Automatic Classification of Amplitude, Frequency, and Phase Shift Keyed Signals in the Wavelet Domain

Ka Mun Ho, *Student Member, IEEE*, Canute Vaz, *Student Member, IEEE*, and David G. Daut, *Senior Member, IEEE*
Department of Electrical and Computer Engineering
Rutgers, the State University of New Jersey
94 Brett Road, Piscataway, NJ 08854, U.S.A.
(email: vivianho@ece.rutgers.edu; kenvaz@ece.rutgers.edu; daut@ece.rutgers.edu)

Abstract— **In this study, automatic recognition of digitally modulated signals is investigated using the Continuous Wavelet Transform (CWT) in conjunction with techniques typically used in pattern recognition. In particular, the method of template matching is used. The templates used for the Automatic Modulation Recognition (AMR) process are determined based on the features, i.e., fractal patterns in the scalograms, of specific modulation schemes as they appear in the Wavelet Domain (WD).**

The digital modulation schemes considered include both binary and quaternary Amplitude (ASK) and Frequency Shift Keying (FSK), as well as M-ary Phase Shift Keying (MPSK) signals, where M=2, 4, and 8. The modulated signals used in this study have been corrupted by Additive White Gaussian Noise (AWGN) resulting in Signal-to-Noise Ratios (SNRs) in the range of -5 dB to 10 dB. Through the use of Monte Carlo computer simulations, it has been determined that the average overall correct classification rate for M-ary PSK signals was 99.1%; 98.9% for BASK and 4-ASK signals; and 90.4% for BFSK and 4-FSK signals over the range of SNR values.

I. Introduction

Automatic Modulation Recognition (AMR) can be described as the process of blind detection of the modulation scheme employed by a received signal. In a radio receiver system, AMR can be used as the intermediate step between signal reception and signal demodulation to recognize the unknown modulation scheme. More significantly, AMR plays the important role of enabling the development of agile radio receivers for both civilian and military applications, such as electronic warfare, electronic surveillance systems, spectrum management and threat analysis [1].

AMR techniques can be largely separated into two broad categories: the decision theoretic approach and the statistical pattern recognition approach [2]. The decision theoretic approach employs hypothesis testing on the basis of specific signal parameters to achieve modulation classification. The statistical pattern recognition approach utilizes features extracted from the received signal to implement the classifiers for the AMR process. Regardless of the technique used, the process of automatic classification is extremely challenging since there is very often little, or no, *a priori* information about the signals and other relevant parameters known at the receiver.

In many practical scenarios relevant signal parameters, such as signal power, carrier frequency, carrier phase offset, and symbol timing information, are unknown at the receiver [3]. In the AMR literature, as well as in this study, certain parameters are assumed to be known before invoking an AMR process. The system parameters that are assumed to be known before applying the AMR process include the carrier frequency and perfect symbol timing with no timing offset. In this study, Wavelet Transform (WT)-based techniques in conjunction with pattern recognition methods are systematically explored for the AMR of digitally modulated signals transmitted over an AWGN channel.

Wavelet-based AMR studies that have been reported in the literature have used both the Continuous Wavelet Transform (CWT) and the Discrete Wavelet Transform (DWT) [4]-[7]. Most of these studies have involved computing histograms of the CWT and/or DWT wavelet coefficients of the received signals. Based on the characteristic number of peaks contained in the histograms, different types of digitally modulated signals can be identified [4], [5], [8], [9]. The communications signals considered in those studies were: M-ary PSK versus M-ary FSK [5]; Quadrature Phase Shift Keying (QPSK) versus Gaussian Minimum Shift Keying (GMSK) signals [10]; as well as M-ary QAM and M-ary ASK signals [11].

It has been found that the CWT is particularly useful for the analysis of communications signals [14]. In this study, noise-free WD templates containing the common features of digitally modulated signals are constructed using the CWT. The CWT is also used to extract the WT coefficients of the received signals that have been corrupted by AWGN. Prior to invoking the AMR process, two initial steps must be carried out. First, signal-dependent templates that represent amplitude, frequency, and phase features are constructed from a set of 65 wavelets to use for the signalsnhf. In the second step, the best match wavelet for use in the AMR process is identified by analyzing the cross-correlation results of the various WD templates corresponding to 65 candidate wavelets [14]. The best wavelet to use for the signals in this study has been found to be the Reverse Biorthogonal Spline 1.3 (rbio1.3).

The AMR process itself consists of three steps. First, a received modulated signal, typically corrupted with AWGN, is transformed into the WD using the CWT that employs the rbio1.3 wavelet as determined in [14]. Second, the resulting WD signal is cross-correlated with pre-defined templates, which are also in the WD. Third, based on the cross-correlation results, decision metrics are employed in order to recognize the digital modulation scheme implicit in the signal.

The remainder of this paper is organized as follows. In Section II a brief primer about the CWT, relevant signal models, and the cross-correlation operation in the WD are presented. The WD AMR algorithm and specialized procedures are described in Section III. In Section IV, the setup and results of the simulations are presented, and comparisons of these results with representative results found in the literature are made in Section V. The conclusions of this study are presented in Section VI.

II. Mathematical Preliminaries

A. The Continuous Wavelet Transform

For a time-domain function, $x(t)$, and a wavelet, $\psi(t)$, the CWT of $x(t)$, i.e., $W_x(a,b)$, is defined as

$$W_x(a,b) \equiv \int_{-\infty}^{\infty} x(t)\psi^*_{a,b}(t)\,dt \tag{1}$$

where a is the dilation variable, b is the translation variable, $\psi^*(t)$ is the complex conjugate of $\psi(t)$, and

$$\psi_{a,b}(t) \equiv \frac{1}{\sqrt{|a|}}\psi\left(\frac{t-b}{a}\right). \tag{2}$$

With the use of (1) and (2), a function $x(t)$ can be analyzed at various levels of resolution. This is accomplished by varying the dilation and translation of the selected wavelet. Wavelets that are used for the CWT are required to have finite energy over all time, i.e.,

$$\int_{-\infty}^{\infty} |\psi(t)|^2 < \infty . \tag{3}$$

B. The Cross-Correlation Operation

The cross-correlation operation is defined in the time-domain as [15]

$$R_{x,y}(\tau) = \int_{-\infty}^{\infty} x(t)\,y^*(t-\tau)\,dt \tag{4}$$

where $x(t)$ and $y(t)$ are the two functions being cross-correlated.

In the case of a time-domain communications signal, $s(t)$, the signal can be expressed in the WD with the use of a wavelet, $\psi(t)$, as

$$W_s(a,b) = \int_0^T s(t)\psi^*_{a,b}(t)\,dt \quad 0 < t \le T . \tag{5}$$

For the AMR process described in this study, a signal template is represented in the WD according to

$$W_g(a,b) = \int_{t_1}^{t_2} g(t)\psi^*_{a,b}(t)\,dt , \quad t_1 < t \le t_2 \tag{6}$$

where $g(t)$ is the time-domain representation of the template, i.e., the sinusoidal carrier component within a symbol period.

The CWT representation of the two WD functions defined in (5) and (6) can be expressed in discrete-time notation as

$$\{W_s(a,b)\}[n] = \sum_{n=1}^{N} s[n]\psi^*_{a,b}[n] \tag{7}$$

and

$$\{W_g(a,b)\}[n] = \sum_{n=1}^{N} g[n]\psi^*_{a,b}[n]. \tag{8}$$

The cross-correlation between two functions defined in the WD can, therefore, be expressed as

$$W_{R_{s,g}(a,b)}[n] = \left(\{W_s(a,b)\}[n_a,n_b]\right) \otimes \left(\{W_g(a,b)\}[n_a,n_b]\right). \tag{9}$$

Note that in (9) the symbol $\otimes$ denotes the correlation operator. Equation (9) can also be expressed as

$$W_{R_{s,g}(a,b)} = \sum_{n_a}\sum_{n_b} \left(\{W_s(a,b)\}[n_a,n_b]\right)\cdot\left(\{W_g(a,b)\}[n_a,n_b]\right). \tag{10}$$

C. Signal Definitions

The ASK signals used in this study are defined as

$$s(t) = \begin{cases} A_i\sqrt{\dfrac{2E_b}{T}}\cos(2\pi f_c t), & 0 \le t \le T \\ 0, & \text{otherwise} \end{cases} \tag{11}$$

where $i = 1,2,3,4$. The four amplitudes, A_1, A_2, A_3 and A_4, are constants such that $\{A_i\} \in \mathbb{R}$, and represent the data symbols 00, 01, 10, and 11, respectively. The parameter E_b denotes the energy per bit, T denotes the temporal duration of the bit, and the carrier frequency is denoted by f_c.

The FSK signals used are defined as [16]

$$s(t) = \begin{cases} \sqrt{\dfrac{2E_b}{T}}\cos(2\pi f_i t), & 0 \le t \le T \\ 0, & \text{otherwise} \end{cases} \tag{12}$$

where $i = 1,2,3,4$ correspond to four signaling frequencies which represent the data symbols 00, 01, 10, and 11, respectively.

The M-ary PSK signals are defined as [17]

$$s_i(t) = \begin{cases} \sqrt{\dfrac{2E_b}{T}}\cos\left[2\pi f_c t + \dfrac{2\pi}{M}(i-1)\right], & 0 \le t \le T \\ 0, & \text{otherwise} \end{cases} \tag{13}$$

where $i = 1,\ldots,M$. Each value of i represents a carrier phase corresponding to a unique data symbol sequence of length $\log_2(M)$. In this case M corresponds to the size of the signal set.

D. *Template Definitions*

The set of templates used in this study is taken to be the common features contained within the transmitted data symbols, namely the sinusoidal carrier components, for all of the digital modulation schemes. These templates are called the common features templates. The analytical models of the templates are defined as follows.

1) *Templates with Variations in Phase*

Depending upon the temporal location of the template within a signal, the template is described generally as

$$g(t) = \cos(2\pi f_c t + \theta), \qquad t_1 < t \le t_2 \tag{14}$$

The phase variable, θ, represents the shifting of the common features template within a symbol period as needed. A graphical representation of this concept is shown in Fig. 1, where the duration of Template 1 is from t_1 to t_2 and the duration of Template 2 is from t_1' to t_2'. Specifically, three values of θ are used, 0, $\pi/2$ and $5\pi/4$, and are denoted as Templates 1, 2 and 3 respectively.

2) *Templates with Different Frequencies*

In an M-ary FSK signal, different carrier frequencies are used to represent different data symbols within the signal. Therefore, another common features template can be described as

$$g(t) = \cos(2\pi f_i t), \qquad t_1 < t \le t_2 \tag{15}$$

where f_i is the active carrier frequency within a specific symbol data time slot.

In the case of an FSK modulation scheme, multiple carrier frequencies are required to represent different data symbols using FSK. Therefore, two variations of (15) are used. Specifically, f_i is either f_1 or f_2, and they are denoted as Templates 4 and 5, respectively.

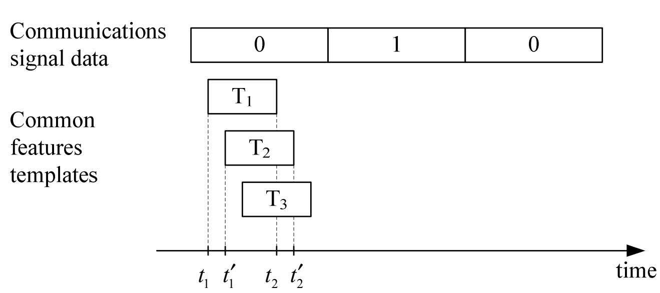

Fig. 1. Illustration of common features templates at different locations within a data symbol period.

III. Modulation Classification Techniques

The WD AMR process developed in this study is based on cross-correlating, in the WD, a received communications signal having an unknown modulation scheme with a set of common features templates. The templates had been previously constructed and stored within the receiver. The choice of wavelet used for the AMR process is the Reverse Biorthogonal Spline wavelet (rbio1.3).

Fig. 2 illustrates an example of two noise-free common features templates in both the time- and wavelet-domains for an ASK signal. The magnified versions of the WD templates are also presented. The templates are extracted at the different temporal locations within the scalogram which contain the common features of the received signal present within the data symbol periods.

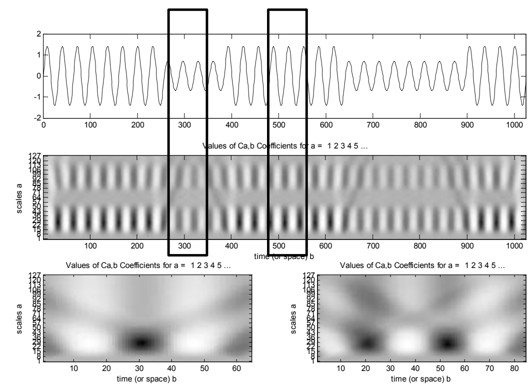

Fig. 2. ASK signal in the time domain (top), wavelet-domain (middle) and common features templates in the WD (bottom).

A. *Algorithm of the Overall AMR Process*

The AMR process is intended to take place after front-end signal processing and signal digitization within the receiver. Fig. 3 depicts the system-level description of the proposed communications receiver system.

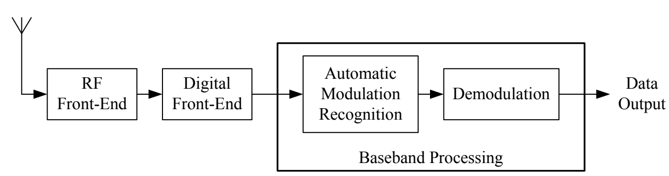

Fig. 3. Overall system-level description of a radio receiver employing AMR.

With the use of the common features templates, the WD AMR process is according to the following algorithm.

1. Compute the CWT of the received signal to up to 128 levels of resolution using the rbio1.3 wavelet.
2. Cross-correlate the WD coefficients of the signal obtained in Step 1 with Template 1 and Template 2.
3. Normalize the cross-correlation coefficients in Step 2 to have a dynamic range from -3 to 3.
4. The results from Step 3 are then input to Decision Block 1.
5. Based on the decision results of Step 4, the signal is either sent to the ASK/FSK Classifier or to the PSK Classifier for further processing.

The overall system-level block diagram of the WD AMR algorithm described above is depicted in Fig. 4. The data normalization procedure of Step 3 is carried out in the Pre-Processing Block shown in Fig. 4.

B. Procedure for Decision Block 1

In this work, cross-correlation results are used to develop the decision making algorithm for the AMR process. Based on the cross-correlation results, the modulated signals can be separated into two groups based on the "dynamic range" attribute of the cross-correlation coefficients. The group of signals in the ASK/FSK families have cross-correlation coefficients obtained with Template 1 that possess a dynamic range which is always positive. Specifically, they are in the range from 0 to 3. The PSK group has coefficients with values in the range from -3 to 3. Based on these criteria, the procedure for Decision Block 1 is described as follows.

1. Apply a dynamic range test to the normalized cross-correlation data set inputted to Decision Block 1. If the data set has dynamic range from 0 to 3, then the signal group is that of ASK/FSK. If the data span the range from -3 to 3, then the signal group is that of PSK.
2. Based on the result of Step 1, activate the appropriate classifier procedure.

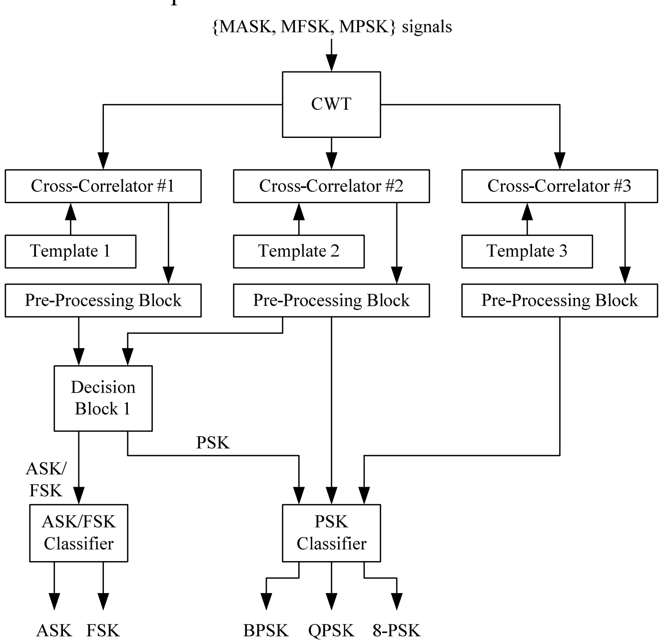

Fig. 4. System-level block diagram of the wavelet-based AMR process.

C. PSK Classifier Procedure

The decision metric for the group of PSK signals is based on the "multi-level" attribute. Note that the cross-correlation coefficients obtained using Templates 1 and 3 are considered. The algorithm is based on whether the values of the cross-correlation coefficients are of a single-level or multi-level character. The procedure is carried out according to the following.

1. A multi-level test is applied to the resulting set of normalized cross-correlation coefficients. If the data set is composed of single-level values, then the signal is declared to be BPSK. If the data set is composed of multi-level values, the signal is either QPSK or 8-PSK.
2. Next cross-correlate the received signal in the WD with Template 3, and then normalize the coefficients appropriately.
3. Repeat Step 1. If the data set is composed of single-level values, then it is declared to be a QPSK signal. If the data set is composed of multi-level values, then it is an 8-PSK signal.

D. ASK/FSK Classifier Procedure

Those signals that are determined to have variations in either amplitude, or frequency as determined by Decision Block 1 require additional templates for classification. Template 4 and Template 5, defined in (15), are used. The procedure is described as follows.

1. Cross-correlate the received signal with Template 4 in the WD.
2. If the cross-correlation coefficients in Step 1 are all zero, then the unknown modulation scheme is of the ASK type. If not, then the modulation scheme is of the FSK type. This step is called the Zero Test.
3. If the modulation scheme is of type ASK, apply a multi-level test to the normalized cross-correlation coefficients obtained with Template 1. If the cross-correlation coefficients are single-level, then it is a BASK signal. Otherwise, if the coefficients are multi-level, the received signal employs a 4-ASK modulation.
4. If the modulated signal of type FSK, cross-correlate the received signal with Template 5 and normalize the results. Apply a Zero Test to the normalized cross-correlation values. If the data are all zero, the signal is BFSK signal; otherwise, it is a 4-FSK signal.

The ASK/FSK Classifier procedure is depicted as a system-level block diagram in Fig. 5.

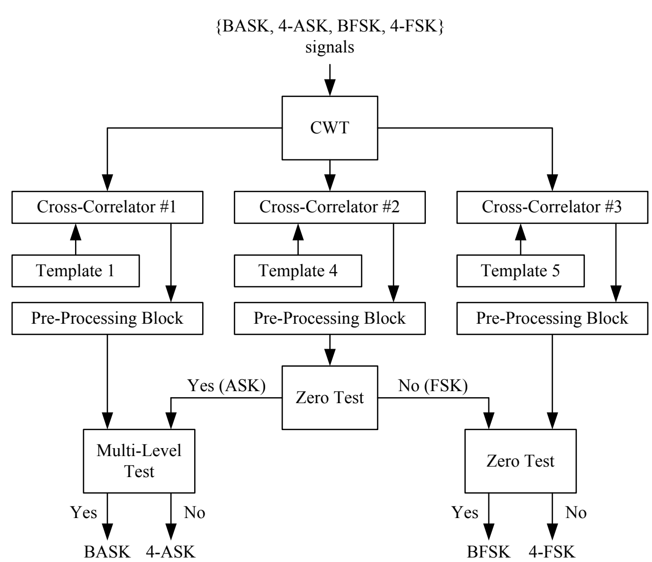

Fig. 5. A detailed block diagram implementing the ASK/FSK Classifier procedure.

IV. Simulation Experiments and Results

All of the signals used in this work have been corrupted by zero-mean AWGN to produce sets of signals with SNR values in the range from -5 to 10 dB. The rates of correct classification have been obtained based on 2,000 Monte Carlo trials, wherein each simulation experiment employs 192 data bits per block.

The simulations were performed using MATLAB. The results of the experiments are given in Tables 1-6, which contain the rates of correct classification for three SNR values, i.e., 10 dB, 0 dB, and -5 dB.

TABLE 1
RATES OF CORRECT CLASSIFICATION FOR SNR = 10 DB

		Signal classified as (%)		
		BPSK	QPSK	8-PSK
T_x Signal	BPSK	100	0	0
	QPSK	0	100	0
	8-PSK	0	0	100

TABLE 2
RATES OF CORRECT CLASSIFICATION FOR SNR = 0 DB

		Signal classified as (%)		
		BPSK	QPSK	8-PSK
T_x Signal	BPSK	100	0	0
	QPSK	0	97.3	2.7
	8-PSK	0	0	100

TABLE 3
RATES OF CORRECT CLASSIFICATION FOR SNR = -5 DB

		Signal classified as (%)		
		BPSK	QPSK	8-PSK
T_x Signal	BPSK	100	0	0
	QPSK	0	94.6	5.4
	8-PSK	0	0	100

TABLE 4
RATES OF CORRECT CLASSIFICATION FOR SNR = 10 DB

		Signal classified as (%)			
		BASK	4-ASK	BFSK	4-FSK
T_x Signal	BASK	100	0	0	0
	4-ASK	0.2	99.8	0	0
	BFSK	0	0	100	0
	4-FSK	0	0	0.2	99.8

TABLE 5
RATES OF CORRECT CLASSIFICATION FOR SNR = 0 DB

		Signal classified as (%)			
		BASK	4-ASK	BFSK	4-FSK
T_x Signal	BASK	100	0	0	0
	4-ASK	0.7	99.3	0	0
	BFSK	0	0	99.9	0.1
	4-FSK	0	0	4.7	95.3

TABLE 6
RATES OF CORRECT CLASSIFICATION FOR SNR = -5 DB

		Signal classified as (%)			
		BASK	4-ASK	BFSK	4-FSK
T_x Signal	BASK	95.8	4.2	0	0
	4-ASK	4.1	95.9	0	0
	BFSK	11.7	0	75.8	12.5
	4-FSK	14.2	0	22.6	63.2

The rates of correct classification for M-ary PSK signals are presented in Tables 1-3. It is worth mentioning that the performance of the AMR process for M-ary PSK signals is better than those reported in the literature. For SNR = 10 dB, 100% recognition is achieved. At SNR = 0 dB, 100% recognition for both BPSK and 8-PSK signals is also achieved, while a rate of 97.3% for QPSK signals is realized. For SNR = -5 dB, both BPSK and 8-PSK achieve a 100% classification rate and 94.6 % is obtained for QPSK.

The rates of correct classification of ASK and FSK signals are presented in Tables 4-6. At SNR = 10 dB, the rates of correct classification for both BASK and BFSK are 100%, while the rates are 99.8% for both 4-ASK and 4-FSK. The classification rates decreased to 75.8% for BFSK and 63.2% for 4-FSK signals at an SNR = -5 dB, however, none of the studies reported in the literature had shown classification results at SNR values lower than 0 dB. On the other hand, the classification rates for ASK signals are above 95% for both SNR = 0 dB and SNR = -5 dB.

V. Comparisons of Results

Several prior studies found in the literature that have used both WT-based and non-WT based AMR methods were surveyed. The relevant results of prior work are compared with the results obtained in this study. The comparisons are presented in Tables 7 and 8.

TABLE 7
SURVEY OF NON-WAVELET TRANSFORM-BASED AMR METHODS IN THE LITERATURE

AMR method devised by	Modulation Scheme	Correct classification at highest SNR	Correct classification at lowest SNR
Azzouz, et. al. [18]	BASK	96% at 20 dB	95.3% at 15 dB
	4-ASK	80.2% at 20 dB	77.3% at 15 dB
	BPSK	100% at 20 dB	100% at 15 dB
	QPSK	100% at 20 dB	96% at 15 dB
	BFSK	92% at 20 dB	92% at 15 dB
	4-FSK	88% at 20 dB	100% at 15 dB
Hsue and Soliman [19]	BPSK	99% at 15 dB	-
	QPSK	98% at 15 dB	-
	8-PSK	100% at 15 dB	-
	BFSK	100% at 15 dB	-
	4-FSK	100% at 15 dB	-
Dobre, et. al. [3]	BPSK	100% at 10 dB	78% at 0 dB
	{QPSK, 8-PSK}	100% at 10 dB	100% at 0 dB

It must be pointed out that a direct comparison of the different AMR methodologies is not possible due to the fact that the prior works do not necessarily use the same general *a priori* assumptions and often consider different SNR values, different numbers of symbols per transmission, etc.

TABLE 8
SURVEY OF WAVELET TRANSFORM-BASED AMR METHODS IN THE LITERATURE

AMR method devised by	Modulation Scheme	Correct classification at highest SNR	Correct classification at lowest SNR
Ho, et. al. [4]	BPSK	97% at 13 dB	-
	QPSK	97% at 13 dB	-
	8-PSK	97% at 13 dB	-
	2-FSK	100% at 13 dB	-
	4-FSK	100% at 13 dB	-
Hong and Ho [20]	QPSK	100% at 20 dB	97.6% at 5 dB
	4-FSK	100% at 20 dB	100% at 5 dB
Jin, et. al. [8]	BPSK	100% at 13 dB	100% at 8 dB
	QPSK	100% at 13 dB	97.5% at 8 dB
	8-PSK	100% at 13 dB	100% at 8 dB
	BFSK	100% at 13 dB	95.3% at 8 dB
	4-FSK	100% at 13 dB	100% at 8 dB
This Work	BPSK	100% at 10 dB	100% at -5 dB
	QPSK	100% at 10 dB	94.6% at -5 dB
	8-PSK	100% at 10 dB	100% at -5 dB
	BASK	100% at 10 dB	95.8% at -5 dB
	2-ASK	99.8% at 10 dB	95.9% at -5 dB
	BFSK	100% at 10 dB	77.3% at -5 dB
	4-FSK	99.8% at 10 dB	63.2% at -5 dB

VI. CONCLUSIONS

In this paper, it has been demonstrated that by using the pattern recognition methodology of template matching, along with appropriately defined WD templates characterizing features of digitally modulated signals, an effective AMR process can be implemented in the WD. It has been demonstrated that the AMR process can correctly classify modulation schemes with very high reliability even for low values of SNR. For example, at a value of SNR = -5 dB, the rates of correct classification achieved are 100% for both BPSK and 8-PSK signals, 94.7% for QPSK signals, and above 95% for both BASK and 4-ASK signals. The rates of correct classification obtained in this work are equal to, or better than, those reported in the AMR literature.

Furthermore, the WD AMR process developed in this work can be extended to enable the classification of additional modulation schemes by using similar methodologies along with multiple wavelet families.

Given the reliability of the AMR process devised in this study, it can be used to advance the state-of-the-art in the design of communications receivers, and perhaps, to enable interoperability between different communications standards. Such a receiver would have immediate application in military signal analysis applications, such as threat analysis, spectrum management, electronic warfare, and electronic surveillance systems.

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