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AUTOMATIC MODULATION RECOGNITION USING THE DISCRETE WAVELET TRANSFORM

By

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and approved by

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ABSTRACT OF THE THESIS

Automatic Modulation Recognition using the Discrete Wavelet Transform

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Professor David G. Daut

Abstract: An Automatic Modulation Recognition (AMR) process using the Discrete Wavelet Transform (DWT) is presented in this work. The AMR algorithm involves the use of wavelet domain signal templates derived from digitally modulated signals that are used to transmit binary data. The signal templates, locally stored in a receiver, are cross-correlated with the incoming noisy, received signal after it has been transformed into the wavelet domain. The signal template that yields the largest cross-correlation value determines the type of digital modulation that had been employed at the transmitter.

The specific binary-valued digital modulation schemes considered in this work include BASK, BFSK and BPSK. The discrete wavelet used for the creation of the signal templates is the Haar, or Daubechies 1, wavelet. Extensive computer simulations have been performed to evaluate the modulation recognition performance of the AMR algorithm as a function of channel SNR. It has been determined that the rate of correct classification for BASK signals is 68% for an SNR = 5 dB and 90% for an SNR = 10 dB SNR. The rate of correct classification for BFSK signals is 71% for an SNR = 5 dB and 92% for an SNR = 10 dB. Correct classification of BPSK signals is 71% for an SNR = 5 dB and 92% for an SNR = 10 dB. In comparison to alternative AMR methods reported in the literature,

the AMR algorithm developed in this study produces reliable results even at relatively low values of SNR which are characteristic of realistic communications channels.

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Dedication

To my family

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1. Introduction

Digital communication has become the typical contemporary method of transmitting data, where the data is encoded digitally, transmitted as signals via a channel and decoded at the receiver.

A typical contemporary communications receiver contains the subsystems illustrated in Fig. 1.1 [1]:

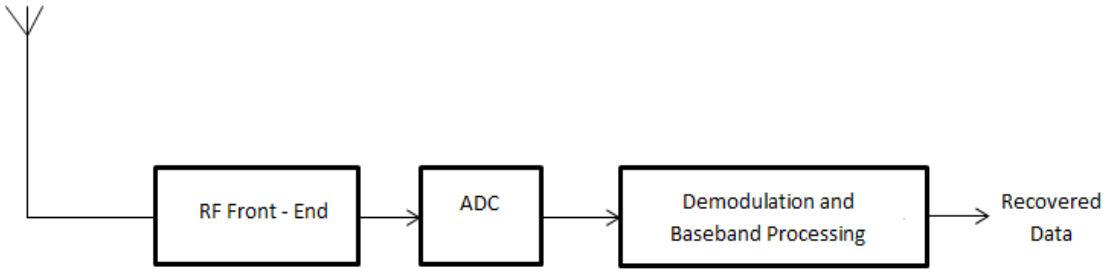


Figure 1.1 Contemporary communications receiver.

The RF (Radio Frequency) front-end gathers the analog signals, the ADC (Analog-to-Digital Converter) converts the signals to digital signals, and the signals are then demodulated to recover the intended message bit sequence.

A typical contemporary communications transceiver contains the subsystems illustrated in Fig. 1.2 [1]:

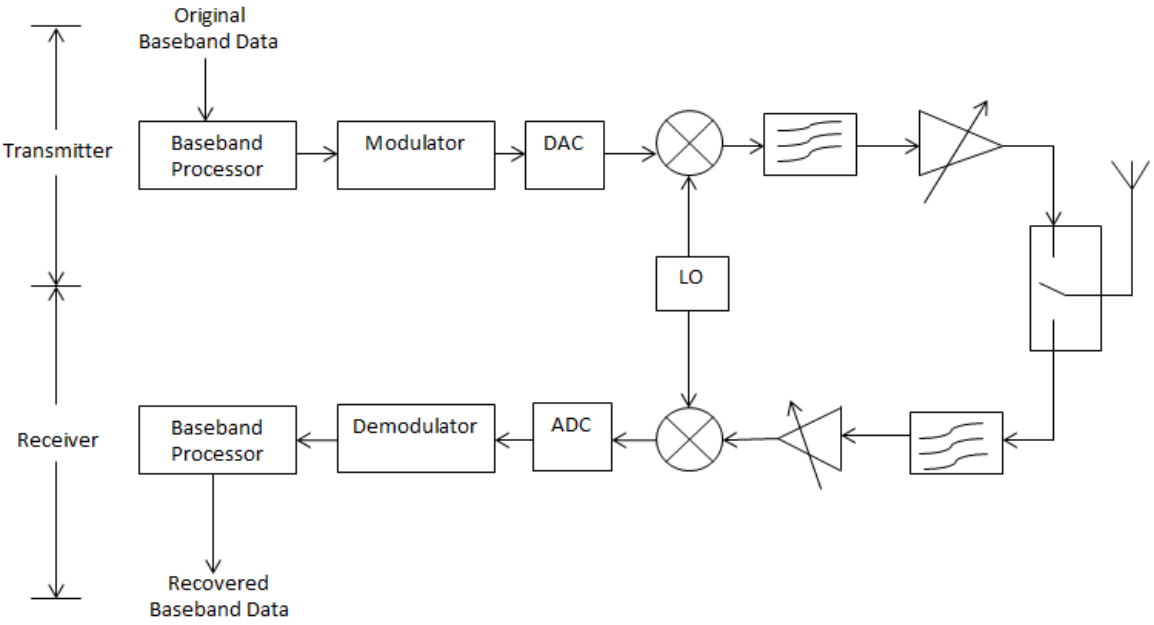


Figure 1.2 Radio transceiver for digital data transmission.

The transceiver possesses the operations of both a transmitter and a receiver for communication via a channel. The transmitter obtains the data, processes it, modulates the digital data, converts it into analog, and sends this processed data through the channel to the receiver. The receiver operation essentially reverses the operations described above.

This process of transmission and reception differs widely in different communication systems. The protocols and standards governing the communication process could be different; for example, cellular systems could use CDMA (Code Division Multiple Access) or GSM (Global System for Mobile Communications), Wi-Fi (Wireless Local Area Network) or WiMAX (Worldwide Interoperability for Microwave Access) standards could be used for data, and so on. The method of encoding the data can be different. Formats such as NRZ (Non-return-to-zero) or Manchester could be used. The data could even be scrambled. The available transmission bandwidth varies from channel to channel. Thus, each system that is designed is tailored to meet the requirements and specifications of the application for which the system is used. This

lack of a common platform is one of the major reasons for the lack of inter-operability between different classes of transmission over a communication system. An agile radio system is a communication system which can co-exist and communicate with other systems, irrespective of the

- Radio Frequency Carrier, which is has the purpose of the carrier transmitting the information through space as an electromagnetic wave. The carrier frequency differs from one communication system to another.
- Bandwidth, which is the available spectrum for the transmitter and receiver to communicate in.
- Waveform, which is the modulation type utilized by the transmitter for the purpose of communication.

Additionally, an agile radio system should be able to demodulate and detect the signals in real time, or near real time.

An agile radio system is illustrated in Fig. 1.3. The Radio-Frequency (RF) front-end receives the analog signals and converts them to digital signals, just as in the case of a contemporary receiver. These baseband digital signals are then classified based on modulation type and subsequently demodulated.

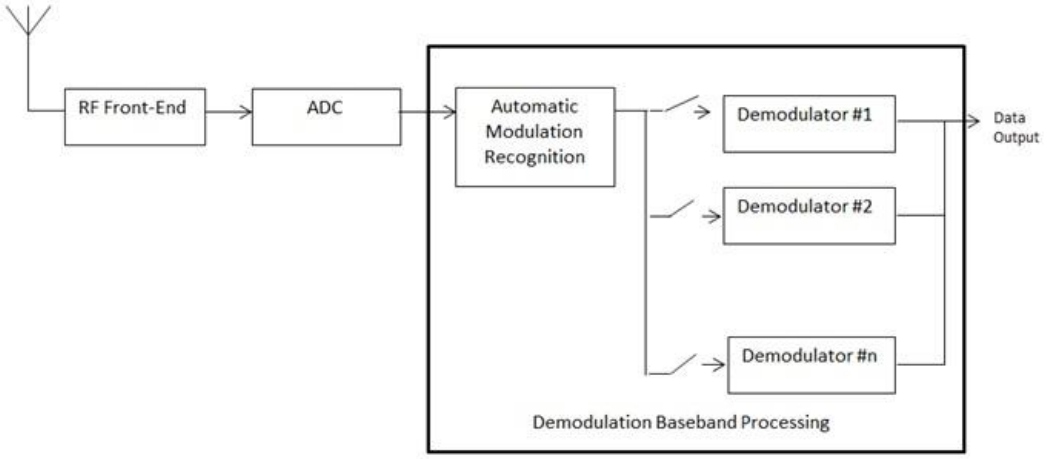


Figure 1.3 Agile radio receiver system.

Agile radio systems have obvious military applications, one of which would be to intercept a wide variety of information-bearing signals, regardless of the type of signal. They also have a commercial application of permitting the unification of various communications standards within a single receiver platform.

In this work, the development of an agile radio system using Discrete Wavelet Transforms (DWT) is studied. This work is divided into the following sections:

- Identification of relevant signals used in various modulation techniques.
- Motivation for the use of the DWT in developing an agile radio.
- Development of an algorithm to perform Automatic Modulation Recognition (AMR) using the DWT.
- Evaluation of the AMR algorithm performance.

a. Literature Survey

In this study, modulation recognition is explored by using a standard cross correlation technique on the coefficients of the wavelet transformed digitally modulated binary data. This approach is derived from the various techniques already in place, such as the technique which uses pattern recognition in conjunction with DWT-based methods, as in [2].

Several non- wavelet and wavelet-based approaches to AMR have been studied to compare the results.

Seminal work such as [3] and [4] rely on the maximum likelihood function, where the unknown signal is estimated, and the variance of the signal level directly influences the accuracy of the method.

There are many works which have utilized some of the features of the wavelet transform in order to recognize and/or to demodulate the signal. Many of these techniques use the Continuous Wavelet Transform. In [5], transient characteristics of a modulation type are derived from the peaks in the magnitude of the wavelet transform. This study recognizes FSK and PSK signals, and classifies BFSK correctly at an SNR of 13 dB and BPSK with accuracy of 98% at the same SNR.

The variance of the amplitude of the signal is used to broadly classify the various signals in [6], and further classification is done using CWT magnitude peaks and approximate likelihood function. Characteristics obtained from the coefficients of the wavelets of each modulated signal can also be used for AMR, as shown in [9], with 100% accuracy at 13 dB SNR for BPSK and BFSK. Accuracies of 99.5% and 95.3% have been found for BPSK and BFSK, respectively. Statistical signal characterization has been used by [7] to extract four numerical parameters which are then fed into an Artificial Neural Network to identify the signals and the identification

is robust to about 3 dB SNR. Artificial Neural Networks have been used by [8] as well, but the functioning is robust only in the high SNR region.

Other CWT based works, such as [9] use histogram processing, for BASK classification with approximately 92% accuracy at an SNR of 0 dB. For BASK classification with 97.5% accuracy at 10 dB, Neural Networks have been used by [10], operating on the Recursive Orthogonal Least Squares algorithm. A binary decision tree algorithm has been used by [11] for 100% accuracy at 2 dB for a BPSK modulated waveform. A CWT has been used by [19] as well, specifically a Complex Shannon Wavelet Transform to provide a probability of correct classification among binary PSK (BPSK), binary continuous-phase FSK (CPBFSK) and minimum-shift keying (MSK).

DWT based AMR is a relatively new concept. Results from [12] and [13] have been studied and compared with the results from the algorithm developed in this work. The classifier in [12] uses the peaks in the histogram of the DWT of the modulated signal. Down sampling has been used by [13], and median filters on CWT and DWT signals. The accuracy for BPSK is 93% at 10 dB and 98% for BFSK at 10 dB**.**

Discrete wavelet neural network (DWNN) and discrete wavelet adaptive network based fuzzy inference system (DWANFIS) are intelligent systems used in [14] to produce correct recognition rates for digital modulation of 96.51% and 90.24%, respectively.

It is found that the DWT-based AMR developed in this work compares favorably. The range of SNR which this paper deals with is larger, and the lowest SNR where this algorithm is still dependable is quite low. Another major advantage of this work is the simplicity of the algorithm, and ease of practical implementation on an SDR. The resources and memory requirements for the algorithm are minimal.

2. Signal Definition

There are three different kinds of modulation types used in this study. They are, Binary Amplitude Shift Keying (BASK), Binary Frequency Shift Keying (BFSK), and Binary Phase Shift Keying (BPSK).

a. Binary Amplitude Shift Keying

ASK uses a finite number of amplitudes, each assigned a unique pattern of binary digits. Each amplitude encodes an equal number of bits. Each pattern of bits forms the symbol that is represented by the particular amplitude. In this study, only binary ASK is considered, and therefore there are two amplitudes representing data bit '0' and data bit '1'.

Frequency and phase of the carrier are kept constant.

The BASK signals in general are defined as:

$$s(t) = \begin{cases} A_1 cos(2\pi f_c t) & 0 \le t \le T \\ A_2 cos(2\pi f_c t) & elsewhere \end{cases} \quad (2.1)$$

Where A_i is the amplitude of the signal and f_c is the carrier frequency.

In this study the BASK signaling waveforms are defined as:

$ASK\ zero\ bit\ template = A_1 cos(2 * \pi * f_c * t)$;

$ASK\ one\ bit\ template = A_2 cos(2 * \pi * f_c * t)$;

With the following values:

Amplitude for zero-bit, A_1 = 10

Amplitude for one-bit, A_2 = 100

Carrier frequency, f_c = 8 kHz, all the processes are carried out in baseband only.

The carrier frequency and all the other parameters used are scaled down, as the signals are being processed in the baseband only. It is noted here that the change in carrier frequency, if the change is made in all the three modulation types, does not alter the decision statistics.

The BASK signal templates are created for modulating the data stream, and they are as illustrated below in Fig. 2.1 and Fig. 2.2. The horizontal axis units are in Hertz. As can be seen, the BASK bit '1' template differs from the bit '0' template in amplitude. The bit '1' template has higher amplitude.

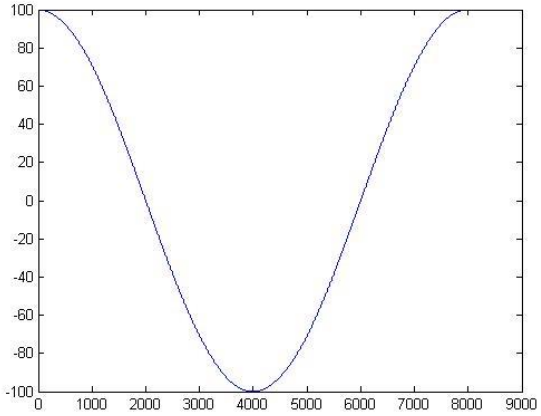


Figure 2.1 Bit '1' BASK modulated.

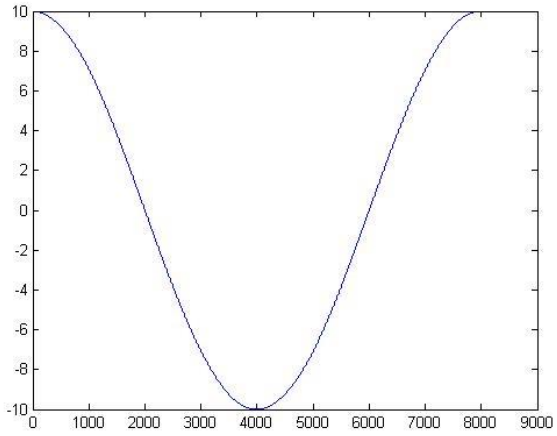


Figure 2.2 Bit '0' BASK modulated.

b. Binary Frequency Shift Keying

Frequency-shift keying is a frequency modulation scheme in which digital information is transmitted through discrete frequency changes of a carrier wave. The simplest FSK is binary FSK (BFSK). BFSK uses a pair of discrete frequencies to transmit binary (0s and 1s) information and is used in this study. The amplitude and phase are kept constant. Here, the amplitude is kept constant at 1, and phase is set to 0, for both zero and one bit BFSK templates.

The BFSK signals in general are defined as:

$$s(t) = \left\{ \begin{array}{ll} Asin(2\pi f_{c1}t) & 0 \leq t \leq T \\ Asin(2\pi f_{c2}t) & elsewhere \end{array} \right\} \quad (2.2)$$

Where *A* is the amplitude of the signal and f_{cn} is the carrier frequency, with *n* = 1 for the BFSK zero-bit template, and n = 2 for the BFSK one-bit template.

In this study the BFSK signaling waveforms are defined as:

$FSK\ zero\ bit\ template = sin(2 * \pi * 10 * f_c * t);$

$FSK\ one\ bit\ template = sin(2 * \pi * 100 * f_c * t);$

With the following values:

Frequency for zero-bit, $f_{c1} = 10 * f_c$

Frequency for one-bit, $fc_2 = 100 * f_c$

Amplitude, *A* = 1

The BFSK signal templates are created for modulating the data stream, and they are as illustrated in Fig. 2.3 and Fig. 2.4. The horizontal axis units are in Hertz. As can be seen, the BFSK bit '1' template differs from the bit '0' template in frequency. The bit '1' template has a higher carrier frequency.

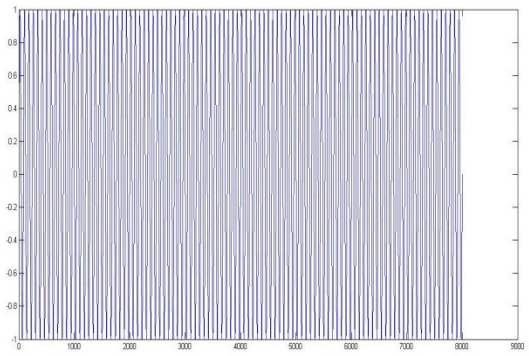


Figure 2.3 Bit '1' BFSK modulated.

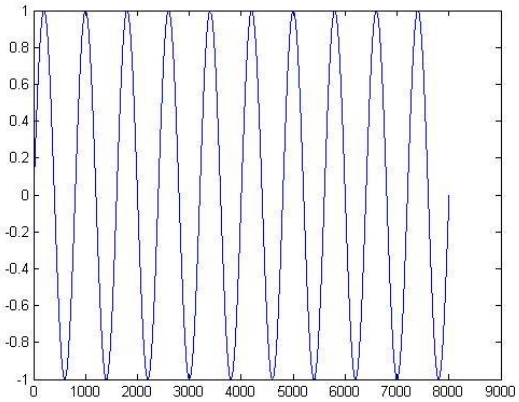


Figure 2.4 Bit '0' BFSK modulated.

c. Binary Phase Shift Keying

Phase-shift keying (PSK) is a digital modulation scheme that conveys data by changing, or modulating, the phase of the carrier wave. PSK uses a finite number of phases; each assigned a unique pattern of binary digits. Each phase encodes an equal number of bits. Each pattern of bits forms the symbol that is represented by the particular phase. In this study, only binary PSK is considered, and therefore there are two phases representing data bit '0' and data bit '1'.

The BPSK signals in general are defined as:

$$s(t) = \left\{ \begin{array}{ll} Asin(2\pi f_c t + \theta_0) & 0 \leq t \leq T \\ Asin(2\pi f_c t + \theta_1) & elsewhere \end{array} \right\} \quad (2.3)$$

Where *A* is the amplitude of the signal and f_c is the carrier frequency. $\theta_0$and θ_1 represent the shift in phase in zero-bit and one-bit templates, respectively.

In this study the BPSK signaling waveforms are defined as:

$PSK\ zero\ bit\ template = sin(2 * \pi * f_c * t + \theta_0);$

$PSK\ one\ bit\ template = sin(2 * \pi * f_c * t + \theta_1);$

With the following values:

Phase shift for zero-bit, $\theta_0 = 0$

Phase shift for one-bit, $\theta_1 = \pi$

Amplitude, $A = 1$

The BPSK signal templates are created for modulating the data stream and are illustrated as shown below in Fig. 2.5 and Fig. 2.6. The horizontal axis units are in Hertz. As can be seen, the BPSK bit '1' template differs from the bit '0' template in phase. The bit '1' template is the 180 degree phase-shifted version of the bit '0' template.

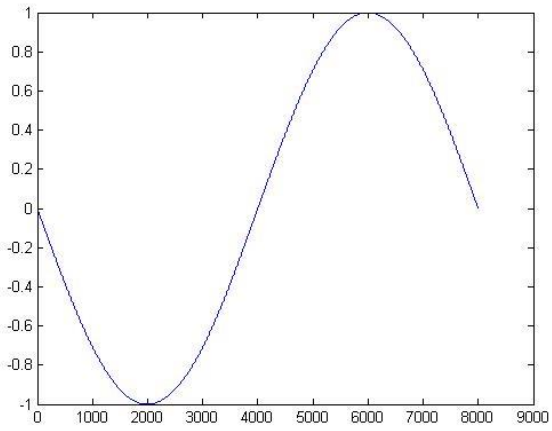


Figure 2.5 Bit '1' BPSK modulated.

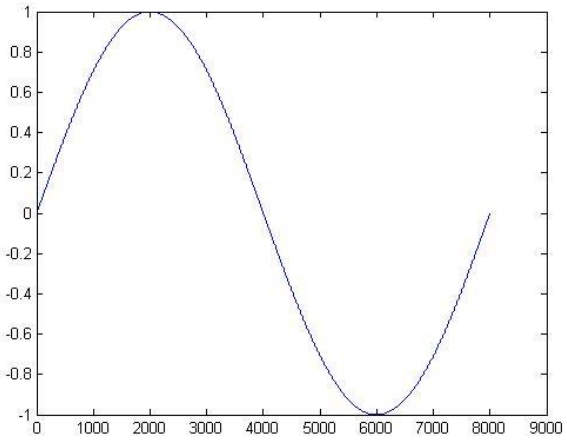


Figure 2.6 Bit '0' BPSK modulated.

3. Discrete Wavelet Transform

A wavelet is a waveform of effectively limited duration that has an average value of zero and wavelet analysis is the breaking up of a signal into shifted and scaled versions of the original wavelet [16].

Wavelets provide scale-based analysis, as opposed frequency-based analysis such as Fourier transform. Scale-based analysis measuring average fluctuations at different scales could possibly prove less sensitive to noise.

In the signal, the low-frequency content gives the identity and the high-frequency gives the nuance to the signal.

In discrete wavelet analysis, the two parameters taken into consideration are approximations and details. The high-scale, low-frequency components are called approximations, and the low-scale, high-frequency components are called details. Scaling refers to stretching or compressing a signal. Higher the scale, the signal is more stretched out [16].

Multiresolution Analysis (MRA) is a digital signal processing technique based on the orthonormal wavelet bases for signal analysis. The sampled signal is passed through a series of Finite Impulse Response (FIR) filters.

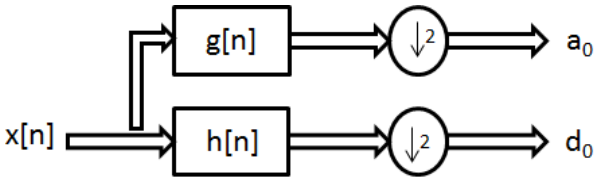


Figure 3.1 Depiction of one-stage filtering.

The above figure is one-stage filtering, where the input to the filters is the signal, x[n]. 'a_0' and 'd_0' refer to approximation and detail, respectively. The filter h[n] in the Fig. 3.1 refers to the impulse response of high-pass filter, and the filter g[n] refers to the impulse response of low-pass filter.

This process of filtering can be performed multiple times, that is, the filters can be applied repeatedly on the successive approximations and the wavelet decomposition tree can be formed [16]:

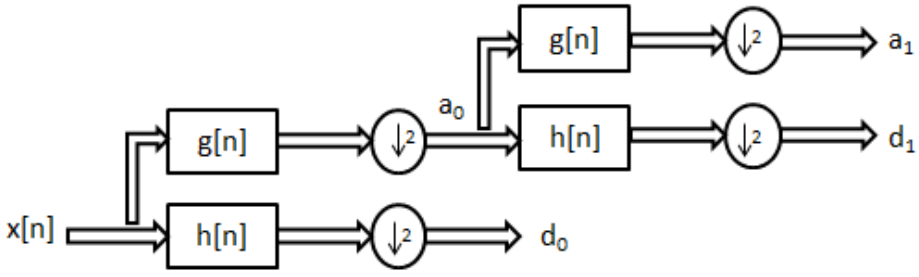


Figure 3.2 Decomposition tree.

In this work, only a 2-level discrete wavelet transform has been used, so as to keep the complexity of the overall AMR algorithm to a minimum.

The Fast Wavelet Transform is an algorithm which is used to change a signal which is in the time domain into a sequence of coefficients based on an orthogonal basis of wavelets. The Fast Wavelet Transform is used in MATLAB to create the DWT coefficients.

a. Haar wavelet

The characteristics of the Haar wavelet [15] are that it is a compactly supported wavelet and also the oldest and the simplest wavelet.

The scaling function of the Haar wavelet can be represented according to:

$$\phi(x) = 1, if\ x\ \in [0,1]$$

$$\phi(x) = 0,\ otherwise \tag{3.1}$$

The wavelet function of the Haar wavelet can be represented thus:

$$\psi(x) = 1, \qquad if\ 0 \leq x < \frac{1}{2}$$

$$\psi(x) = -1, \qquad if\ \frac{1}{2} \leq x < 1$$

$$\psi(x) = 0, \qquad otherwise \tag{3.2}$$

The Haar wavelet is the same as Daubechies1 wavelet. Also, the Haar wavelet is not continuous, as is illustrated in Fig. 3.3.

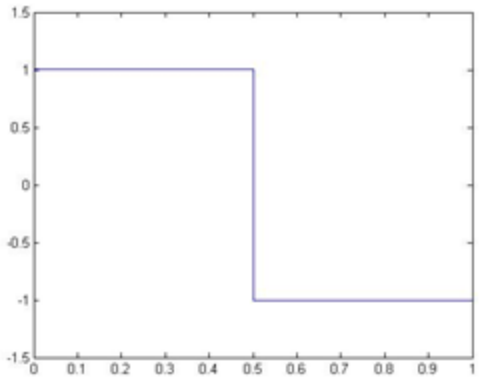


Figure 3.3 Haar Wavelet Transform.

4. Proposed Automatic Modulation Recognition Algorithm

This algorithm characterizes the performance of an Automatic Modulation Recognition methodology for signals which are modulated using Binary Amplitude Shift Keying (BASK), Binary Frequency Shift Keying (BFSK) or Binary Phase Shift Keying (BPSK).

The following assumptions are made:

- The transmitter system outputs only one of the three types of modulation formats described above.
- The channel introduces Additive White Gaussian Noise system into the communications system.
- The entire system assumes perfect carrier synchronization and symbol timing.

The algorithm can be broken down into the following steps.

As presented in Chapter 1, there are modifications made on the receiver, which is the introduction of the AMR algorithm subsystem, and the receiver processes being performed in the wavelet domain, which make it different, compared to the conventional digital receiver. In this section, this modified receiver is going to be implemented; and for that, a transmitter is

required which can be used to send signals to the receiver to test the performance of the modified receiver.

The transmitter sends a stream of data which is encoded in the form of 0 or 1 bit sequence. This is user generated. For example, a JPEG picture could be inputted to a transmitter which then encodes the values of the pixels as a binary stream. As the transmitted sequence is of importance only as a test stream, values which are known, to test the performance of the receiver, a transmitter which generates a sequence of bit 0s and bit 1s in a random fashion, suffices. Of course, the random bit stream must be different every time the receiver is tested so as to obtain statistically meaningful results for an accurate probability of correct classification evaluation.

The overall algorithm can be summarized in the following subsections, and can be depicted as in Fig. 4.1 and Fig 4.2.

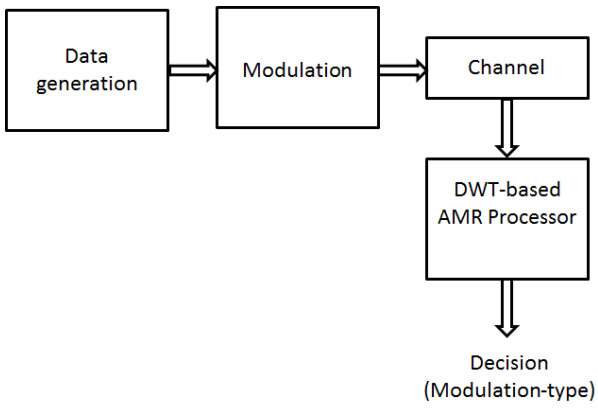


Figure 4.1 Overall Digital Communication System.

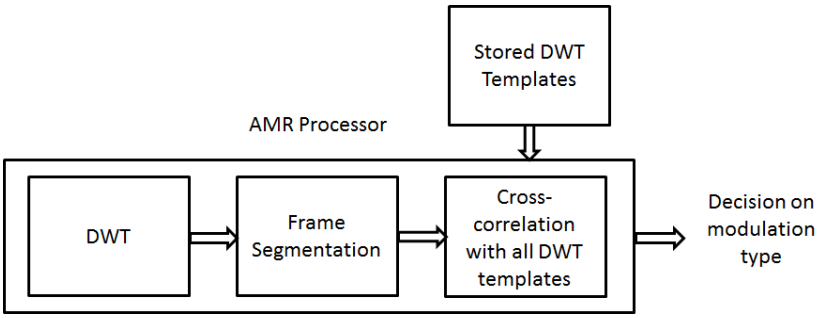


Figure 4.2 AMR Processor.

a. Data Stream Generation

A random binary data source is used, which generates random bits 0 and 1, implemented as a built-in function in Matlab, a Mersenne twister, with a long period $2^{19937} – 1$. The Mersenne twister has proved to be robust in many statistical tests for randomness. The length of the data stream is decided by the user. The transmitter program prompts the user to input the length of the data stream. This input value can be set in the program as well. For testing purposes, as Monte-Carlo trials are used, the length of the data stream, called a frame, is set to 1000. A total of 1000 frames, or trials, are performed. That is, 10^6 bits are generated, modulated, sent by the transmitter via the channel and demodulated at the receiver. The data stream generation is illustrated in Fig. 4.3.

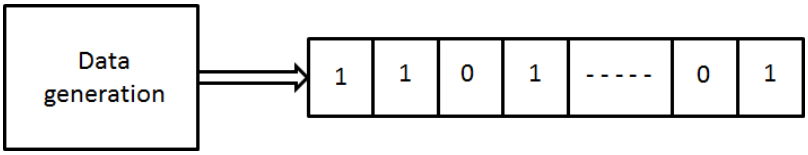


Figure 4.3 Data Generation.

b. Modulation

The next step in the transmitter is modulation. All the data bits are modulated onto a carrier. The different types of modulation possible in this algorithm are BASK, BPSK, BFSK. A frame is

modulated using one of three possible modulation schemes. Each bit in a frame is modulated separately and then placed side-by-side to make one long contiguous modulated frame. The process can be depicted as in Fig. 4.4. In this example, BASK modulation is assumed.

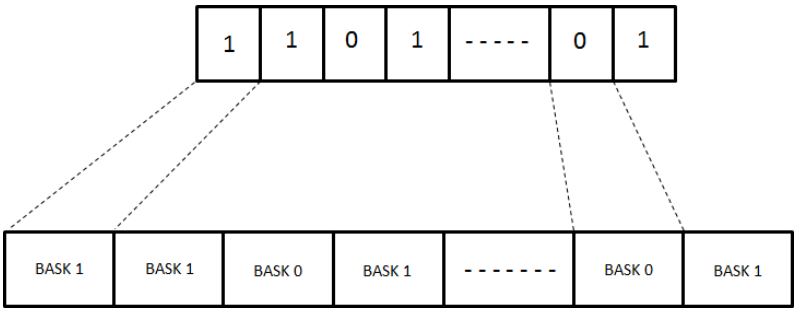


Figure 4.4 Modulation of the Data Bits.

The modulation waveforms corresponding to different data bits for each modulation type is given according to:

ASK bit 0

$$BASK_0(t) = A_1 \cos(2\pi f_c t) \quad (4.1)$$

ASK bit 1

$$BASK_1(t) = A_2 \cos(2\pi f_c t) \quad (4.2)$$

FSK bit 0

$$BFSK_0(t) = \sin(2\pi f_{c1} t) \quad (4.3)$$

FSK bit 1

$$BFSK_1(t) = \sin(2\pi f_{c2} t) \quad (4.4)$$

PSK bit 0

$$BPSK_0(t) = \sin(2\pi f_c t) \quad (4.5)$$

PSK bit 1

$$BPSK_1(t) = \sin(2\pi f_c t + \pi) \quad (4.6)$$

Where A_i represents the amplitudes, f_i represents the symbol frequencies and f_c denotes the carrier frequency of the modulated signals.

Since there are 3 different modulation types, and a total of 6 templates are created. For each trial, the same modulation type is used. This modulation type is known only to the transmitter.

c. Channel

Once the frame has been generated and the bits are modulated, the next step is for the modulated signal to be transmitted over the AWGN channel. The noise level of the AWGN channel impacts the accuracy of the recognition of the data stream and the subsequent demodulation of the data bits. The testing of the receiver and its robustness to noise should be tested for a range of signal-to-noise ratio levels. This algorithm is tested for the range of 0 dB to 10 dB signal-to-noise ratio levels. This SNR range is typical of an acceptable transmission environment for systems.

So far, a transmitter and an AWGN channel have been created. The next step is to build the receiver. But before that, the way the DWT templates are created is presented.

d. DWT Template Creation

The modulation templates in the time domain have been created already. Similarly, a set of templates transforming these modulation types using the chosen Haar discrete wavelet are to

be created. These templates will then be compared with the noisy transformed and modulated data stream.

Six such templates are created, which are, DWT of $BASK_0(t)$, DWT of $BASK_1(t)$, DWT of $BFSK_0(t)$, DWT of $BFSK_1(t)$, DWT of $BPSK_0(t)$, and DWT of $BPSK_1(t)$.

These 6 templates are stored in a basic memory system that is present in the receiver, and they are illustrated below.

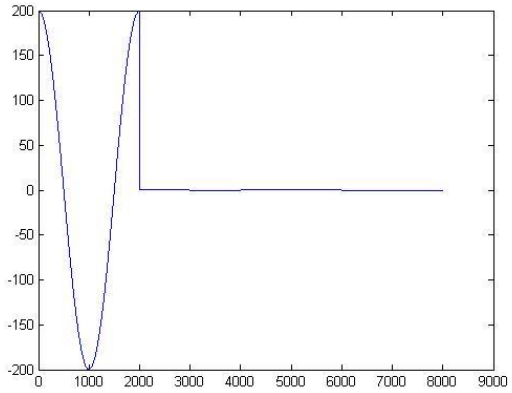


Figure 4.5 BASK one-bit, level 2, Haar, DWT template.

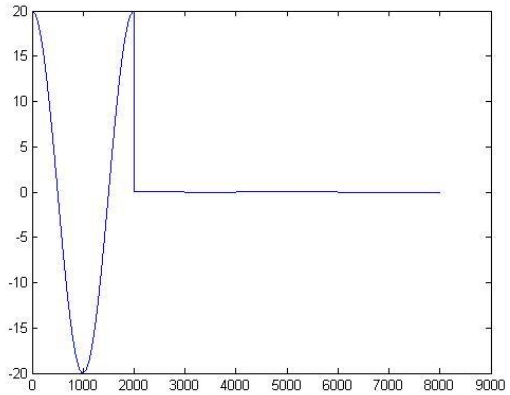


Figure 4.6 BASK zero-bit, level 2, Haar, DWT template.

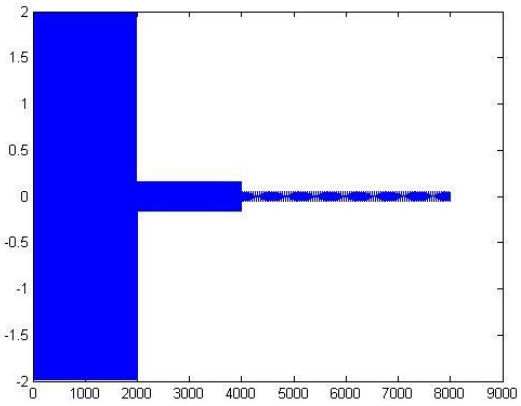


Figure 4.7 BFSK one-bit, level 2, Haar, DWT template.

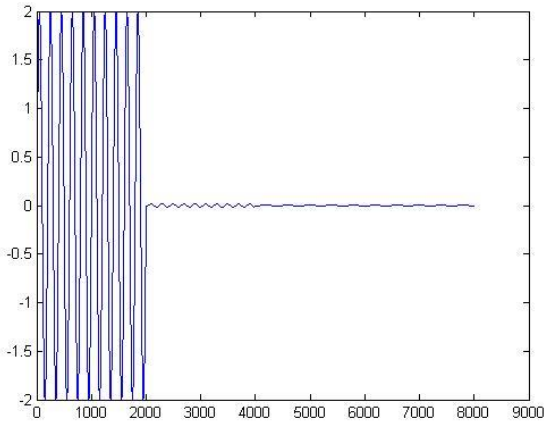


Figure 4.8 BFSK zero-bit, level 2, Haar, DWT template.

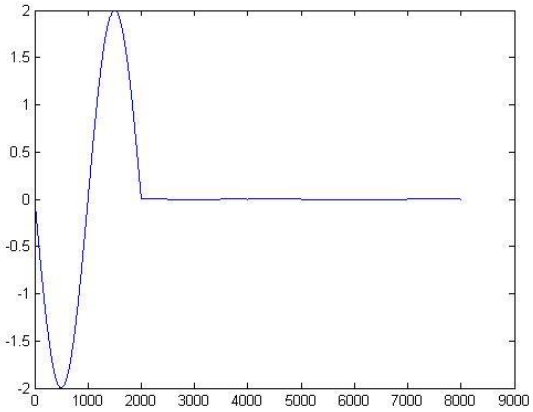


Figure 4.9 BPSK one-bit, level 2, Haar, DWT template.

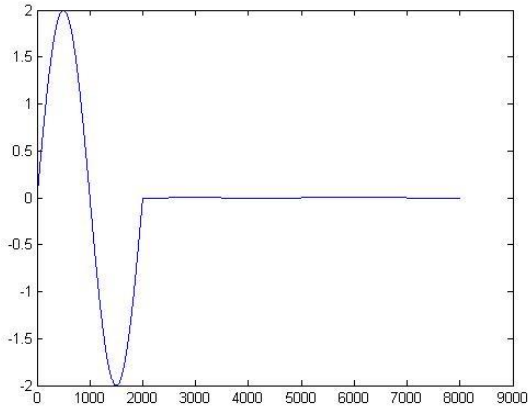


Figure 4.10 BPSK zero-bit, level 2, Haar, DWT template.

e. Frame segmentation

The system transforms the signal analysis processes from the time-domain into the wavelet-domain. All the other operations being performed in the receiver are also in the wavelet domain, without having to go back to the time domain. This is an advantage, as will be noted later.

Now the modulated signal which has passed through the noisy channel reaches the receiver. This entire noisy modulated signal is then transformed into the wavelet domain using the Haar transform. This can be depicted as in Fig. 4.11.

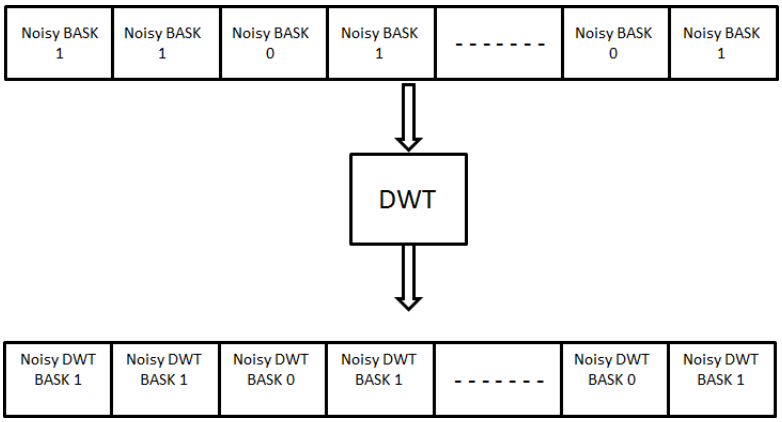


Figure 4.11 DWT of the received signal.

The number of data bits that are sent by the transmitter within a frame is known to the receiver. The receiver then segments the noisy modulated signal into the same number of segments as the number of data bits. Therefore, each segment is the noisy modulated and discrete-wavelet transformed version of a bit. This is shown in Fig. 4.12. It is interesting that if the channel was noise-free, each segment would be the same as one of the DWT templates.

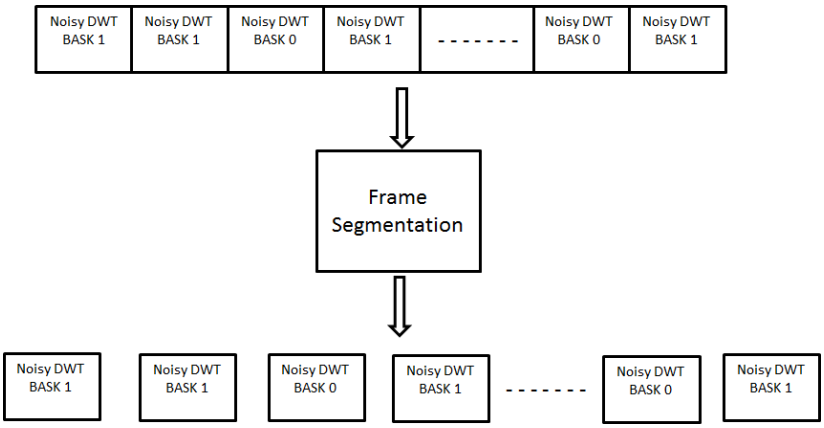


Figure 4.12 Frame Segmentation.

f. Cross-Correlation

Cross-correlation of any two discrete functions *f* and *g* is given by

$$(f * g)[n] \stackrel{\text{def}}{=} \sum_{m=-\infty}^{\infty} f^*[m]g[n+m]. \tag{4.7}$$

Here, the signal values are all real valued. Therefore, $f^*[m] = f[m]$.

Cross-correlation of two similar signals will lead to a peak in the correlation results. This is the property that is exploited. Once the signal is segmented, as described above, each segment is cross-correlated with the six templates. The template that is the noise-free version of the segment is expected to have the maximum correlation with the received waveform segment that has been corrupted by AWGN. The overall process of cross-correlation and comparison of results can be represented in Fig. 4.13.

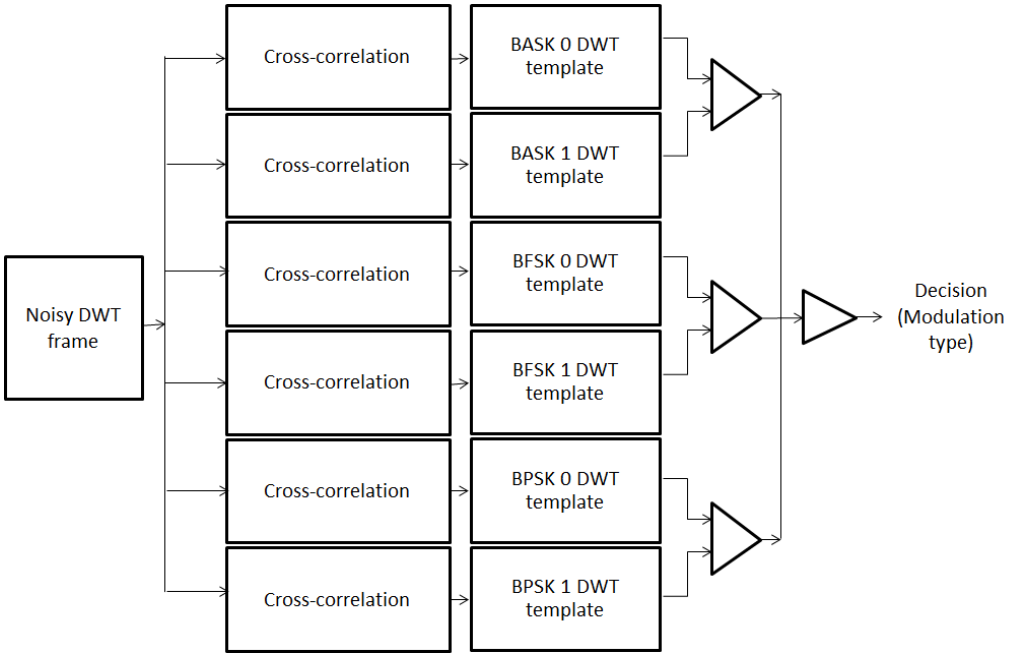


Figure 4.13 Cross-correlation and Comparison.

g. Demodulation

The demodulation result can also be calculated by the template which has the maximum correlation with the segment. The type of modulation can be recognized and stored for subsequent use in assessing the probability of correct classification. The bit value, whether it is a bit 1 or a bit 0 can also be noted and stored.

The data bit value, as well as the type of modulation; can also be found in one processing step.

h. Testing

The overall system performance evaluation routine executes the AMR algorithm and stores the number of times the Automatic Modulation Recognition algorithm successfully identifies the received signal modulation type. It also documents the number of times the algorithm failed to properly identify the modulation. In the frames the algorithm fails to perform the identification of the modulation type correctly, the faulty identification is also noted for the purpose of analysis and a table is created, as will be discussed in the Results section. This procedure is followed for all data bits and for all trials, for a complete and thorough understanding of the AMR behavior of the algorithm.

5. Simulation Experiments and Results

All of the binary digitally modulated test signals used in this study have been transmitted over an AWGN channel which corrupts the signal with an SNR between 0 dB and 10 dB. This is a large range of SNR which includes values of SNR encountered in many practical applications.

The calculation of correct classification is based on 1 million bits being transmitted and subsequently identified with regard to the modulation type employed. There are 1000 frames of

bits, sent through this system, 1000 times, and as the system has no memory as regards the classification, that is, a decision on the classification of a bit at any given time has no impact on subsequent decisions regarding the modulation type of another received data bit. The trials are conducted using a Monte Carlo method. Monte Carlo trials are a type of computational algorithm that use repeated random sampling to obtain statistically significant results for parameters of an underlying random experiment. All simulations have been performed using MATLAB.

The Table 5.1 is a compilation of the simulated results characterizing the correct classification performance of the AMR algorithm.

TRANSMITTED SIGNAL = ASK

SNR (in dB)	0	1	2	3	4	5	6	7	8	9	10
% of correct classification	41.2008	44.5986	48.3312	52.5704	57.2848	62.3815	67.936	73.5667	79.2958	84.6656	89.4315
% classified as ASK	41.2008	44.5986	48.3312	52.5704	57.2848	62.3815	67.936	73.5667	79.2958	84.6656	89.4315
% classified as FSK	26.2486	24.8775	23.2952	21.5331	19.4574	17.2284	14.7871	12.3277	9.7313	7.2842	5.0547
% classified as PSK	32.5506	30.5239	28.3736	25.8965	23.2578	20.3901	17.2769	14.1056	10.9729	8.0502	5.5138

TRANSMITTED SIGNAL = FSK

SNR (in dB)	0	1	2	3	4	5	6	7	8	9	10
% of correct classification	54.5045	57.1246	60.0131	63.5094	67.1731	71.1834	75.468	79.8358	84.2202	88.43	92.0355
% classified as ASK	13.0232	12.3435	11.5509	10.6765	9.664	8.6021	7.36	6.1145	4.8444	3.6214	2.5167
% classified as FSK	54.5045	57.1246	60.0131	63.5094	67.1731	71.1834	75.468	79.8358	84.2202	88.43	92.0355
% classified as PSK	32.4723	30.5319	28.436	25.8141	23.1629	20.2145	17.172	14.0497	10.9354	7.9486	5.4478

TRANSMITTED SIGNAL = PSK

SNR (in dB)	0	1	2	3	4	5	6	7	8	9	10
% of correct classification	55.8182	58.0194	60.6175	63.3438	66.8339	70.5704	74.7244	79.1435	83.5864	87.8619	91.6864
% classified as ASK	14.6568	13.9678	13.0939	12.195	11.0764	9.7855	8.3773	6.9089	5.437	4.0297	2.7783
% classified as FSK	29.525	28.0128	26.2886	24.4612	22.0897	19.6441	16.8983	13.9476	10.9766	8.1084	5.5353
% classified as PSK	55.8182	58.0194	60.6175	63.3438	66.8339	70.5704	74.7244	79.1435	83.5864	87.8619	91.6864

Table 5.1 Rates of correct classification of modulation type.

AMR method devised by	Correct classification at highest SNR (%)	Correct classification at lowest SNR (%)
Hossen, et al. [7]	97.5 at 3 dB	82.5 at -5 dB
Azzouz, et al. [8]	100 at 20 dB	98.25 at 10 dB
Yang, et al. [10]	-	97.5 at 10 dB
Ge, et al. [2]	100 at 10 dB	100 at -5 dB
This work	90 at 10 dB	41 at 0 dB

Table 5.2 Survey of BASK classification rates in the literature.

AMR method devised by	Correct classification at highest SNR (%)	Correct classification at lowest SNR (%)
Hossen, et al. [7]	100 at 5 dB	75 at 3 dB
Azzouz, et al. [8]	100 at 20 dB	91 at 10 dB
Ho, et al. [5]	-	100 at 13 dB
Jin, et al. [17]	100 at 13 dB	95.3 at 8 dB
Ou, et al. [18]	100 at 20 dB	~54 at -5 dB
Ge, at al. [2]	98 at 10 dB	97 at -5 dB
This work	92at 10 dB	54 at 0 dB

Table 5.3 Survey of BFSK classification rates in the literature.

AMR method devised by	Correct classification at highest SNR (%)	Correct classification at lowest SNR (%)
Hossen, et al. [7]	100 at 5 dB	87.5 at 3 dB
Azzouz, et al. [8]	90.75 at 20 dB	96.25 at 10 dB
Dobre, et al. [11]	-	100 at 2 dB
Ho, et al. [5]	-	98 at 13 dB
Jin, et al. [17]	100 at 13 dB	99.5 at 8 dB
Ou, et al. [18]	100 at 20 dB	~54 at -5 dB
Ge, et al. [2]	100 at 10 dB	95 at -5 dB
This work	92 at 10 dB	56 at 0 dB

Table 5.4 Survey of BPSK classification rates in the literature.

6. Conclusions

In this work, it has been demonstrated that a discrete wavelet platform can be used to perform AMR. The AMR algorithm presented here can make reliably accurate decisions even at realistically low values of SNR for input signals that are BASK/BFSK/BPSK modulated. The accuracy of decisions is approximately 68% at an SNR of 5 dB, and 90% at 10 dB SNR for BASK modulation, 71% at an SNR of 5 dB and 92% at 10 dB SNR for BFSK modulation, 71% at an SNR of 5 dB and 92% at 10 dB SNR for BPSK modulation. While these rates of correct classification may not be suitable for applications with high demand for precision,

in extremely noisy conditions, they are suitable for a wide variety of applications that operate in a moderate-to-high SNR environment. The classification results for the proposed AMR algorithm in a moderate-to-high SNR environment are comparable to those found in the literature, as demonstrated in Tables 5.2 to 5.4.

The features of this AMR algorithm can be summarized as follows:

Complexity	Low
Run-time	Fair
Accuracy	Fair
Comprehensibility level	Low

Table 6.1 Features of the AMR algorithm.

Another aspect of this AMR algorithm is that it can perform data demodulation. The data bit-value can be determined without having to revert back to the time-domain. All calculations are performed in the wavelet domain, thus allowing for possible improvements in the agile receiver, such as including a channel equalization subsystem.

7. Future Work

This work focusses on the use of a particular type of discrete wavelet for the AMR algorithm, that is, the Haar wavelet. One of the most obvious extensions of this work would be to study the behavior of other types of wavelet. Although a basic search was made in order to find what wavelet would be suitable for this AMR algorithm, it would be interesting to see what wavelet would be suitable if, for example, the number of possible modulation types was changed, or a longer window of observation was employed.

Another area which could be explored further is that of accommodating other types of modulation. In this work, BASK, BFSK and BPSK modulation types were used. Consideration of M-ary modulation types, as well as M-QAM, MSK, etc. would yield a more versatile AMR algorithm.

A few modifications could be performed on the algorithm for better performance. Instead of making a decision on each DWT-modulated and noisy frame, a small memory system could be put in place to store a few prior decisions, and then a collective decision could be made about a current bit type. That is, for example, let the memory system hold up to 8 frames. The first frame decision is BASK, the next is BPSK, the next four frames are decoded as BASK and the last two frames placed in the memory are decoded as BPSK, as the number of BASK decisions becomes larger, the collective decision could be made that BASK is the active modulation type. If the algorithm in this work had been followed, 3 frames would have been labeled wrong. Intuitively as well, this modification in the present algorithm would yield better correct classification performance.

The present work limits the type of channel. The AMR algorithm, the wavelet chosen, and all the system parameters are tailored for the AWGN channel. A more flexible AMR algorithm, which operates in conjunction with flat and fading channels, as well as band-limited channels, is one of the suggested improvements to be considered.

8. References

[1] Vaz, C. and Ho, K. M., "Development of Adaptive Radio Transceivers," Technical Report 06/09, Dept. Elect. Comput. Eng., Rutgers, The State University of New Jersey, Piscataway, NJ, June 2009.

[2] Ge,Y., Daut, D. G., Ho, K. M., Vaz, C., "Automatic Modulation Recognition Using DWT-Based Signal Templates," Proc. SDR-Winncomm 2013, January 8-11, 2013, Washington, D.C.

[3] Hong, L. and Ho, K. C., "Classification of BPSK and QPSK Signals with Unknown Signal Level Using the Bayes Technique," Proc. 2003 International Symposium on Circuits and Systems, Vol. 4, pp. 1- 4, May 2003.

[4] Xu, J. L., Su, W., and Zhou, M., "Likelihood-Ratio Approaches to Automatic Modulation Classification," IEEE Transactions on Systems, Man, and Cybernetics, Part C: Applications and Reviews, vol. PP, no. 99, pp. 1–15, Oct. 2010.

[5] Ho, K. C., Prokopiw, W. and Chan, Y. T., "Modulation Identification by the Wavelet Transform," Proc. 1995 IEEE Military Commun. Conf., Vol. 2, pp. 886-890, November 5-8, 1995, San Diego, CA.

[6] Chen, J., Kuo, Y., Li, J., Fu, F., Ma, Y., "Digital Modulation Identification by Wavelet Analysis", Proceedings of the Sixth International Conference on Computational Intelligence and Multimedia Applications, p.29-34, August 16-18, 2005

[7] Hossen, A., Al-Wadahi, F. and Jervase, J. A., "Classification of Modulation Signals Using Statistical Signal Characterization and Artificial Neural Networks," Engineering Applications of Artificial Intelligence, Vol. 20, Issue 4, pp. 463-472, Jun. 2007.

[8] Azzouz, E. E., Nandi, A. K., "Automatic Modulation Recognition of Communication Signals", Kluwer Academic Publishers, Norwell, MA, 1996.

[9] Liedtke, F. F., "Computer Simulation of an Automatic Classification Procedure for Digitally Modulated Communication Signals with Unknown Parameters," Signal Processing, Vol. 6, Issue 4, pp. 311-323, August 1984.

[10] Yang, C.-Q., Zhong, Z.-F. and Yang, J.-A., "Recognition of Digital Modulation Using Radial Basis Function Neural Networks," Proc. 2003 Int. Conf. Machine Learning and Cybernetics, Vol. 5, pp. 3012-3015, Nov. 2003.

[11] Dobre, A., Abdi, A., Bar-Ness, Y., and Su, W., "The classification of joint analog and digital modulations," in Proc. IEEE MILCOM, vol. 5, Atlantic City, NJ, Oct. 2005, pp. 3010–3015.

[12] Prakasam, P., Madheswaran, M., "Automatic modulation identification of QPSK and GMSK using wavelet transform for adaptive demodulator in SDR," in Proceedings of the International Conference on Signal Processing Communications and Networking (ICSCN '07), pp. 507–511, February 2007, Chennai, India.

[13] Yanti, E. H.," Automatic Modulation Classification of Communication Signal Using Wavelet Transform", International Conference on Electrical Engineering and Informatics (ICEEI), 17-June-2007.

[14] Acvi, E., and Acvi, D., "The Performance Comparison of Discrete Wavelet Neural Network and Discrete Wavelet Adaptive Network Based Fuzzy Inference System for Digital Modulation Recognition," Expert Systems with Applications, pp. 90-101, Vol. 35, Issue 1-2, July 2008, Pergamon Press, Inc., Tarrytown, NY, USA.

[15] Daubechies, I., Ten lectures on wavelets, CBMS, SIAM, 61, 1994, 194-202.

[16] Matlab Wavelet Toolbox

[17] Jin, J.-D., Kwak, Y., Lee, K.-W., Lee, K. H. and Ko, S.-J., "Modulation Type Classification Method using Wavelet Transform for Adaptive Demodulator," Proc. 2004 IEEE Int. Symp. Intell. Signal Process. and Commun. Syst., pp. 282-292, November 18-19, 2004, Seoul, Republic of Korea.

[18] Ou, X., Huang, X., Yuan, X. and Yang, W., “Quasi-Haar Wavelet and Modulation Identification of Digital Signals,” Proc. 2004 IEEE Int. Conf. Commun. Circuits and Syst., Vol. 2, pp. 733-737, June 27-29, 2004, Chengdu, People’s Republic of China.

[19] Pavlik, R., “Binary PSK/CPFSK and MSK Bandpass Modulation Identifier Based on the Complex Shannon Wavelet Transform,” J. Elect. Eng., Vol. 56, No. 3-4, pp. 71-77, 2005.