MODULATION CLASSIFICATION FOR RADIO INTEROPERABILITY VIA SDR

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ABSTRACT

Robust methods for identifying incoming waveforms, referred to as Modulation Classification (MC), are a capability required for future Cognitive Radio (CR) systems. Most SDR platforms contain an analog front end to receive and/or transmit the signal and a software processor to perform the demodulating and modulating functions of the radio in which the modulation scheme must be known *a priori*. This research seeks to devise solutions to dynamically identify waveforms by their analog and digital characteristics. The detection would then be used to aid in radio "bridging," i.e., allowing multiple radio platforms to communicate autonomously with each other. This paper outlines the implementation of an MC system that utilizes a signal's In-phase and Quadrature (IQ) components to generate a constellation diagram for modulation classification. The goal of the research is to provide a method for classifying the modulation scheme of an unknown signal that is both resource-conservative and robust. We have used a MATLAB and Simulink model-based development environment with SDR hardware from Lyrtech.

1. INTRODUCTION

A software-defined radio (SDR) is a radio communication device that allows for a flexible communication system. It can be programmed to receive AM, FM, or any of the myriad of digitally modulated signals. For example, car radio could ship with basic AM/FM and digital radio functionality and new software could be downloaded if the user desired GPS or Bluetooth capabilities. A not-so-obvious advantage presents itself when the areas of SDR and artificial intelligence (AI) combine. These radios, often called Cognitive Radios (CRs), employ SDR technology and AI to sense their environment and dynamically adjust to improve quality of service and bandwidth utilization [1]. Ideally, the entire process, from signal acquisition to data retrieval, will be handled seamlessly and automatically by the SDR.

In CR, and to an extent in SDR, it becomes clear that a method for signal modulation recognition is needed. To have a fully automated radio, it is necessary to be able to recognize the modulation used on a signal to properly demodulate it, whether it be in a civilian environment to cope with different communication standards, or in a military environment to perform real-time signal interception and efficient jamming [2,3].

2. MODULATION CLASSIFICATION

5.1. Modulation Methods

Modulation consists of encoding data onto a carrier signal. There are several practical uses of modulation that make it absolutely essential in today's radio communication environment. Most importantly, modulation allows the frequency spectrum of the message signal to be shifted by an arbitrary amount. There are three parameters of a radio signal that can change to produce modulation. They are the signal's amplitude, frequency, and phase. Modulation generally consists of multiplying a message signal, $m(t)$, with a carrier, $c(t)$. The message signal is at a much lower frequency than the carrier and contains the actual data of interest: speech, for example. The carrier is a sinusoid with a frequency equal to the desired transmission frequency. Modulation techniques can fall into the analog or digital categories. Analog modulation, in particular amplitude modulation (AM) and frequency modulation (FM), are perhaps the most widely known and used over-the-air modulation schemes. Due to their abundance and relatively low frequency on the radio-frequency (RF) spectrum, they are the focus of this initial research.

AM uses the message signal to alter the amplitude of the carrier. AM demodulation can be done either by locally generating a signal at the carrier frequency (coherent demodulation) or by transmitting the carrier along with the message (non-coherent demodulation). The latter approach is used more frequently since it allows for inexpensive and simple receivers. A typical AM signal is given by

$$\varphi_{AM}(t) = A\cos(\omega_c t) + m(t)\cos(\omega_c t) \tag{1}$$

Note that the carrier is transmitted along with the message signal. The carrier frequency is ω_c and the gain factor is A.

Demodulation of an AM signal of the type in equation 1 can be easily accomplished by a technique called envelope detection. An envelope detector works by locating the signal peaks and reconstructing the message signal (Figure 1).

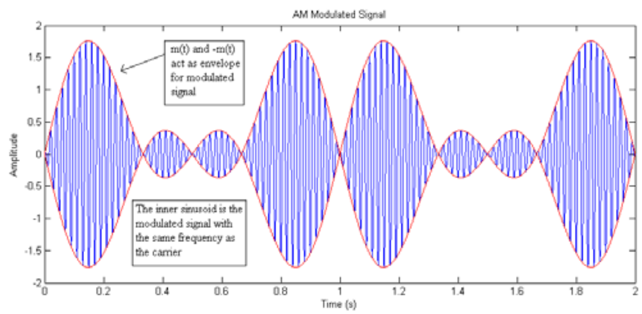

Figure 1 – Time domain view of AM modulation

FM modulation uses the message signal to vary the frequency of a constant amplitude carrier. The equation

$$\varphi_{FM}(t) = A \cos\left(\omega_c t + k_f \int_{-\infty}^{t} m(\alpha) d\alpha\right) \tag{2}$$

illustrates a typical FM signal. Once again, the carrier frequency is ω_c and k_f is a constant. In the case of FM, we can see that the instantaneous frequency of the FM signal is varied linearly with the modulating signal, $m(t)$ (Figure 2). Demodulation of a FM signal is typically done using a phase-locked loop (PLL). FM is the preferred method of analog modulation because it is much less susceptible to noise than AM is and it requires a lower transmission power to achieve the same quality [4]. Both of these advantages stem from the fact that a FM signal occupies a larger bandwidth than an AM signal. In fact, a commercial AM station has a bandwidth of 20 kHz, while a commercial FM station has a bandwidth of 200 kHz.

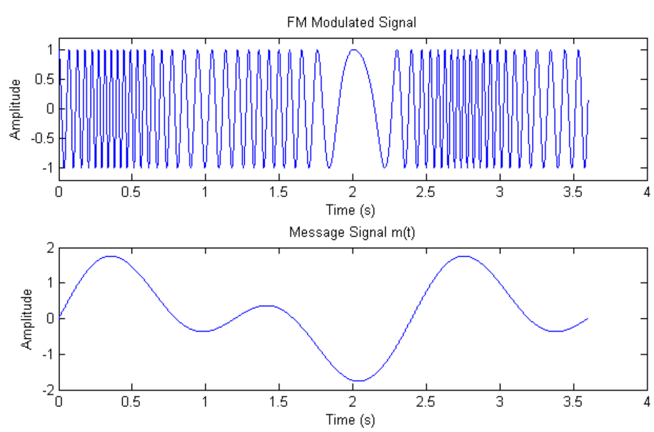

Figure 2 – Time domain view of FM modulation

Digital modulation schemes differ from analog ones primarily in that fact that the signals are converted from analog to digital format before modulation takes place [7]. Most digital modulation techniques use vector modulation or in-phase–quadrature (IQ) modulation. Vector modulation can be thought of as simultaneously changing both amplitude and frequency (or phase) of a signal. The name IQ modulation is fitting since it describes the preferred means of visualizing a vector modulation scheme. An IQ diagram is basically a means of plotting the in-phase (I) and quadrature (Q) components of a signal.

The IQ diagram is a complex plane where I corresponds to the real part of the signal and Q to the imaginary part. IQ diagrams are typically used to view digital modulation schemes but they can also be used to understand analog schemes. In a digital scheme, each point on the diagram corresponds to a symbol. In analog schemes, the symbols "blur" into line segments, but they still follow easy-to-understand rules. AM modulation, for example, produces an IQ diagram with constant phase but varying amplitude. FM modulation is the opposite, with constant amplitude and varying phase (Figure 3). Digital modulation is preferred over analog because of its more efficient use of the spectrum and resistance to channel effects such as noise [5]. In digital modulation, data is commonly referred to as symbols, and the number of symbols in a particular scheme corresponds to the number of bits per symbol. The symbols can be easily viewed on an IQ diagram (Figure 4). Some common types of digital modulation include QPSK for cellular phones (CDMA) and 256-QAM for digital television (in the US) [6].

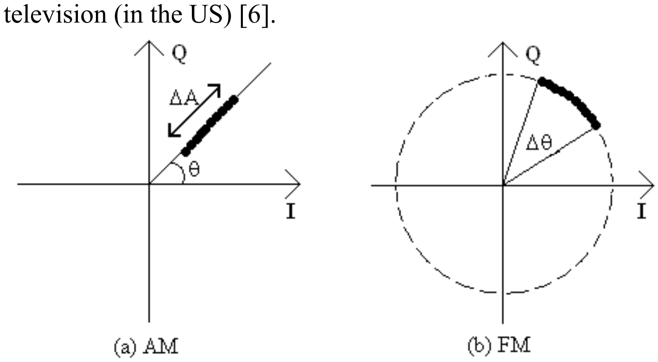

Figure 3 – Typical IQ diagrams for (a) AM signal and (b) FM signal

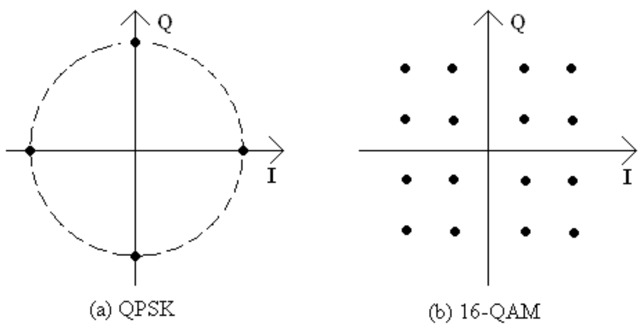

Figure 4 – Typical IQ diagrams for (a) QPSK signal and (b) 16-QAM signal

5.1. Modulation Classification

The field of modulation classification (MC) has been around since the mid 1980s, well before the advent of SDR. Techniques have been developed that examine the signal in the time domain, frequency domain, and vector space. Algorithms for modulation classification can be separated in two categories, likelihood based (LB) and feature based (FB) [3]. Most methods proceed with signal classification by first extracting a set of features, and then applying a classification algorithm to the extracted features.

The feature set can be comprised of time domain, frequency domain, or vector space aspects of the signal, and can include carrier frequency estimation, symbol timing, power spectral density (PSD), constellation shape, and various statistical measurements. Signal preprocessing, such as noise reduction, is often performed prior to feature extraction [3].

In the LB category, a likelihood function computes a likelihood value for a given signal and compares it to some threshold value. Based on the value, the modulation scheme can be determined. The FB methods use several signal features and base the classification on the signal's feature values [3]. Although LB approaches usually have better performance in terms of correct classification percentage, they are computationally complex and, therefore, not a viable option in most real-time scenarios [3]. FB methods can come close to meeting the performance of LB approaches when the features are carefully chosen. Since our interest is in real-time classification, we will only examine some of the more prominent FB classification schemes in this paper. For a more complete survey of automatic modulation classification schemes see Dobre *et al.* [3].

When features are extracted from a signal and compared to a set of "ideal" features to determine the modulation scheme of an incoming signal, the problem essentially becomes one of pattern matching. The goal is to find a feature pattern from a library of patterns that matches the feature pattern of the unknown signal. Several approaches to this pattern matching problem have been studied. For example, one of the earlier works by Aisbett used a feature set based on time-domain signal parameters and attempted to isolate features that were not strongly influenced by Gaussian noise [7]. More recent works on this area include also research on digital modulation schemes. For instance, work by Le *et al.* [1], and Nandi and Azzouz [8], use neural networks to classify modulation schemes of unknown signals. One benefit of neural networks is that they can be designed to be fairly computationally simple, and have the potential to work in real-time systems. Nandi and Azzouz [10] also worked on the decision theoretic approach to pattern matching, which is considered by many as the current state-of-the-art method for modulation classification [9,10]. The decision theoretic approach can be modeled with a flowchart. Signal features are compared to some threshold value at each node of the flowchart and branches are followed until the end is reached and the modulation scheme is determined.

Another popular area of research is using constellation diagrams to determine the modulation scheme. Many claim that a constellation diagram serves as a unique signature, and is more immune to poor channel effects (e.g., noise) than other signal features [9–12,15]. Hero and Hadinejad–Mahram worked on a system that would convert constellation data into gray scale images, and then use image processing techniques to evaluate the constellation and determine the modulation scheme [13]. The image processing system performed well; however, it was complex and could not be done in real-time [14]. Another method of assessing constellation similarity is by using a fuzzy c-means (FCM) algorithm to find constellation points. FCM is a clustering algorithm that allows data points to belong to two or more clusters. A simple difference measurement can then be used to compute the probability of a match [9,11,12]. Shahmohammadi and Nikoofar devised a mathematical method for determining the similarity between the constellation diagram of a received signal and the geometric pattern of a candidate modulation constellation. This approach led to a system that required far fewer computations than with decision theoretic algorithms [10]. Recent works also include a hierarchical view of MC, combining several methods to do a step-by-step modulation classification. It first identifies single-carriers vs. multi-carriers and in the following steps goes further into detecting the specific modulation of the receiving signal[17].

3. SIMULATION

The following section describes the SDR platform that was used to implement the IQ modulation classification system.

The system consists of hardware and software components. The hardware consists of an analog front end (for acquiring real-world signals), a simple signal generator (for test signals), and the Lyrtech SignalWAVe board (Figure 5). Software consists of Simulink models created to run on the board's DSP and FPGA. Test signals are generated with a Fluke 6060B signal generator capable of modulating an RF signal (freq range 0.01–1050 MHz) with a 400-Hz or 1-kHz tone using either AM or FM.

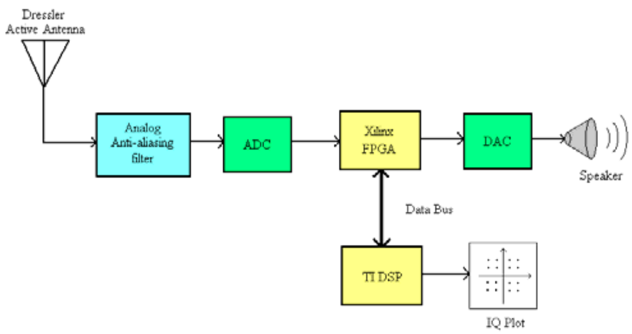

Figure 5 – SDR Platform

Real-world signals are acquired via an antenna and consist of AM and FM radio stations in State College, PA. The analog front end consists of an active antenna and a simple filter. The antenna used is a Dressler ARA-60 active antenna, chosen for its ability to pick up a large range of frequencies; 40 kHz to 60 MHz (although with a slightly reduced gain of 2–3 dB the frequency range can be extended to ~100 MHz to include the FM band). The filter depends on what type of signal is being monitored. A Mini-Circuits 1.9-MHz lowpass filter is used to tune into AM stations while a FM bandpass filter is used to tune into FM stations.

The board used is a Lyrtech SignalWAVe board that has an integrated DSP and FPGA. The DSP is a Texas Instruments TMS320C6713. The DSP has a 225-MHz clock and access to 32 MB of onboard shared memory. The FPGA is a Xilinx Virtex II XC2V3000. The FPGA has 3 million gates and access to 32 MB of onboard shared memory. The SignalWAVe board also contains an ADC (Analog Devices' AD6644) capable of 65 MSPS with 14-bit resolution and a DAC (Analog Devices' AD9754) capable of 125 MSPS with 14-bit resolution.

Programming the board consisted of using MATLAB and Simulink to build models using block sets provided by Lyrtech. Several pieces of software were required to build and test models on the SignalWAVe board. Table 1 gives a list of all the software as well as version numbers. MATLAB makes use of Code Composer Studio to generate the C code that runs on the DSP while Xilinx Foundation ISE is used to generate the VHDL code for the FPGA. For more detailed instructions on the installation and configuration of the SignalWAVe board see the Lyrtech documentation [16].

In addition to the setup above, a Tektronix RSA 3303A Signal Analyzer was used during development of the system to monitor signals and generate IQ diagrams.

The functionality of the design is split between the FPGA and DSP. The FPGA, which is capable or running at a much higher clock rate than the DSP, is used to separate the incoming signal into I and Q components.

Table 1 – Software Requirements for SDR Platform

Package	Sub-Packages	Version
MATLAB	Main Program	7.0.4.365 (R14) SP 2
	Simulink	6.2
	Communications Blockset	3.1
	Signal Processing Blockset	6.1
Texas Instruments Code Composer Studio	Main Program	2.20.00 (or 3.0.0.21)
Xilinx Foundation ISE	Main Program	7.1.04i
	System Generator	7.1

The sampled signal is sent through a Hilbert transformer that keeps the signal intact while shifting its phase by 90 degrees. The two components (I and Q) are appropriately scaled and packed so they can be sent over the DSP/FPGA bus. The DSP receives the signal's I and Q components and implements the "algorithm" to determine the modulation scheme. As of the writing of this paper, this algorithm has not yet been implemented fully. Currently, I and Q components are simply displayed on a graph in real-time.

5.1. Hilbert Transformer

The Hilbert transformer in the FPGA portion of the design is a crucial component of the MC system. This filter creates a signal that is orthogonal to the incoming signal. The Hilbert transformer ideally leaves the magnitude of the signal unchanged, but shifts the phase by 90 degrees. The effects of the Hilbert transformer can best be viewed by examining the frequency response of the filter. From $H(\omega) = -j\,\mathrm{sgn}(\omega)$, it is easy to see that all negative frequencies receive a phase shift of −90 degrees and all positive frequencies receive a phase shift of +90 degrees.

The actual Hilbert transformer implemented in our design differs from the ideal in a few ways. First, it is impossible to have a completely flat magnitude response. Second, the filter's cutoff frequencies cannot be "brick walls"; there must be some transition region between the passband and stopband. When designing an FIR filter, the number of filter coefficients must be finite—and the number of filter coefficients determines the delay of the filter. It is desirable to have a high accuracy filter (many coefficients) with a low delay (few coefficients). These competing factors must be weighed in the design of the filter. Fewer filter coefficients means that the filter will have either a large transition region or significant passband/stopband ripple (i.e., non-uniform magnitude response).

We used the Simulink FDATool block to design our Hilbert transformer. By specifying the transition region and the desired number of coefficients, the block automatically produced the filter coefficients. Our Hilbert transformer contained 33 taps, or coefficients. This allows a relatively constant magnitude response and a tolerable delay. In our case, at a sampling rate of 30 MHz, the filter delay is 33/30 MHz = 1.1 μs.

Designing and implementing the MC system turned out to be a fairly involved process. From a high-level view, the project consists of a hardware portion that runs on the FPGA, and a software portion that runs on the DSP. The FPGA portion of the design takes the input signal and separates it into I and Q components. These components are correctly scaled and then packed together and sent over the bus to the DSP. The DSP portion of the design unpacks and scales the data from the FPGA and implements the algorithm that, ultimately, will perform the modulation classification based on the I and Q data from the DSP.

Due to the incomplete nature of the system at this point, the testing that could be done was somewhat limited. The FPGA design was verified through simulation. A sinusoidal signal was modulated with AM and FM and passed through the FPGA design. The simulation blocks appear in the gray box in the FPGA model. The IQ diagrams obtained suggested that the design was working properly. It was easy to tell from the different IQ diagrams when the incoming signal was AM or FM (Figure 6). Independently, the DSP model was tested to make sure that data was correctly being passed between the FPGA and DSP. This was verified to work correctly. Next steps will include real-world signal testing.

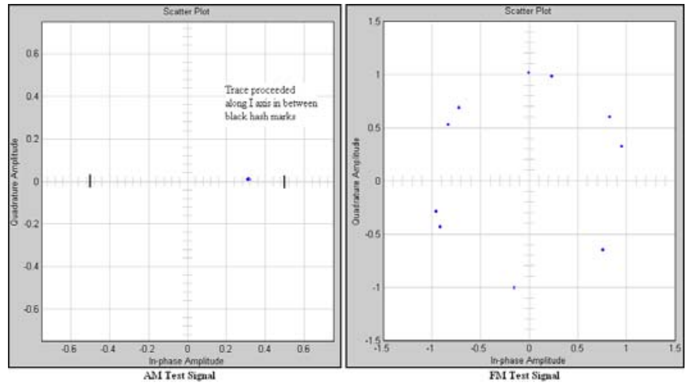

Figure 6 – FPGA Test Results

Although the project is far from complete, the results obtained so far are encouraging. We have shown through simulation that, at least for AM and FM, an IQ diagram can be used as a unique signature to determine modulation classification. In addition, the integration of the DSP and FPGA allowed us to create a system that utilized each component in such a way as to minimize the system footprint. In other words, the project goal of creating a resource-conservative system was realized. Approximately 10% of the available FPGA resource was used, leaving plenty of room for demodulation hardware. On the DSP side, the unpacking and displaying of IQ signals utilized approximately 6% of the DSP's processing power, again, leaving plenty of processing power for the classification algorithm.

4. DISCUSSION AND FUTURE WORK

The project set out to create a completely automated MC system. Although it has not yet been completed, significant progress towards creating the MC system has been made. Initial testing shows that the design is feasible and that it has good potential to meet the original goal of a resource-conservative system. The IQ diagrams produced from simulated signals show that they can be used as unique signatures to classify modulation types.

While these initial strides provide a foundation for completing the project, there are still a number of issues that need to be addressed. Initially, the complete design (DSP and FPGA) will need to be verified with real-world AM and FM signals. Afterwards the design can proceed along different paths.

To have a truly robust system, we must be able to classify not only analog modulation types, but digital ones as well. The system can be tested with various digital modulation types to see if they generate unique signatures as well. This may be a challenging problem since digital IQ diagrams are often more complex than analog ones. In addition, IQ diagrams of digital modulation schemes often require knowledge of the symbol rate to plot correctly.

An equally challenging problem is to create the MC algorithm that will run on the DSP. In the current system, this algorithm will most likely need to be written in C to ensure efficiency and allow flexibility. The Simulink block-building approach allows for quick design and prototyping. In addition to flexibility, efficiency is also desired. The specific design of this algorithm is fairly flexible. A number of potential candidates for MC algorithms were presented in the background section of this paper. Among the most attractive are neural network approaches. They are not computationally intensive (a must for the limited computational power of the DSP), they are fairly simple to implement, and they have been shown to perform well as MC algorithms.

Once our work in an automated MC system is complete, we plan to integrate it with radio bridging systems that we have begun to develop [18].

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