Automatic Modulation Recognition Using DWT-Based Signal Templates

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ABSTRACT

The Wavelet Domain (WD) Automatic Modulation Recognition (AMR) process described in this paper involves the use of unique features templates that represent digital communications signal features that are characteristic of the transitions contained in a stream of data symbols. Such data transitions are indicated by a change in the amplitude, frequency, and/or phase of a digitally modulated signal. It is shown in this paper that a set of WD templates, based on the Discrete Wavelet Transform (DWT), is suitable for the blind identification of binary digitally modulated communications signals acquired by a communications receiver.

The specific binary modulation schemes considered in this work include BASK, BFSK, and BPSK. The wavelet used for both template construction and the decomposition of received signals is the Daubechies 1 (Haar) wavelet. It has been determined via extensive computer simulations that the rate of correct classification for BASK signals is 100% over the range of SNR values considered, that is from -5 dB to 10 dB. The rates of correct classification for BPSK signals are 100%, 96.8%, 95.6% and 94.8% for SNR = 10 dB, 5 dB, 0 dB and -5 dB, respectively. The rates of correct classification for BFSK signals are 98.0%, 96.2%, 100.0% and 97.0% for SNR = 10 dB, 5 dB, 0 dB and -5 dB, respectively. The AMR process presented in this study generally produces higher rates of correct classification than other AMR techniques that have been reported in the literature. This observation is especially significant when considering the cases of BASK and BPSK for systems operating at an SNR value of -5 dB.

1. INTRODUCTION

AMR can be described as blind identification of the modulation scheme used to format digital data embedded in 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 an important role in 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].

The broader topic of AMR has been explored using either of two main approaches. These are (a) decision-theoretic approaches which employ hypothesis testing on the basis of specific signal parameters to achieve modulation classification [2], [3], and (b) pattern recognition-based approaches that utilize features extracted from the received signal to implement the classifiers at the core of 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 either the signals, or other relevant parameters required by the receiver.

In this study, pattern recognition methods in conjunction with DWT-based techniques are systematically explored use in the automatic recognition of digitally modulated signals transmitted over an AWGN channel. Some previous WD-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 are M-ary PSK and M-ary FSK [5]; Quadrature Phase Shift Keying (QPSK) and Gaussian Minimum Shift Keying (GMSK) signals [10]; as well as M-ary QAM and M-ary ASK signals [11]. The wavelets used in these studies have been largely focused on the Haar, although the Daubechies wavelet family has also been used in some cases.

The DWT-based AMR method described in this paper employs the concept of template matching to achieve modulation identification prior to signal demodulation over a wide range of practical SNR values. Specifically, noise-free wavelet-domain templates containing the distinguishing features of each modulation type are constructed. The DWT is also used to extract the WD coefficients of received signals that have been corrupted with AWGN. In developing the AMR process an initialization step is invoked. At the outset, WD templates are stored within the receiver possessing unique features associated with the three modulation types. In this study, the templates are determined based upon the Haar wavelet. The AMR process consists of two main steps. First, a received signal that has been corrupted with AWGN is transformed into the wavelet-domain via the DWT using the Haar wavelet. The resulting wavelet-domain signal is then cross-correlated with the pre-defined templates corresponding to all three types of binary modulation schemes. The modulation type that is declared to be operative at the receiver input is determined on the basis of decision logic that employs a majority vote strategy.

The remainder of this paper consists of five sections. A brief primer on the DWT, along with the signal models used, is provided in Section II. The binary modulation classification algorithm is described in Section III. In Section IV, the simulation setup is described and the results of the simulation experiments are given. These results are compared with representative results from the existing literature in Section V, Conclusions of this study are presented in Section VI, and finally Section VII describes Future Work.

2. THEORETICAL BACKGROUND

2.1 Signal definition [12]:

The BASK signals used in this study are defined as

$$s_i(t) = \begin{cases} A_i\sqrt{\dfrac{2E_b}{T_b}}\cos(2\pi f_c t), & 0 \le t \le T_b \\ 0, & \text{otherwise} \end{cases} \quad (1)$$

where $i = 1, 2$. The two amplitudes A_1 and A_2 are constants, which denote the binary symbols 1 and 0, respectively. The parameter E_b denotes the energy per bit, T_b denotes the temporal duration of the bit, and the carrier frequency is denoted by f_c.

The BFSK signals used are defined by

$$s_i(t) = \begin{cases} \sqrt{\dfrac{2E_b}{T_b}}\cos(2\pi f_i t), & 0 \le t \le T_b \\ 0, & \text{otherwise} \end{cases} \quad (2)$$

where $i = 1$ and $i = 2$ correspond to the binary symbols 1 and 0, respectively.

The BPSK signals are defined as

$$s_i(t) = \begin{cases} (-1)^i\sqrt{\dfrac{2E_b}{T_b}}\cos(2\pi f_c t), & 0 \le t \le T_b \\ 0, & \text{otherwise} \end{cases} \quad (3)$$

where, again, $i = 1$ and $i = 2$ correspond to the binary symbols 1 and 0, respectively.

2.2 Multiresolution Analysis (MRA) and the Discrete Wavelet Transform

Wavelets can be generally viewed as rapidly decaying oscillatory functions that may be used as basis functions to represent signals. They are especially useful in representing all types of signals that appear in practice that have characteristics such as periodicities and/or jump discontinuities. The DWT is any wavelet transform in which the wavelet functions are discretely sampled. It is often conveniently described in terms of the filter-theoretic approach of Multiresolution Analysis (MRA).

MRA is a digital signal processing technique based on the use of orthonormal wavelet bases for signal analysis [13], [14]. In this technique, a sampled signal is passed through a series of Finite Impulse Response (FIR) filters in the manner depicted in Fig. 1.

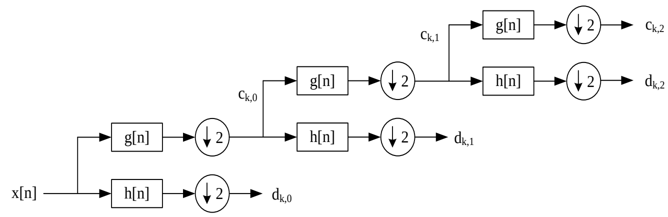

Fig. 1. A three-level filter bank illustrative of the MRA process.

The impulse responses of low-pass and high-pass filters are denoted by g[n] and h[n], respectively. The output of the high-pass filters provides the detail coefficients, $d_{k,j}$, and the output of the low-pass filters provide the approximation coefficients, $c_{k,j}$. With the requirement that the input signal be represented by 2^n samples, the output of each filter is down-sampled by a factor of 2 and the process is continued for as many user-defined levels as desired to obtain the required decomposition of the original signal. In order to use the MRA method to implement the DWT a scaling function, $\phi(t)$, is defined as [15]

$$\phi(t) = \sqrt{2}\sum_{m=0}^{N} h(N-m)\phi(2t-m) \quad (4)$$

where, $N+1$ is the order of the filter and m indexes into the set of filter coefficients under consideration. The mother wavelet, $\psi(t)$, can then be described in terms of the scaling function, and the filter coefficients according to

$$\begin{aligned} \psi(t) &= \sqrt{2}\sum_{m=0}^{N} g'(m)\phi(2t-m) \\ &= \sqrt{2}\sum_{m=0}^{N} -(-1)^m h'(N-m)\phi(2t-m) \end{aligned} \quad (5)$$

In this MRA approach of implementing the DWT both the detail and approximation coefficients of an input signal can be computed at different levels of resolution, as illustrated in Fig. 1. Practically, the DWT can be used for the compression of data prior to transmission through a noisy channel, for the de-noising of signals acquired by a communications receiver, reconstruction of time-domain signals described in the wavelet-domain, among others [16]. It is used here for the characterization, i.e., analysis of signals. By identifying the changes in the wavelet coefficients obtained from different scales and translations of a communications signal, the characteristic amplitude, phase and frequency fluctuations inherent within a communications signal corresponding to information data symbols can be recognized.

In summary, a signal can be represented by wavelet coefficients at different levels of resolution, and thereby preserve the important data transition pattern content of the signal. The wavelet transform is particularly useful for capturing the jump discontinuities which often occur in digitally modulated communications signals.

2.3 Wavelet-Domain Cross-Correlation Operation

In this section the concept of the cross-correlation operation in the wavelet-domain is described. The WD AMR process developed in this work uses WD cross-correlation values in several decision making algorithms. In the time-domain, the cross-correlation of two functions x(t) and y(t) is described as [17]

$$R_{x,y}(\tau) = \int_{-\infty}^{\infty} x(t)\, y^{*}(t-\tau)\, dt \tag{6}$$

The DWT of the two functions x(t) and y(t) can be named as $\{W_x(a,b)\}[n]$ and $\{W_y(a,b)\}[n]$. The cross-correlation between two functions defined in the wavelet domain can, therefore, be expressed as

$$W_{R_{x,y}(a,b)} = \sum_{n_a}\sum_{n_b}\left(\{W_x(a,b)\}[n_a,n_b]\right)\cdot\left(\{W_y(a,b)\}[n_a,n_b]\right) \tag{7}$$

3. DWT-BASED AMR METHODOLOGY

The modulation classification technique developed in this study is based upon cross-correlating the Discrete Wavelet Transformation (DWT) of digitally modulated binary signals of unknown modulation type, which is considered to be input to a receiver, with pre-defined discrete wavelet-domain templates that have been previously stored within the receiver. In this study, three signaling schemes have been considered: Binary ASK (BASK), Binary FSK (BPSK) and Binary PSK (BPSK). The received signals have been corrupted by AWGN having SNR values of practical interest within the range -5 dB to 10 dB. This wavelet-based AMR platform is illustrated in Fig. 2.

3.1. Templates Selection

The pre-defined templates represent the distinguishing features of the modulated signals in the wavelet-domain, which are based on the time-domain variations of the amplitude, frequency, or phase of the signals. The templates are constructed in the WD using the DWT coefficients of test signals that correspond to each of the three digital modulation schemes considered herein. All the templates are constructed using the Daubechies 1 (Haar) wavelet.

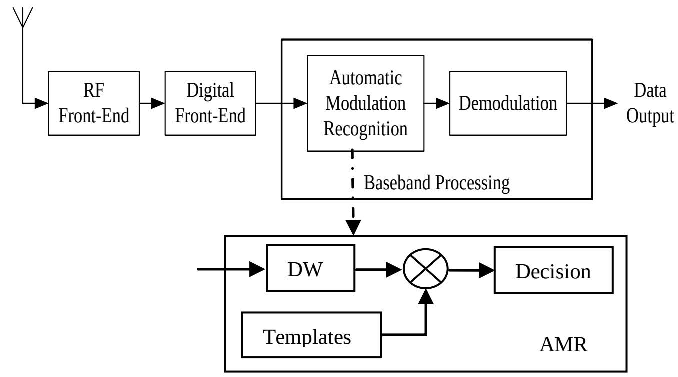

Fig. 2. Overall system-level description of a radio receiver employing an AMR function.

Within a particular modulated binary signal, the pre-defined templates actually represent the transition from either binary symbol 0 to binary symbol 1, or 1 to 0. The pre-defined templates are based on the transitions in the scalogram of the noise-free signal. Therefore, for each of the binary modulation schemes, two templates are required in order to completely characterize the two possible data state transitions. The templates are stored within the receiver for later use in the AMR process.

Figures 3 and 4 illustrate examples of BFSK and BASK signals with corresponding scalograms of DWT coefficients using the Haar wavelet up to 10 levels. Based on observation of the data symbol transition portions of the signals shown in the figures, the similarity between the noise- free scalograms and the noisy scalograms is obvious, especially at the higher levels of resolution. This similarity is the most important feature that is exploited in the AMR algorithm developed in this work. Later, simulations will be conducted to test the similarity using the cross-correlation function. It will be shown that the information contained in the DWT coefficients at the lower levels of resolution is actually sufficient to achieve reliable AMR results.

The WD templates are described based on symbol transitions that occur within a digitally modulated communications signal. Two unique features templates can be extracted from each of the 3 binary digitally modulated signals. The models in the time domain for the templates are

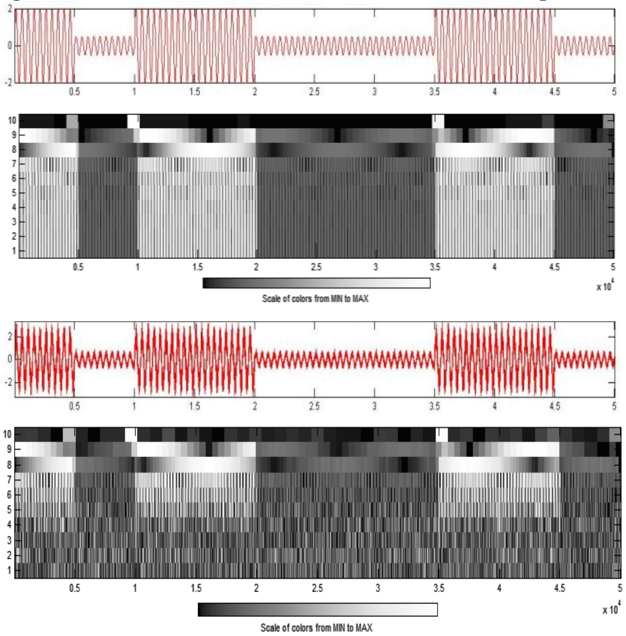

Fig. 3 (a): (Top) BASK signal without noise, 10-level wavelet-domain decomposition using the Haar wavelet; (b): (Bottom) BASK signal at 10 dB SNR, 10-level wavelet-domain decomposition using the Haar wavelet.

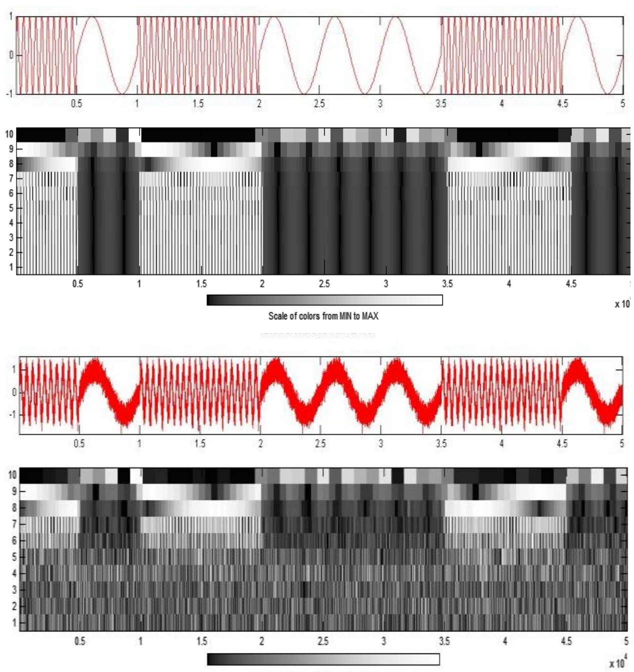

Fig. 4 (a): (Top) BFSK signal without noise, 10-level wavelet-domain decomposition using the Haar wavelet; (b): (Bottom) BFSK signal at 10 dB SNR, 10-level wavelet-domain decomposition using the Haar wavelet.

defined according to the following:

$$p_{BASK,1}(t)=\begin{cases} A_1\cos(2\pi f_c t), & t_1<t\le t_2 \\ A_2\cos(2\pi f_c t), & t_3<t\le t_4 \end{cases} \tag{8a}$$

$$p_{BASK,2}(t)=\begin{cases} A_2\cos(2\pi f_c t), & t_1<t\le t_2 \\ A_1\cos(2\pi f_c t), & t_3<t\le t_4 \end{cases}. \tag{8b}$$

$$p_{BFSK,1}(t)=\begin{cases} \cos(2\pi f_1 t), & t_1<t\le t_2 \\ \cos(2\pi f_2 t), & t_3<t\le t_4 \end{cases} \tag{9a}$$

$$p_{BFSK,2}(t)=\begin{cases} \cos(2\pi f_2 t), & t_1<t\le t_2 \\ \cos(2\pi f_1 t), & t_3<t\le t_4 \end{cases} \tag{9b}$$

$$p_{BPSK,1}(t)=\begin{cases} \cos(2\pi f_c t), & t_1<t\le t_2 \\ \cos(2\pi f_c t+\pi), & t_3<t\le t_4 \end{cases} \tag{10a}$$

$$p_{BPSK,2}(t)=\begin{cases} \cos(2\pi f_c t+\pi), & t_1<t\le t_2 \\ \cos(2\pi f_c t), & t_3<t\le t_4 \end{cases}. \tag{10b}$$

In (8)-(10), A_i represents the amplitudes, f_i represents the symbol frequencies and f_c denotes the carrier frequency of the modulated signals. The time instant t_i represents the locations of the template boundaries within the communications signal under consideration. As seen in Fig. 5, a communications signal having a frame length of 3 symbols is shown with each of the two possible symbol transitions present, i.e., “0” to “1” and “1” to “0.” The two unique features templates, T_1 and T_2, can be described based on the mathematical models presented in (8)-(10).

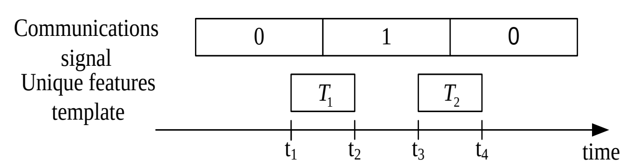

Fig. 5. Illustration of time-domain unique features templates.

3.2. Algorithm Details

Once the pre-defined templates are generated, the AMR process is implemented according to the following algorithm:
Step 1.) Compute the DWT of the received signal, up to 6 levels of resolution using the Haar wavelet.
Step 2.) Cross-correlate the WD signal obtained in Step 1 with all six of the pre-defined WD templates. This step is illustrated more clearly in Fig. 6, wherein the process of the sliding cross-correlation operation between a template and a communications signal is illustrated. In this process, the template is cross-correlated with the first signal segment.

Subsequently, the cross-correlation values between the signal and template within each data symbol section of the signal are computed. A signal segment is shown in Fig. 6 representing a data symbol period within the received signal. The template is then slid so as to be aligned with the next signal segment, and the two are cross-correlated. The process is continued until the template has been cross-correlated with all segments of the signal.

Step 3.) Compare the resulting cross-correlation values of the two BASK templates with the signal specifically at multiples of each baseband symbol period. Select the larger of the two values in each comparison, and in this manner generate a set of "time-and-merged" cross-correlation results for the two BASK templates. This operation is depicted in Fig. 7.

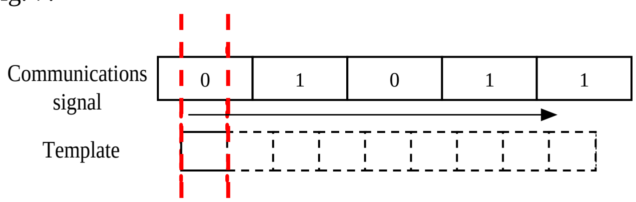

Fig. 6. Illustration of the sliding cross-correlation process between a template and a communications signal.

BASK Test Signal bit sequence	1	1	0	1	1	0	0	1
Cross-correlation values with BASK Template 1	L	H	L	L	H	L	L	
Cross-correlation values with BASK Template 2	L	L	H	L	L	L	H	
BASK "time-and-merged" cross-correlation results	L	H	H	L	H	L	H	

Fig. 7 Example of a "time-and-merged" operation in the WD AMR process.

Step 4.) Repeat Step 3 using the BFSK templates, and then again for the BPSK templates.

Step 5.) Compare each data element in the three sets of "time-and-merged" cross-correlation values. Select the largest value and record the template type to which the value belongs, i.e., whether it corresponds to BASK, BFSK or BPSK.

Step 6.) Declare the specific modulation type of the received signal to be that of the same type as the template that was selected most often in Step 5, i.e., select by a majority vote.

The procedural block diagram depicted in Fig. 8 illustrates Steps 1 through 6 of the algorithm for the AMR process.

Detailed description of Step 3: An important procedure in the WD AMR process is the "time-and-merged" operation described in Step 3. For the example illustrated in Fig. 7, a BASK test signal having a frame length of 8 symbols is cross-correlated with the two BASK unique features templates at consecutive data symbol locations. Then, the cross-correlation values obtained using both templates at each symbol period are compared. The cross-correlation result having the largest value is selected. These resulting sets of data are termed the "time-and-merged" cross-correlation values. These values are used in the WD AMR process for identification of the unknown modulation scheme of a received signal. In Fig. 7, L denotes a small cross-correlation value, while H represents a large cross-correlation value. A more complete example of the recognition procedure for a BASK signal is illustrated in Fig. 9. In the figure, the top row is representative of a noisy BASK signal having a random data bit sequence, which is input to a communications receiver that is initially unaware of the actual modulation type. The received BASK signal is a noisy digitally modulated signal that is transformed into the discrete wavelet-domain using the Haar wavelet. Hence, in actuality, the BASK signal in the top row of Fig. 9 is a

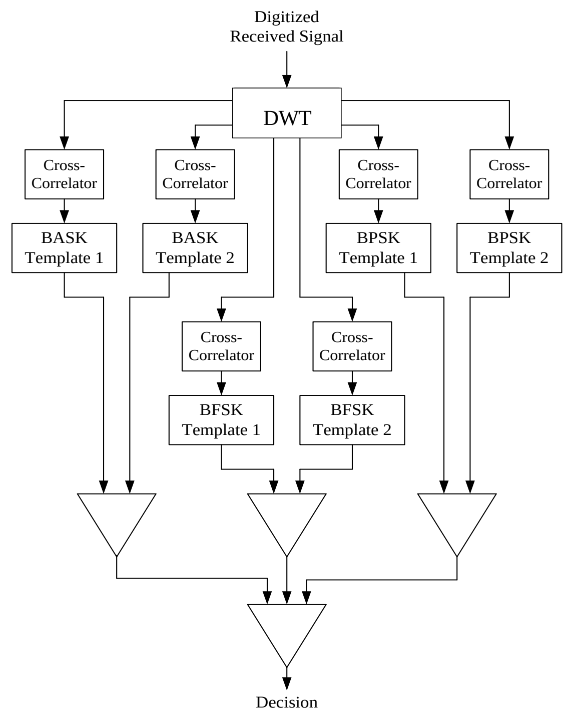

Fig. 8. System-level block diagram of the wavelet-based AMR processor.

WD scalogram. Next, this transformed received signal is cross-correlated with 6 unique features templates (2 templates for each of the 3 binary modulation schemes). Consequently, 3 sets of "time-and-merged" cross-correlation results are generated. In Fig. 9, the following notations are used:

H	High cross-correlation value
L	Low cross-correlation value
MA	Intermediate cross-correlation value within the BASK template dataset

MF Intermediate cross-correlation value within the BFSK template dataset

MP Intermediate cross-correlation value within the BPSK template dataset.

The "time-and-merged" results for the example are highlighted in the box shown in Fig. 9. It is the input to the following decision processor. For each symbol period, the three "time-and-merged" data results are compared. The template having the best match to a candidate modulation type is identified based on the largest value contained in the "time-and-merged" data. The classification of the unknown modulation scheme is then accomplished via a majority vote of all the element-wise template identifications previously made. In the example of Fig. 9, BASK templates are identified as being present in the received signal most often. Therefore, the modulation scheme employed by the received test signal is recognized to be that of BASK.

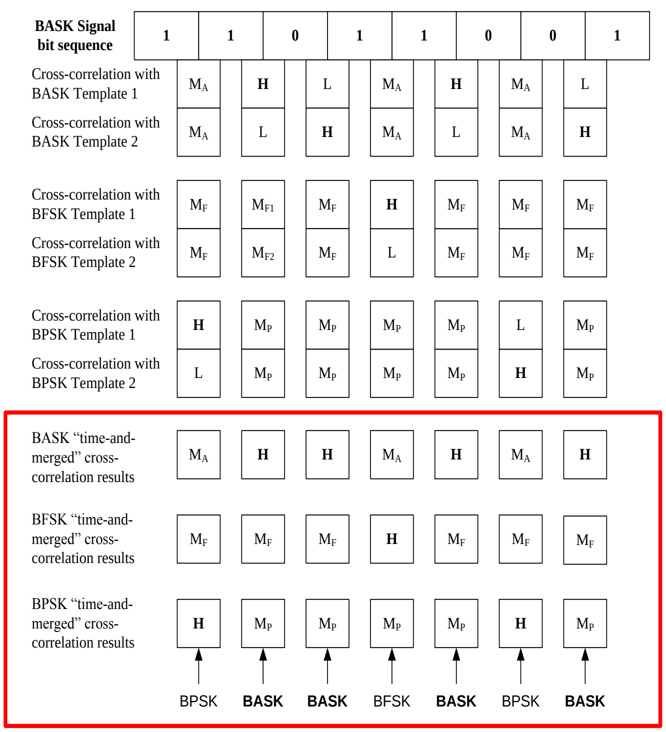

Fig. 9. Example of WD AMR process using the unique features templates.

4. SIMULATION EXPERIMENTS AND RESULTS

All of the binary digitally modulated test signals used in this study have been corrupted by zero-mean AWGN during transmission to produce received signals with SNR values in the range of -5 dB to 10 dB. The rates of correct classification produced by the WD AMR algorithm based on the unique features templates have been obtained using 20,000 Monte Carlo trials, where each simulation experiment employs 50 bits per frame. Each test signal used in the 20,000 trials randomly employs one among the BASK, BFSK or BPSK modulation schemes. The signals are oversampled by a factor of sixteen over the Nyquist rate corresponding to the carrier frequency. Oversampling is used because more signal content can be represented in the WD scalogram, which in turn enhances the WD AMR process. Perfect symbol timing, with no timing offset, is also assumed throughout this work.

All simulations have been performed using MATLAB. The carrier in each signal segment, representing a baseband data symbol, is composed of 128 samples per symbol. Due to the number of samples contained in a symbol, the maximum template length is 128 samples. Then the possible template lengths are 128, 64, 32, 16, 8, 4 and 2 samples. The length of the templates representing the WD templates, however, cannot be too short due to the loss of resolution in the WD scalogram. The loss of resolution directly affects the performance of the WD AMR process. A graphical representation of the sliding process with different template lengths is shown in Fig. 10. For the sake of illustration, only templates of size 128, 64 and 32 samples are used.

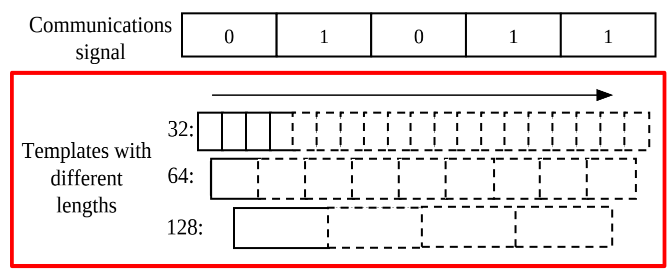

Fig. 10. Graphical representation of the cross-correlation operation using different template lengths.

In the simulations conducted in this study, the length of the templates is chosen to be 64 samples so as to achieve a balance, or tradeoff, between complexity and resolution. The results of the simulations are provided in Tables 1-4, which contain the rates of correct classification for signals with unknown modulation schemes corrupted by AWGN resulting in SNR values of 10 dB, 5 dB, 0 dB and -5 dB.

TABLE 1 RATES OF CORRECT CLASSIFICATION FOR SNR = 10 dB

		SIGNAL CLASSIFIED AS (%)		
		BASK	BFSK	BPSK
T_X SIGNAL	BASK	100	0	0
	BFSK	1.53	98.37	0
	BPSK	0	0	100

TABLE 2 RATES OF CORRECT CLASSIFICATION FOR SNR = 5 dB

		SIGNAL CLASSIFIED AS (%)		
		BASK	BFSK	BPSK
T_X	BASK	100	0	0

SIGNAL	BFSK	2.57	96.15	1.28
	BPSK	2.06	1.10	96.84

TABLE 3 RATES OF CORRECT CLASSIFICATION FOR SNR = 0 dB

		SIGNAL CLASSIFIED AS (%)		
		BASK	BFSK	BPSK
T_X SIGNAL	BASK	100	0	0
	BFSK	2.96	95	2.04
	BPSK	2.93	1.46	95.61

TABLE 4 RATES OF CORRECT CLASSIFICATION FOR SNR = -5 dB

		SIGNAL CLASSIFIED AS (%)		
		BASK	BFSK	BPSK
TX SIGNAL	BASK	100	0	0
	BFSK	3.98	94.32	1.7
	BPSK	3.42	1.71	94.87

5. COMPARISON OF RESULTS

Some prior studies found in the literature that have used both WD-based and non-WD-based AMR methods have been surveyed and compared with the results obtained in this study. The comparisons are presented in Tables 5-10. Specifically, Tables 5, 6 and 7 show the comparison between the results of this work and existing non-WD-based and CWT-based AMR methods. Tables 8, 9 and 10 compare previous DWT-based AMR results to the results of the DWT-based AMR algorithm developed in this work. It must be noted 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, such as SNR values, number of symbols per transmission, etc.

The values in Tables 5-7 were obtained from existing CWT-based and non-WD-based AMR techniques. More specifically, works [4], [8], [23] employ CWT-based techniques, while works [3], [18], [19], [20], [21], [22] use non-WD-based methods. Upon careful comparison, it has been found that the performance of the DWT-based AMR algorithm developed in this work is generally better than those obtained using other existing non-DWT-based AMR techniques with respect to two significant improvements. The first improvement is that of the performance enhancement at an SNR of -5 dB for BFSK and BPSK signals. The CWT-based AMR can only achieve a rate of correct classification of 54% [23], while the DWT-based AMR can identify the correct modulation with a 97% success rate.

The second improvement is the reduction of the computational complexity due to the differences between the nature of the CWT and DWT. The overall computational

TABLE 5
SURVEY OF BASK CLASSIFICATION IN THE NON-DWT-BASED LITERATURE

AMR method devised by	Correct classification at highest SNR (%)	Correct classification at lowest SNR (%)
Hossen, et al. [18]	97.5 at 3 dB	82.5 at -5 dB
Azzouz, et al. [19]	100 at 20 dB	98.25 at 10 dB
Lopatka, et al. [20]	100 at 30 dB	~92 at 0 dB
Yang, et al. [21]	-	97.5 at 10 dB
This work	100 at 10 dB	100 at -5 dB

TABLE 6
SURVEY OF BPSK CLASSIFICATION IN THE NON-DWT-BASED LITERATURE

AMR method devised by	Correct classification at highest SNR (%)	Correct classification at lowest SNR (%)
Hossen, et al. [18]	100 at 5 dB	87.5 at 3 dB
Azzouz, et al. [19]	90.75 at 20dB	96.25 at 10 dB
Dobre, et al. [22]	-	100 at 2 dB
Ho, et al. [4]	-	98 at 13 dB
Jin, et al. [8]	100 at 13 dB	99.5 at 8 dB
Ou, et al. [23]	100 at 20 dB	~54 at -5 dB
This work	100 at 10 dB	95 at -5 dB

TABLE 7
SURVEY OF BFSK CLASSIFICATION IN THE NON-DWT-BASED LITERATURE

AMR method devised by	Correct classification at highest SNR (%)	Correct classification at lowest SNR (%)
Hossen, et al. [18]	100 at 5 dB	75 at 3 dB
Azzouz, et al. [19]	100 at 20 dB	91 at 10 dB
Ho, et al. [3]	-	100 at 13 dB
Jin, et al. [8]	100 at 13 dB	95.3 at 8 dB
Ou, et al. [23]	100 at 20 dB	~54 at -5 dB
This work	98 at 10 dB	97 at -5 dB

complexity consists of: Generation of templates; Transformation of the received signal into the WD; Cross-correlation operations; and, Decision processor steps. For example, consider the case where a test signal has a length of 30 bits with 128 samples for each bit, and the template size is set at 64 samples. For the CWT-based AMR process, the size of each WD template would be a 128x64 matrix. The cross-correlation operation is based on the same size as well. Hence, the computational cost of the cross-correlation processing operations plus the computational cost of the

Decision Algorithms will result in the total complexity for the CWT-based AMR to be O(128*64). However, in the case of the DWT, because the resolution scale is taken to be a power of 2, level 7 is equivalent to the level 128 in the CWT. Now, the size of one DWT-based template is a matrix of size only 7x64. For similar AMR algorithm operations, the total computational complexity for DWT-based AMR is O(7*64). It is additionally observed that the matrix of DWT-based templates is a sparse matrix because of the down sampling operation at each level of resolution, which further makes the DWT-based AMR a computational efficiency process.

TABLE 8
SURVEY OF BASK CLASSIFICATION IN THE DWT-BASED LITERATURE

AMR method devised by	Correct classification at highest SNR (%)	Correct classification at lowest SNR (%)
Effrina, et al. [24]	-	-
Prakasam, et al. [10]	-	-
This work	100 at 10 dB	100 at -5 dB

TABLE 9
SURVEY OF BPSK CLASSIFICATION IN THE DWT-BASED LITERATURE

AMR method devised by	Correct classification at highest SNR (%)	Correct classification at lowest SNR (%)
Effrina, et al. [24]	100 at 25 dB	93at 10 dB
Prakasam, et al. [10]	98.6 at 3 dB	-
This work	100 at 10 dB	95 at -5 dB

TABLE 10
SURVEY OF BFSK CLASSIFICATION IN THE DWT-BASED LITERATURE

AMR method devised by	Correct classification at highest SNR (%)	Correct classification at lowest SNR (%)
Effrina, et al. [24]	99 at 25 dB	98 at 10 dB
Prakasam, et al.[10]	100 at 3 dB	-
This work	98 at 10 dB	97 at -5 dB

E. Avci, et al. [25], report mean correct recognition rates for digital modulation recognition of 96.51% and 90.24% when using DWNN and DWANFIS intelligent systems, respectively.

Also, from the comparison of results obtained with existing DWT-based AMR methods in Tables 8-10, generally, it is once again found that the DWT-based AMR algorithm developed in this work compares favorably. The range of the SNR considered in this paper is wider and centered in a more practical range of interest for radio receivers.

6. CONCLUSIONS

In this paper, it has been demonstrated that with the use of the pattern recognition methodology of template matching, along with appropriately defined WD templates, an effective AMR process can be developed operating within 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. At SNR = -5 dB, the correct rates of classification are achieved at a rate of 100% for BASK signals, 94.9% for BPSK signals, and above 97% for BFSK.

In this paper, it has been systematically established that, based on the AMR methodology devised in this study, and from the associated results, that an effective AMR process for binary digital modulation schemes can be implemented in the WD. While one of the immediate benefits gained from this study would serve to advance the state-of-the-art in communications receiver design, the near-term consequence is that of enabling adaptive and agile transceivers that have the potential to efficiently interoperate with a variety of communications standards that use different modulation types. Applications of such transceivers are present in both the military and civilian sectors, especially in the context of software defined radios and cognitive radio systems.

7. FUTURE WORK

A question readily arises as to whether the DWT-based AMR process can be extended to enable the classification of M-ary modulation schemes by using similar methodologies.

TABLE 11
Number of unique feature templates needed for different modulation schemes.

Modulation Scheme	Number of Unique Features Templates Needed
BASK	2
4-ASK	16
BFSK	2
4-FSK	16
BPSK	2
QPSK	16
8-PSK	64
4-QAM	16
16-QAM	256
64-QAM	4096

256-QAM	65536

The answer is yes, but not all that efficiently. This is due to the large number of unique feature templates that are required in the AMR algorithm. The higher-order modulation schemes contain more unique features, caused by an increase in the number of possible symbol transitions that exist, when compared to lower-order modulation schemes. Table 11 shows the number of unique features templates that must be extracted from different modulation schemes for use in the DWT-based AMR process.

From Table 11, it is easily seen that as the order of the digital modulation scheme increases, the number of unique features templates required for the WD AMR process also increases rapidly.

Therefore, it can be concluded that the computational effort for classifying the correct type of modulation scheme will also be significantly increased. Due to this observation, the unique features templates is best suited for developing a WD AMR process dedicated to classifying binary digitally modulated communications signals. Hence, a new DWT-based AMR algorithm must be designed to classify M-ary signals.

Another aspect of ongoing work is that of determining the optimal wavelet to use in the development of the WD templates employed in the AMR algorithm. It is expected that the rates of correct classification can be further enhanced by the use of wavelets that are well-matched to the time-domain structures of the digitally modulated communications signals.

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