}{N_O}\sum_{a_{cn}>t_a} a_{cn}[i]\right)^2} \tag{2}$$

The LB-PSK signals, with an amplitude modulation introduced only by the pulse shape filter, will have low values of σ_a, while ASK signals get higher values because the amplitude modulation is produced by the data variation.

Step 7: Classification between QAM and MPSK band limited signals (M>2)

The classification between QAM and MPSK signals is accomplished by the following figure of merit:

$$\sigma_a' = \sqrt{\frac{1}{N_O}\left(\sum_i a_{cn}^2[i]\right) - \left(\frac{1}{N_O}\sum_i a_{cn}[i]\right)^2} \tag{3}$$

It is a parameter similar to that seen in previous classification step, with the only difference that, from the calculation of the standard deviation, the low values have not been deleted, because the histogram of the amplitude of a QAM signal is concentrated to low amplitude values.

B. Experimental results

In order to validate the method, it has been first tested by means of a test session on 100 simulated signals for each modulation type and Signal to Noise Ratio (SNR) in the set {20dB, 30dB, 40dB}. As it can be seen in Table 1, a high correct classification rate can be achieved even with a SNR

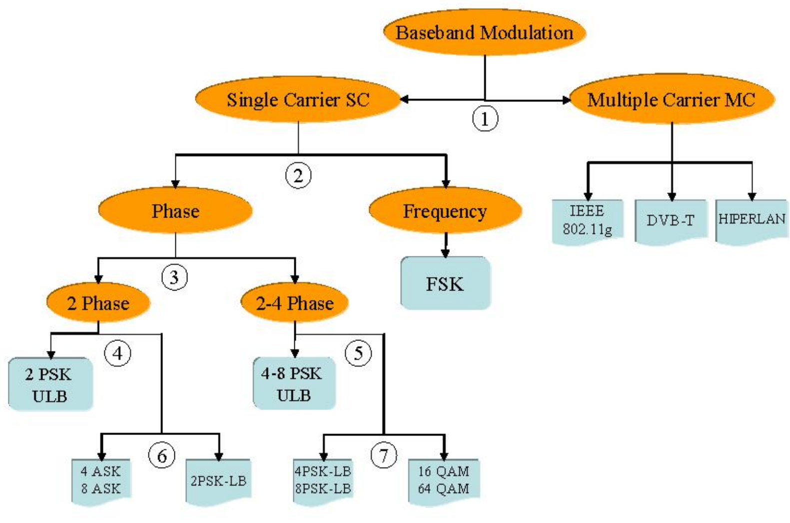

Fig. 3. Decision tree of the method operating on a waveform digitizer.

equal to 20 dB. When the SNR is equal to 30 dB, the correct classification rate increases until to obtain all right detection and only for 4PSKbl-8PSKbl, the method falls in mistake 6 times. In the last case, when the SNR is equal to 40 dB, the various modulated signal has been always classified correctly and for 4PSKbl-8PSKbl, the method falls in mistake only 5 times.

Table 1. Modulation classification rate on simulated signals with SNR=20dB.

	2PSKbl	2PSKnbl	MPSKbl	MPSKnbl	MASK	FSK	QAM	OFDM
2PSKbl	100	0	0	0	0	0	0	0
4PSKbl	0	0	86	0	0	0	14	0
8PSKbl	0	0	89	0	0	0	11	0
2PSKnbl	0	100	0	0	0	0	0	0
4PSKnbl	0	0	0	100	0	0	0	0
8PSKnbl	0	0	0	100	0	0	0	0
4ASK	0	0	0	0	100	0	0	0
8ASK	0	0	0	0	83	0	17	0
2FSK	0	0	0	0	0	100	0	0
4FSK	0	0	0	0	0	100	0	0
8FSK	0	0	0	0	0	100	0	0
16QAM	0	0	0	0	0	0	100	0
64QAM	0	0	0	0	0	0	100	0
4ASKbl	0	0	0	0	92	0	8	0
8ASKbl	0	0	0	0	79	0	21	0

IV. VERSION OF THE NEW METHOD OPERATING ON VECTOR SIGNAL ANALYZERS

A. Method description

The previously presented method allows classifying the modulation type of signals using the pass-band representation. In this case the whole signal in the time domain should be acquired, comprising both the carrier frequency and its modulating information. This scheme requires a very high sampling frequency of the acquisition block, which should be at least greater than the carrier frequency plus half the signal bandwidth. It is often obtained at the expense of the resolution of the involved analog to digital conversion.

Most of the signal analyzers actually on the market use instead an analytic representation of the signal. Before being acquired, the signal is first demodulated in its *in-phase* and *in quadrature* (IQ) components. Then, these two components are acquired. In this way the bandwidth of the acquisition block can be slightly greater than the modulating signal bandwidth, allowing an increased resolution of the analog to digital conversion.

In order to fit the IQ-based acquisition hardware, a second version of the new method has been designed.

The structure of the classification tree of the IQ-based method has been modified as shown in Fig.4. In this case the verification of the presence of a frequency modulation has been moved down in the classification tree, because the estimation of the instantaneous frequency is obtained from the instantaneous phase instead of using a zero-crossing technique as in the previously presented method in Section III. Instead, the first step consists of dividing the incoming signals in two subsets, one constituted by all SC modulations and the other by the MC ones (Step 1). The second step, if the previous one has given as result SC, executes the distinction between "amplitude" and "not amplitude" modulations (Step 2). In the case the outcome of the first step is MC, the specific MC modulation standard is identified (Step 2'). Finally, on the third and fourth steps, the recognition of the type of modulation is carried out. In the following, the steps of this version of the method, are shown in detail:

Step 1: Classification between SC and MC signals

This distinction has not been changed, respect to the previously described method.

Step 2: Classification between amplitude/no amplitude modulated signal.

This step is based on the evaluation of the key parameter $\gamma_{\max}$. It is calculated starting from the instantaneous amplitude of the considered signal. The mathematical expression of this parameter is shown in (1).

If the $\gamma_{\max}$ value is greater then a certain threshold $t_{\gamma max}$ evaluated experimentally, the signal is identified as amplitude modulated. Otherwise, it is recognized as not amplitude modulated.

Step 3: Classification between phase/no phase modulated signal.

This step is based on the evaluation of another key parameter called σ_p defined as follows:

$$\sigma_p = \sqrt{\frac{1}{N_O}\left(\sum_{a_n(i)>(t_p)} \phi_{NL}^2(i)\right) - \left(\frac{1}{N_O}\sum_{a_n(i)>(t_p)} \left|\phi_{NL}(i)\right|\right)^2} \qquad (4)$$

It is the standard deviation of the absolute value of the instantaneous non linear phase computed on all segments such that $a_n(i) > t_p$, where t_p is a threshold empirically computed and N_O is the number of such samples. The non linear phase can be calculated from the following expression:

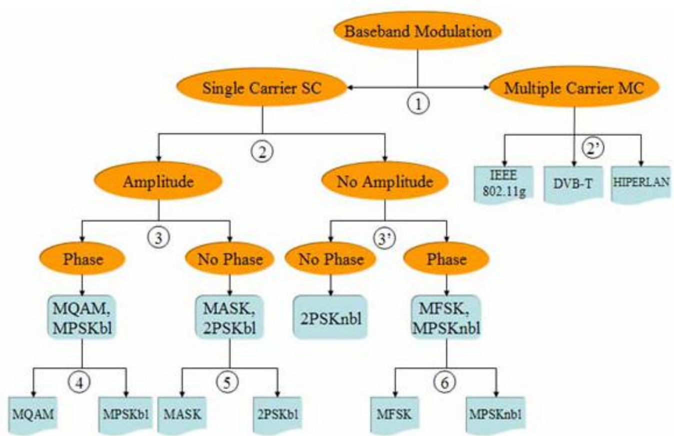

Fig. 4. Decision tree for VSA hardware system.

$$\phi_{NL}(i) = unwrap(\tan(y(i))) - \frac{2\pi f_c i}{f_s} \quad (5)$$

where *y(i)* is the acquired signal, f_c is the carrier frequency and f_s is the signal frequency.

Step 4: Classification between MQAM and LB-MPSK modulated signal.

In this case, the classification is done looking at the kurtosis k_a of the a_{cn} sequence.

The kurtosis is a measure of the "peakedness" of the probability distribution around a value. In fact, the MPSK signals, having constant envelope, will presents a kurtosis value greater then QAM signal, which have several amplitude levels. Moreover, the threshold t_a is used to discern between signals that introduce some information about amplitude ($k_a > t_a$) from those ones that do not introduce it, like ($k_a \leq t_a$).

Step 5: Classification between MASK and LB-2PSK modulated signal.

In this case, the distinction between these two modulation schemes is obtained using the standard deviation of the instantaneous amplitude σ_a:

$$\sigma_a = \sqrt{\frac{1}{N}\left(\sum_{a_n(i)>(t_a)} a_{cn}^2(i)\right) - \left(\frac{1}{N}\sum_{a_n(i)>(t_a)} |a_{cn}(i)|\right)^2} \quad (6)$$

The 2PSK signal has a constant envelope or just a little variation respect to the ASK signal. Fixing opportunely a threshold, it is possible to classify correctly the two modulations.

Step 6: Classification between MFSK and ULB-MPSK modulated signal.

In this last step, the modulation classification is obtained evaluating the standard deviation of the instantaneous frequency, as defined in (7).

$$\sigma_f = \sqrt{\frac{1}{N}\left(\sum_{a_n(i)>(t_{fa})} f^2(i)\right) - \left(\frac{1}{N}\sum_{a_n(i)>(t_f)} f(i)\right)^2} \quad (7)$$

For discerning the *MPSKnbl* from the *MFSK* modulation, the signal is filtered using a third order median filter. So it is possible to smooth the phase shifts and to obtain a more robust classification.

B. Experimental results

In order to validate the proposed methods, a virtual instrument implementing the methods, has been realized in MATLAB. In this development environment, an experimental analysis with actual signals has been carried out in order to verify the performance of the method, using test signals with different filter shapes and roll off factors.

Signals have been generated using an Agilent E4435C vector signal generator and acquired using a Tektronix WCA280A Real Time Spectrum Analyzer. The acquired signals have been, then, given to the virtual instrument to execute the modulation classification.

A first validation phase has been carried out on sets of 100 trials for each different signal and with different filter shapes. In order to simplify the data table representation, the following acronyms have been used: *ULB* and *LB* for the unlimited bandwidth and limited bandwidth modulations, respectively; *N0.15*, *N0.35* and *N0.6* to indicate the use of a raised cosine filter with a roll-off factor of 0.15, 0.35 and 0.6, respectively; *Rn0.15*, *Rn0.35* and *Rn0.6* to indicate the use of a root raised cosine filter with a roll-off factor of 0.15, 0.35 and 0.6, respectively; *g0.15*, *g0.35* and *g0.6* to indicate the use of a Gaussian filter with a BT parameter equal to 0.15, 0.35 and 0.6 (BT represents the product of the filter's 3dB bandwidth and the input signal's symbol period); *rect* to indicate the use of a rectangular window; *NOCP*, *CP0.125*, *CP0.25* to indicate the use of a cyclic prefix fraction of 0, 0.125, 0.25, respectively.

Table 2. Success percentages for modulation subsets recognition.

	QAM, LB-MPSK	MASK, LB-PSK	MFSK, ULB-MPSK (M>2)	ULB-2PSK
2PSK rect			4	96
4PSK rect			100	
8PSK rect			100	
2PSK N0.35		100		
2PSK Rn0.35		100		
4PSK N0.35	100			
4PSK Rn0.35	100			
8PSK N0.35	100			
8PSK Rn0.35	100			
4ASK rect		100		
8ASK rect		100		
4ASK N0.35		100		
4ASK Rn0.35		100		
8ASK N0.35		100		
8ASK Rn0.35		100		
2FSK rect			100	
4FSK rect			100	
8FSK rect			100	
2FSK g0.35			100	
4FSK g0.35			100	
8FSK g0.35			100	
MSK rect			100	
GSM			100	
QAM16 rect	100			
QAM64 rect	100			
QAM16 N0.35	100			
QAM16 Rn0.35	100			
QAM64 N0.35	100			
QAM64 Rn0.35	100			

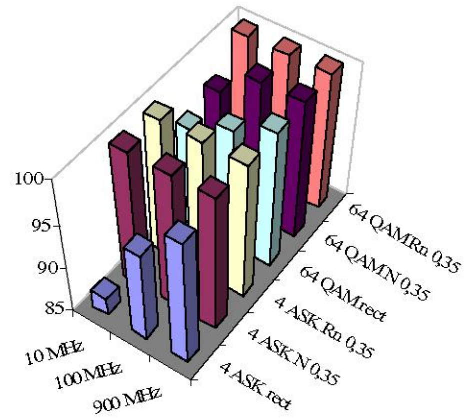

Fig. 5. Success percentages for 4ASK and 64QAM modulations with carrier frequency variation (SNR=15dB).

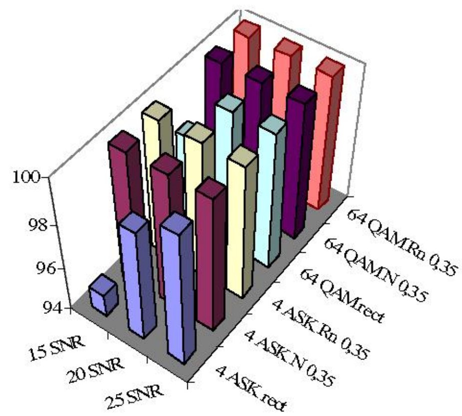

Fig. 6. Success percentages for 4ASK and 64QAM modulations with SNR variation (carrier frequency = 100MHz).

The results are shown in Table 2 in the case the carrier frequency, the symbol rate and the SNR have been fixed to 900 MHz, 100 kHz and 20 dB, respectively. Each row of the table represents the modulated signal given as input to the method and each column shows the identified modulation. For example, the first row contains the classification results of the method, when a 2 PSK signal, filtered with rectangular window, is applied as input. Over 100 tests, the signal has been classified 96 times correctly as 2 ULB-PSK and 4 times as MFSK/ULB-MPSK.

As it can be seen, the success percentages are very high when the SNR is equal to 20 dB. In the worst case, also when the SNR decreases below 10 dB, the success percentages do not decrease below 70%.

In Fig. 5, the success percentages for 4 ASK and 64 QAM modulations are presented, when the carrier frequency has been changed in the range 10 MHz ÷ 900 MHz (SNR is fixed to 15dB). In Fig. 6, the classification results obtained, giving as input the same modulation schemes seen in Fig. 5, when the SNR has been changed in the range 15 dB ÷ 25 dB (carrier frequency is fixed to 100 MHz), are shown.

V. CONCLUSIONS

In the paper, a new method for automatic classification of the digital modulations has been presented. This method overcomes the problems of the other solutions available in literature, like the restricted number of the modulation analyzed, achieving also better results in terms of success percentage. Two different versions of the method have been developed, depending on the hardware on which it is executed. The former is oriented for the use on waveform digitizers, while the latter works on vector signal analyzers.

Both the versions have been tested by means of numerous either simulated or actual signals. They have been shown to be able to recognize correctly 18 classes of single carrier signals and two classes of multicarrier signals, for low SNR values, too.

Further work of the research will be directed to the performance characterization of the new method with signals corrupted by different noises and by the channel distortion, such as the presence of a multipath fading. Another interesting aspect would be to extend the method in order to provide an estimation of the number of levels in the case of SC modulations.

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