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Automatic Modulation Recognition Using DWT-Based Signal Templates

by

Yao Ge, David G. Daut, Ka Mun (Vivian) Ho and Canute Vaz
Department of Electrical and Computer Engineering
Rutgers, The State University of New Jersey

Introduction

- Automatic Modulation Recognition (AMR) can be described as the blind identification of the modulation scheme used to format digital data embedded in a received signal.
- 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 and spectrum management.

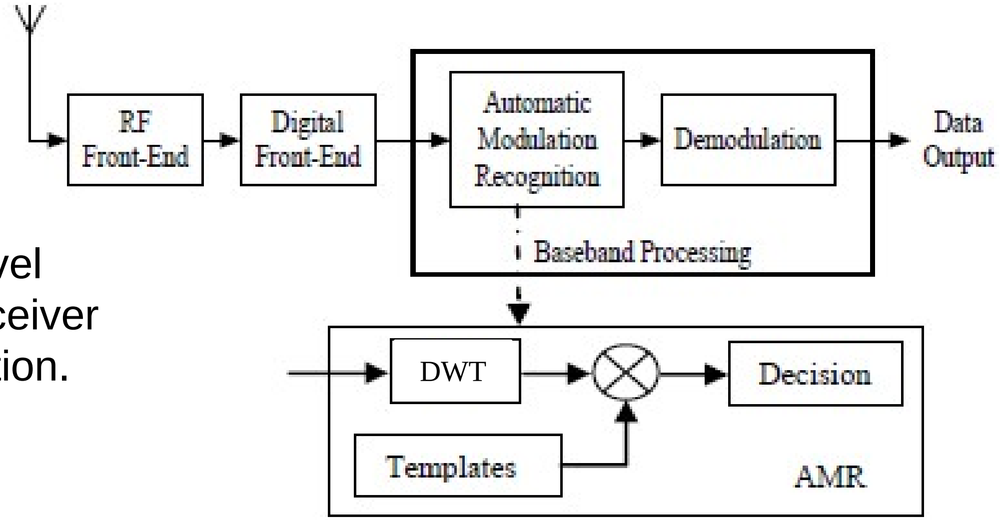


Fig.1. Overall system-level description of a radio receiver employing an AMR function.

Introduction

- AMR is an intermediate step in a communications receiver before demodulation of the data.
- This study investigates the design and performance of an AMR method using pattern recognition techniques in the wavelet-domain for the classification of binary modulated signals: BASK, BFSK and BPSK.
- Received communications signals are transformed using the Discrete Wavelet Transform (DWT).
- Pre-defined templates are extracted in the DWT domain based on transitions from symbol ‘1’ to ‘0’ or symbol ‘0’ to ‘1’.
- Results of cross-correlation between received signal and the pre-defined templates are used in the AMR process.
- Signal-to-Noise Ratios considered range from -5 dB to 10 dB.

Initial Setup for the AMR Process

- Wavelet employed for the DWT is the Daubechies 1 (Haar) wavelet. It is chosen because most previous related works focused on the Haar wavelet.
- Selection of pre-defined templates is based on unique data-dependent waveform transition features. They are constructed in the DWT domain.

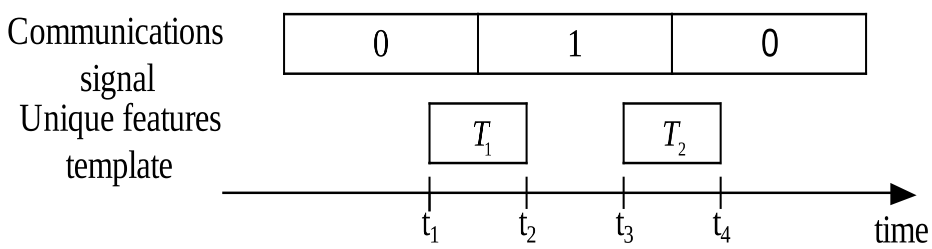


Fig 2. Illustration of time-domain unique features templates

- A total of six (6) pre-defined templates are created and stored for the AMR process designed to classify binary digitally modulated signals.

Template Generation Algorithm

Step 1: Construct the combinations of symbol pairs “1 0” and “0 1” for all three types of binary modulation formats.

Step 2: Transform the time-domain signals using the DWT based on the Haar wavelet.

Step 3: Truncate the two-dimensional wavelet-domain signal so as to capture the data symbol transitions of interest.

Step 4: Store the templates constructed in Step 3 within the receiver for use in the AMR process.

Pre-defined Templates - BASK

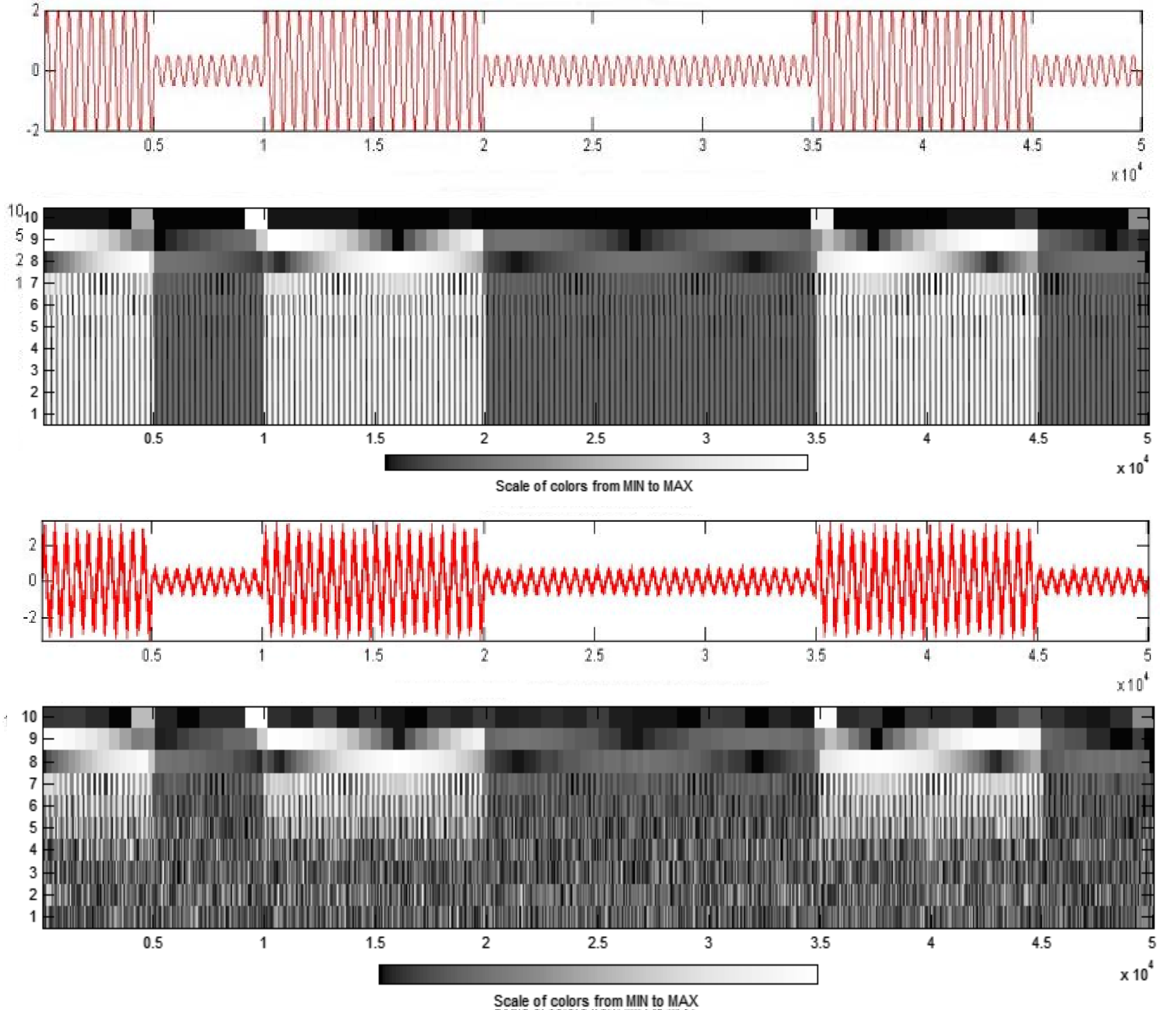


Fig. 3 (a): (Top) BASK signal without noise, 10-level discrete wavelet-domain decomposition using the Haar wavelet;

(b): (Bottom) BASK signal at 10 dB SNR, 10-level discrete wavelet-domain decomposition using the Haar wavelet.

Pre-defined Templates - BFSK

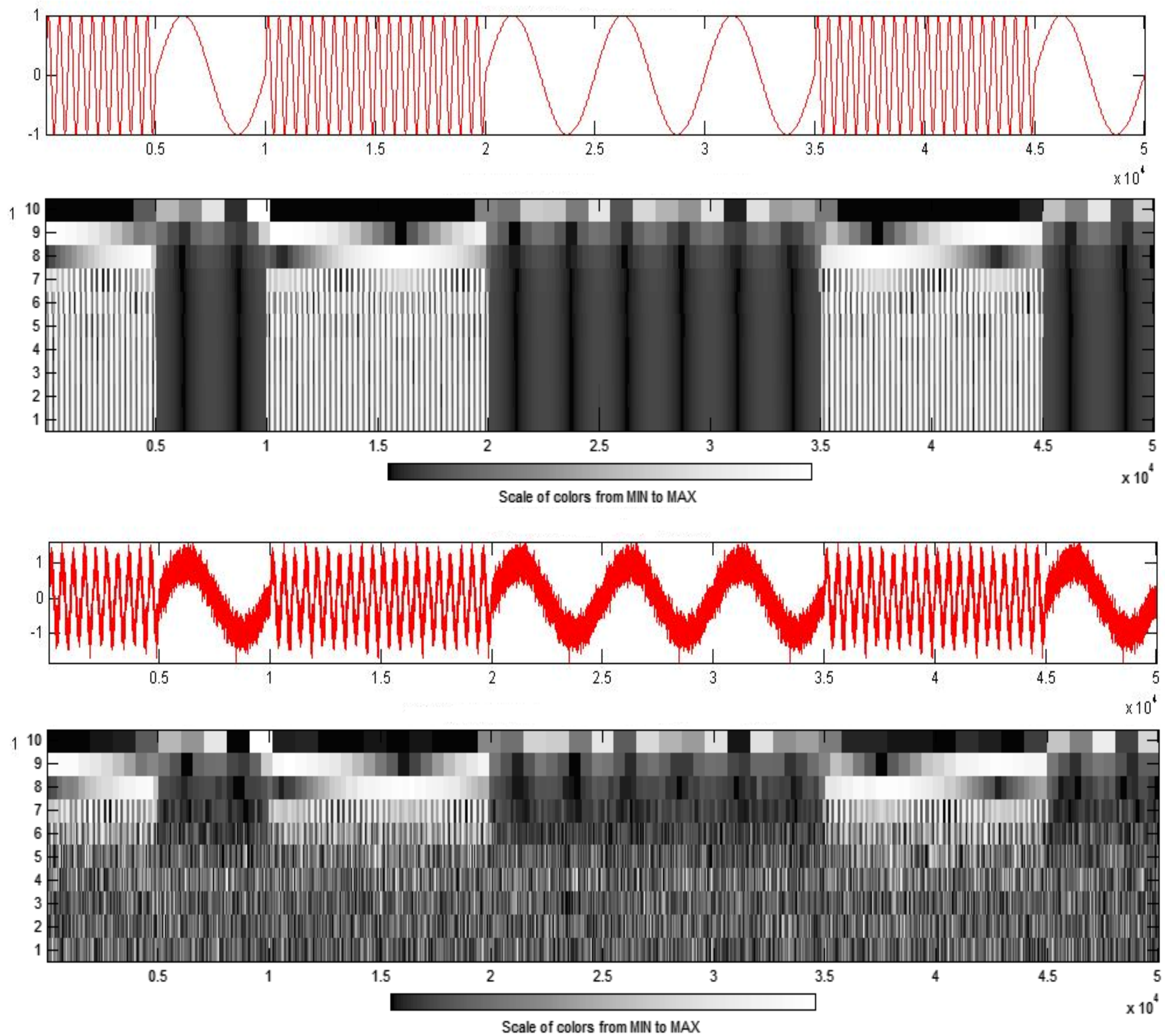


Fig. 4 (a): (Top) BFSK signal without noise, 10-level discrete wavelet-domain decomposition using the Haar wavelet;

(b): (Bottom) BFSK signal at 10 dB SNR, 10-level discrete wavelet-domain decomposition using the Haar wavelet.

Pre-defined Templates – BPSK

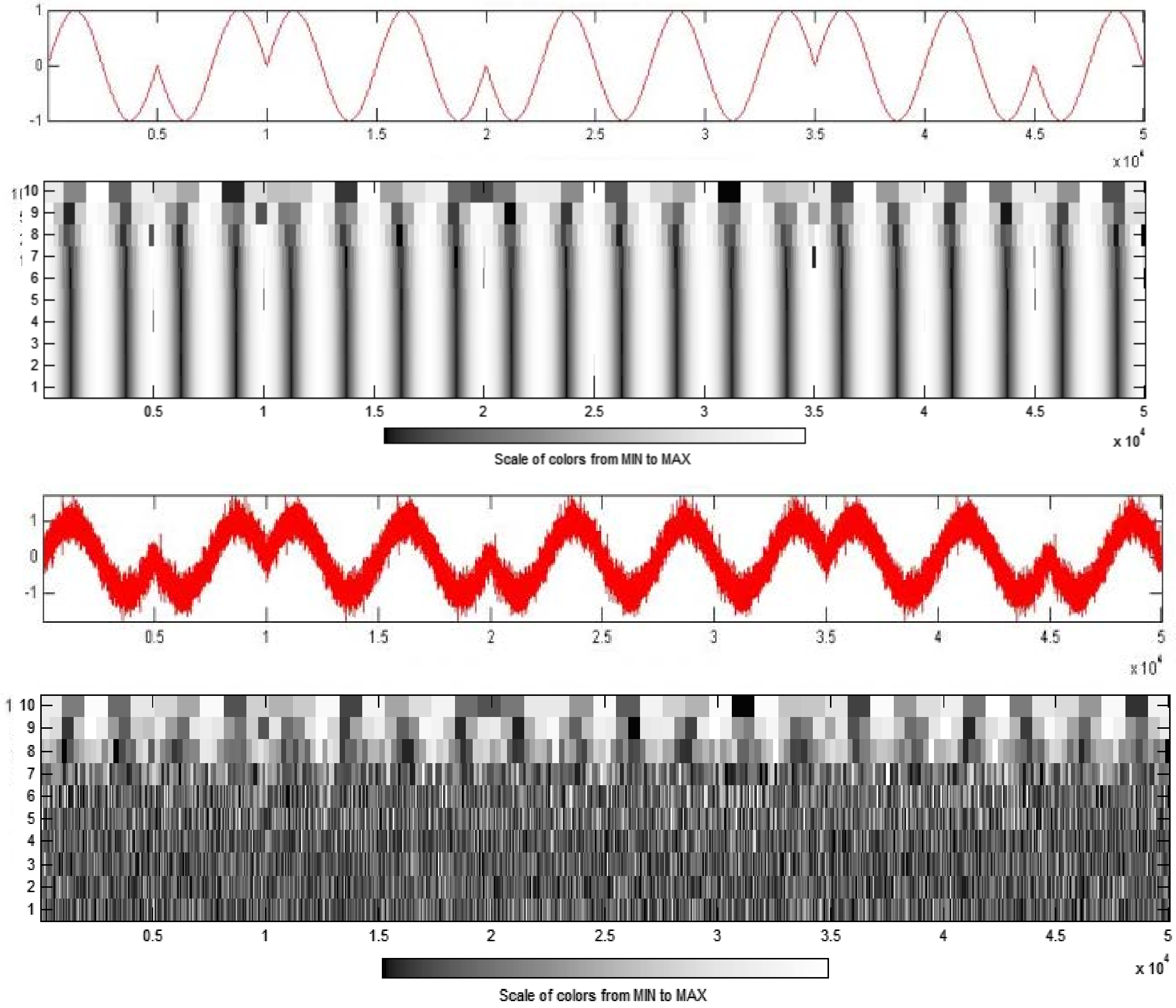


Fig. 5 (a): (Top) BPSK signal without noise, 10-level discrete wavelet-domain decomposition using the Haar wavelet;

(b): (Bottom) BPSK signal at 10 dB SNR, 10-level discrete wavelet-domain decomposition using the Haar wavelet.

Pre-defined Templates: Observations

- Portions of the signals containing data symbol transitions are clearly seen in the DWT scalograms as having distinctive features. The features are quite different from one binary modulation scheme to another. Hence, discrimination between modulation types in the DWT domain is feasible.
- For each modulation, there is a high degree of similarity between the DWT scalograms corresponding to the noise-free signals and the noisy received signals, especially at higher levels of resolution. This similarity is an important feature exploited by the AMR algorithm developed in this work.
- It has been determined that the information contained in the DWT coefficients at the lower levels of resolution is actually sufficient to achieve highly reliable AMR results.

Classification Algorithm

Step 1: Compute the DWT of the received signal up to **6** levels using the Haar wavelet.

Step 2: Cross-correlate the DWT transformed received signal with all six pre-defined templates.

Step 3: Compare the coefficients of the two BASK templates, select the larger values in each comparison and generate a set of "time-and-merge" cross-correlated results.

Step 4: Repeat Step 3 for BFSK and BPSK templates.

Step 5: Compare the results in Steps 3 and 4 to determine which modulation type the cross-correlation results belong to (i.e., BASK, BFSK or BPSK).

Step 6: Based on the result in Step 5, determine the modulation type based on majority vote logic.

Recognition Procedure for BASK Signal

BASK Signal bit sequence	1	1	0	1	1	0	0	1

Cross-correlation with BASK Template 1	M_A	**H**	L	M_A	**H**	M_A	L
Cross-correlation with BASK Template 2	M_A	L	**H**	M_A	L	M_A	**H**
Cross-correlation with BFSK Template 1	M_F	M_{F1}	M_F	**H**	M_F	M_F	M_F
Cross-correlation with BFSK Template 2	M_F	M_{F2}	M_F	L	M_F	M_F	M_F
Cross-correlation with BPSK Template 1	**H**	M_P	M_P	M_P	M_P	L	M_P
Cross-correlation with BPSK Template 2	L	M_P	M_P	M_P	M_P	**H**	M_P
BASK Òtime-and-mergedÓcross-correlation results	M_A	**H**	**H**	M_A	**H**	M_A	**H**
BFSK Òtime-and-mergedÓcross-correlation results	M_F	M_F	M_F	**H**	M_F	M_F	M_F
BPSK Òtime-and-mergedÓcross-correlation results	**H**	M_P	M_P	M_P	M_P	**H**	M_P
	BPSK	**BASK**	**BASK**	BFSK	**BASK**	BPSK	**BASK**

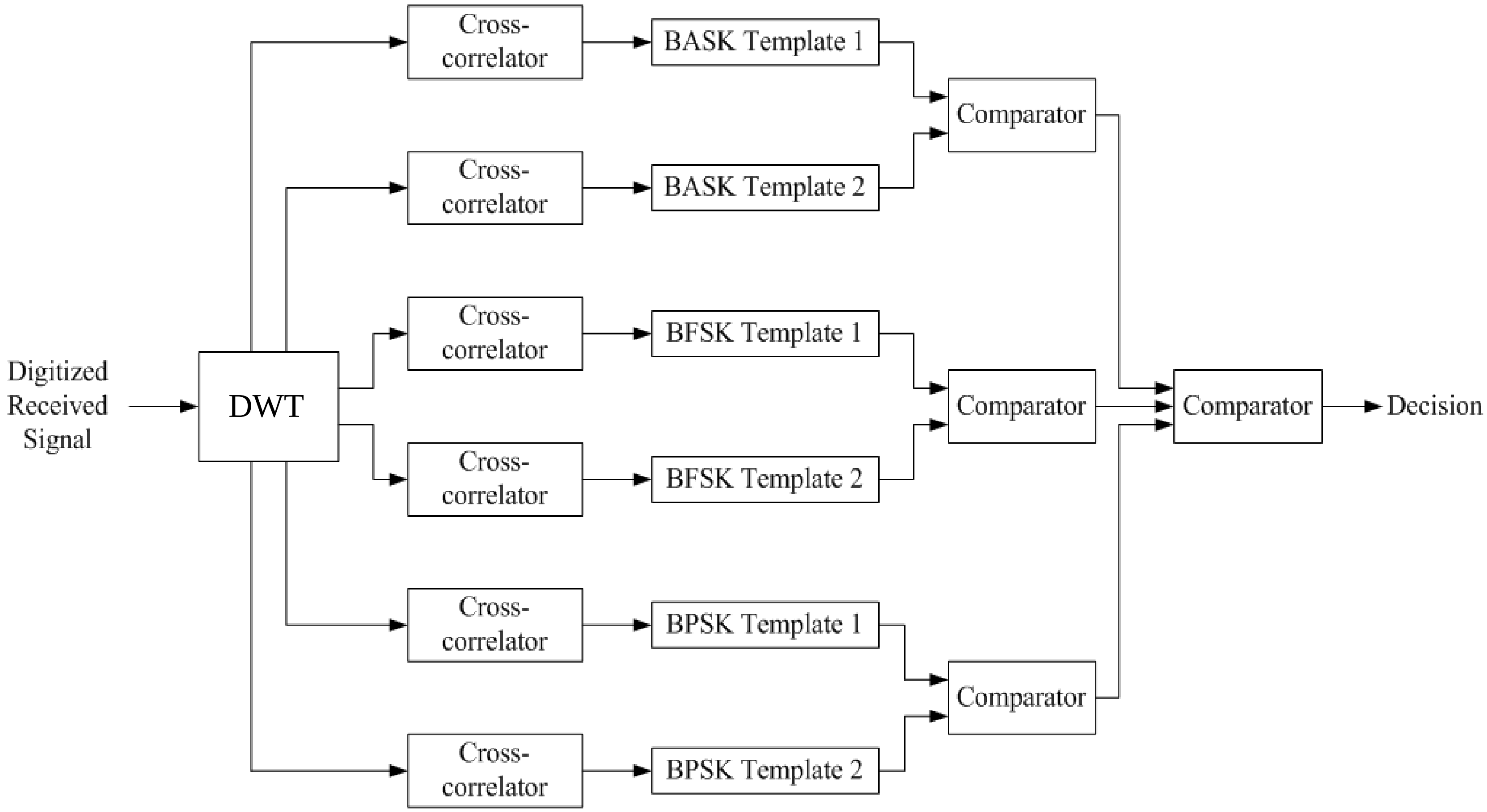
Noisy BASK signal (unknown to receiver) in the DWT domain using Haar wavelet is cross-correlated with 6 pre-defined templates to generate 3 sets of cross-correlation results:

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.

For each symbol period, the largest of the three outputs is considered as the best match.

The final decision about the unknown modulation type is accomplished via majority vote using all of the symbol-based template identifications previously made.

The AMR Block Diagram



Classification Results

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 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 2 RATES OF CORRECT CLASSIFICATION FOR SNR = 5 dB

		SIGNAL CLASSIFIED AS (%)		
		BASK	BFSK	BPSK
T_X SIGNAL	BASK	100	0	0
	BFSK	2.57	96.15	1.28
	BPSK	2.06	1.10	96.84

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

The DWT-based AMR process can correctly classify modulation schemes with very high reliability even at low values of SNR.

Comparison of Results (Non DWT-based AMR)

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	94 at -5 dB

Comparison of Results (DWT-based AMR)

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

Summary and Conclusions

- An effective AMR process for binary digital modulation schemes can be implemented in the Wavelet domain. Classification performance is better than existing AMR techniques, especially significant when considering systems operating at -5 dB SNR.

- The reduced computational complexity of this DWT-based AMR technique compared with existing CWT-based AMR methods provides an implementation advantage.

- Efficient and highly reliable AMR processors enable the development of adaptive and agile transceivers that have the potential to 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, e.g. SDR and cognitive radio systems.