SIGNAL RECOGNITION FOR COGNTIVE RADIOS

Bin Le (binle@vt.edu); Thomas W. Rondeau (trondeau@vt.edu); David Maldonado (davidm@vt.edu); David Scaperoth (scaperot@vt.edu), and Charles W. Bostian (bostian@vt.edu)
Center for Wireless Telecommunications, Wireless @ Virginia Tech
540-231-5096, 466 Whittemore Hall, Virginia Tech, Blacksburg, VA 24061

ABSTRACT

A cognitive radio (CR) must be aware of its radio environment and able to recognize the waveforms that are present. In this paper, we present a global view of the waveform recognition problem and explore the challenges of designing a general receiver architecture that can recognize various modulated waveforms. We present a design for an adaptive signal classification system and analyze its performance with data from real over-the-air waveforms. The whole system is implemented on a GNU Radio SDR platform and an Anritsu™ Signature signal analyzer.

1. INTRODUCTION

Although much of the research interest in cognitive radio (CR) focuses on its potential use for dynamic spectrum access and cognitive network applications, the principles of cognition in the radio node have not been deeply explored. Other CR related work is largely devoted to developing radio hardware platforms to support anticipated cognitive functionalities. However, it is difficult to make an optimal platform design without a full understanding of the required algorithms. There is an urgent need to look into the fundamentals that make a radio cognitive: knowing the radio's environment and optimizing its performance. "Knowing the radio's environment" is the focus of this paper.

In Section 2 we explore the concept of radio environment awareness and its role in cognitive radio systems; Section 3 discusses signal recognition and presents a system level design of a cognitive receiver; Section 4 highlights the design challenges of such a system; and Section 5 shows how the theoretical work may be implemented on a real software defined radio (SDR) platform.

2. RADIO ENVIRINMENT AWARENESS

A cognitive radio is aware of its own capabilities, the needs of its user, the radio environment, and the governing regulations in ways that allow it to configure itself intelligently to optimize its performance in response to novel and rapidly changing environment. For purposes of analysis, it is convenient to represent the world of cognitive radio technology as three domains in order to provide a functional structure. These are the *user* (performance preferences), *policy* (spectral regulations) and *radio* domains.

The radio domain is defined to include both the radio environment and the radio hardware. Our group, the Center for Wireless Telecommunications (CWT) at Virginia Tech, is developing a software cognitive engine (CE) system that can work with a variety of SDR platforms [1, 2]. Middleware is developed between the CE and SDR, which transfers both the radio hardware information and radio environment information to the cognitive algorithms.

The radio environment is further formulated as the superset of waveforms and propagation channel data. Because parametric representation of both the waveform and channel is essential to machine reasoning and learning, the waveform is defined by PHY and MAC layer parameters. We use the term "signal" for the PHY layer parameter set, which includes carrier frequency, channel bandwidth, symbol rate, pulse shape, modulation, error-correction coding, etc. The signal recognition is the starting point of radio cognitive behavior. The design challenges arise because it is inseparable from the signal reception procedure and therefore bears all the challenges of receiver design [3] and adds more because now the signal is to be received "cognitively".

3. SIGNAL RECOGNITION

Signal recognition is often assumed or abstracted in link or network level algorithm design and simulations. However, it is extremely important to understand the problems in recognizing a signal before it can be successfully demodulated. Key challenges include energy detection, signal classification, and general carrier recovery and symbol timing for any modulation scheme. These are not discrete issues. Due to the lack of prior knowledge, joint recognition by multiple stages through the receiver chain is needed as shown in **Figure 1**.

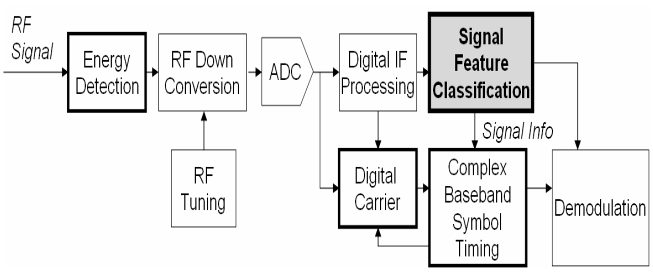

Figure 1. Multi-standard Cognitive Receiver

In signal recognition, there are two system-level challenges: the first is to design a bootstrap process to cycle and refine the knowledge of different input signals, and the second is to design a general-purpose receiver that can provide synchronization and demodulation for all these signals. Signal recognition also needs to adapt to time varying channel characteristics.

The need for sensing a wide bandwidth and reliably detecting the presence of different signals imposes severe requirements on receiver sensitivity, linearity, and dynamic range. Conventional signal detection techniques include matched filtering and energy detection [4]. However, matched filtering requires prior signal knowledge; and energy detection lacks spectral differentiation. Cyclostationarity detection is getting a lot of attention due to its noise suppression [5]; however, the computational cost of bi-frequency domain correlation is prohibitive of real time processing [6]. Given the current improvements in processor technology, a good balance is to use wideband fast Fourier transform (FFT) for coarse energy detection and then run hierarchical FFT with finer resolution in the band of interest.

In a cognitive receiver, key PHY-layer signal parameters, including carrier frequency, baseband bandwidth, modulation, symbol rate and pulse shape, need to be recognized rather than assumed as in a conventional standards-based one. Without such information, the signal cannot be synchronized correctly. It is important to point out that in real receivers, hardware issues like local oscillator (LO) drift, DC bias, and cross-talk all prevent the "accurate" carrier estimate that many simulation-based papers assume. The heart of a radio receiver is carrier phase lock, necessary to make the complex baseband signal available to feed the symbol timing loop. It is actually meaningless to investigate signal recognition after carrier phase lock, because all the signal information is available in the complex baseband information. The difficulty lies in phase lock: certain features of the signal need to be recognized to guide the adaptation of carrier recovery and phase lock.

Carrier phase lock depends on modulation. It is difficult and not necessary to make a "universal" modulation classifier that can classify arbitrary signals. A practical modulation classifier design depends on the target modulations, receiver structure, available processing resource, and signal quality (e.g., SNR). Note that the signal is frequency shifted to some small IF, or complex *quasi-baseband* where residual LO drifting exists due to unlocked phase. From here, signal modulation-dependent features are to be extracted and classified. It is important to obtain the complex signal because carrier-independent information becomes available in complex form.

Signal synchronization consists of carrier and symbol timing recovery. The design philosophy of carrier recovery is based on nonlinear energy extraction for distinct frequency components, and synchronization is maintained by feedback of phase error [3, 7]. Carrier recovery typically depends on one of two assumptions, using a pilot signal or having a symmetric spectrum (to enable carrier regeneration through nonlinear operations). In the pilot-aided case, the receiver should know the modulation standard to recognize the pilot tone; in the carrier regeneration case, the receiver also has to know the modulation scheme in advance to apply an appropriate nonlinear operation. In our approach to the cognitive receiver, a quadrature structure is selected that can be reconfigured for both linear and nonlinear modulation signals. Symbol timing is also essential for coherent demodulation. Although various symbol synchronization and timing algorithms are available [8], most rely on prior knowledge of signal parameters like modulation, symbol rate, pulse shaping filter, etc. To maximize generality, an early-late gate symbol timing loop is incorporated in our cognitive receiver design.

4. MODULATION CLASSIFICATION

A short overview of the pattern classification approach is provided by Nagy [9]. Maximum Likelihood (ML) classifiers [10, 11] require certain prior knowledge, and only MPSK waveforms can be classified in a coherent receiver. Methods based on higher-order nonlinear statistics are also proposed, but only to classify frequency modulation waveforms [12]. These have a huge computational cost for non-coherent cases [13]. Zero-crossing was found effective for non-coherent classification, but is sensitive to SNR [14]. Other approaches include using histograms of the phase, envelope, and instantaneous frequency of the analytic-signal representation of the input signal [15-18]. For the classifier design, using an Artificial Neural Network (ANN) is the most popular choice for a pattern recognition approach [19-21]. More complicated ANN and feature set designs are provided by [22, 23].

Unfortunately, most of the previous works' results are biased on ideal computer simulation environments, thus the validity and robustness remains questionable. Also, the fundamental assumptions in building the classifier system, such as prior signal knowledge, synchronization condition, and timing logic, are usually not explained clearly. However, these are the most important parts of signal recognition design. In this paper we emphasize the system level design principles of modulation classification. We stress that *the purpose of modulation classification is to enable adaptive synchronization for the cognitive receiver*.

The proposed modulation classifier structure is shown in **Figure 2**. The complex IF signal obtained from the analog-to-digital converter (ADC) is quasi-baseband and centered near DC, not phase locked. The modulation classification process consists of three steps: (1) preprocessing, (2) feature extraction, and (3) feature pattern classification.

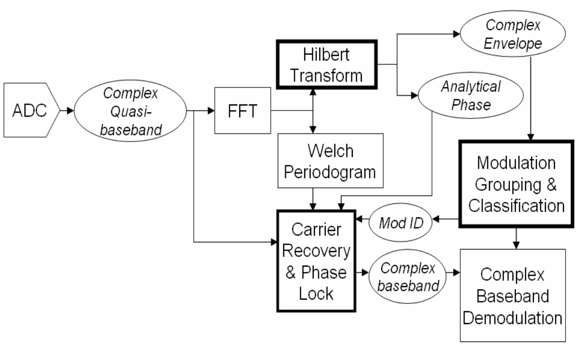

Figure 2. Modulation Classification System

4.1 Preprocessing

Preprocessing is very important in providing stable and clean signal samples. The tasks involved in preprocessing include: (1) centering and normalization against propagation bias and variation, (2) extracting clean signal segments to feed the following feature extraction block, and (3) providing useful estimates of carrier to noise ratio, carrier frequency, etc.

A 20 kbps DBPSK air waveform generated by a GNU Radio SDR and collected by Anritsu™ Signature spectrum analyzer is shown in **Figure 3**. The received signal has an SNR about 20 dB and has strong envelope variation during the one-second collection time. After block-mean normalization, all signal segments have a four volt peak-to-peak swing.

4.2 Feature Extraction

The signal features lie in temporal, spectral, and vector spaces. A temporal feature-based classification using OCON-ANN was detailed in [24]. This paper extends the signal feature extraction to complex quasi-baseband. Both the feature extraction and the classifier are adaptive to varying incoming signal SNR.

When the incoming signal consists of real data samples, a Hilbert transform [3] is applied to obtain the complex envelope and analytical instantaneous phase. **Figure 4** shows the complex spectrum and features of the DBPSK signal from **Figure 3**.

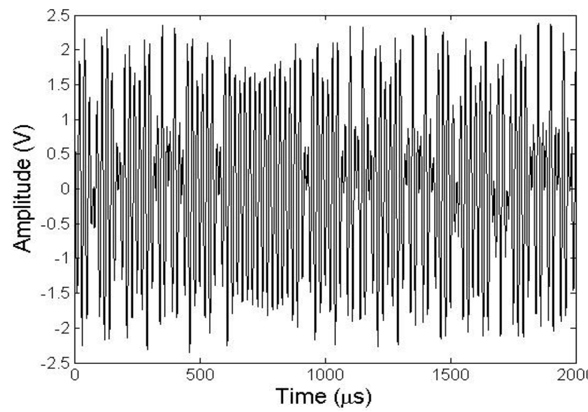

Figure 3. DBPSK Signal, 20kbps, 20dB SNR

Since the complex envelope remains the same when center frequency varies, it becomes a key information source before phase lock. As illustrated in the block diagram of **Figure 2**, both the FFT and the analytical phase derivative can provide instant frequency estimation, but the phase derivative is very susceptible to noise, It is also difficult to extract a clean nonlinear part from the real air signal as shown in **Figure 4c**. Therefore FFT-based Welch periodogram is preferred to provide carrier estimate. The FFT can also be used in generating the Hilbert transform.

Among the features extracted from the complex quasi-baseband, the normalized standard deviation of envelope, $\sigma(env)/\mu(env)$, is the most stable and separable feature characterizing modulation signal groups. On the other hand, most complex amplitude and envelope based features, even with high order statistics like kurtosis, are strongly correlated.

The feature extraction is designed adaptive to the input signal SNR. White noise is effectively suppressed by variable block averaging. Shown in **Figure 5**, even with 5 dB SNR, the feature sets from different modulations are still fully separable. In fact, as far as the feature is defined to be theoretically separable, feature processing in the temporal domain can also get good results at low SNR. The reason is that the envelope is not as noise-sensitive as phase, thus envelope-based features perform better than phase statistics, which is shown relying on high SNR many times in the literature.

Although the envelope-based feature is robust and does not require carrier synchronization, it has limits when classifying higher-order modulations (like QAM8, QAM 16, etc). In the signal recognition process, it is enough for the envelope information to tell the carrier synchronizer what the modulation group is, i.e., is it real or quadrature, analog or digital? Such information is almost enough to configure the phase lock loop. Once the carrier is locked and the complex baseband signal is obtained, refined modulation recognition is trivial in the constellation display [24].

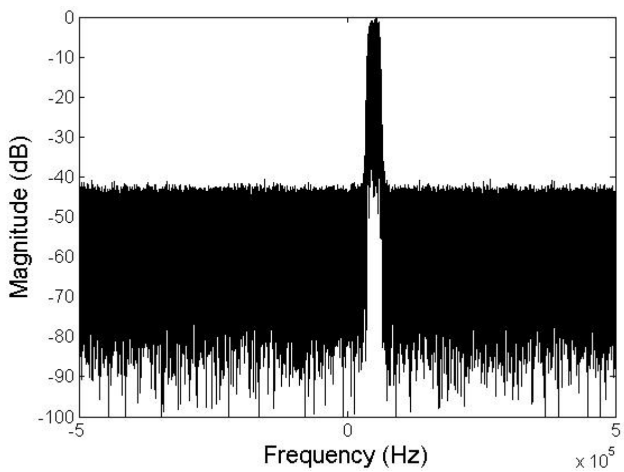

Figure 4a. Complex Low IF DBPSK Signal FFT

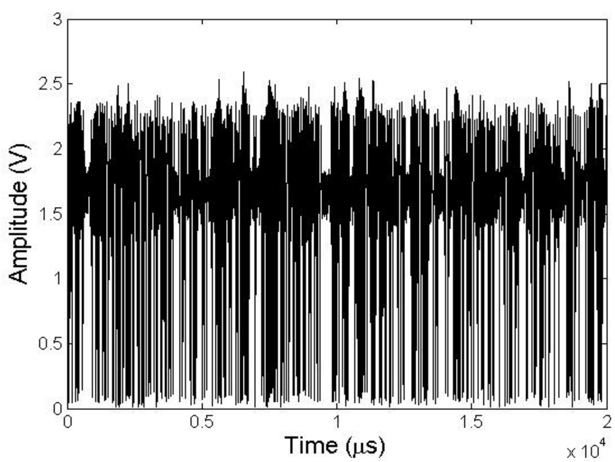

Figure 4b. Complex Envelope of DBPSK Signal

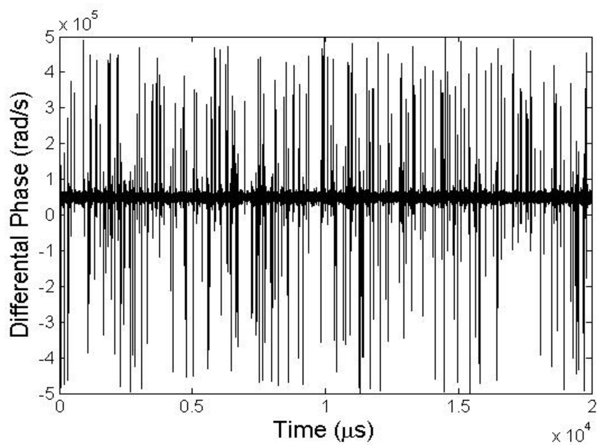

Figure 4c. Phase Derivative of DBPSK Signal

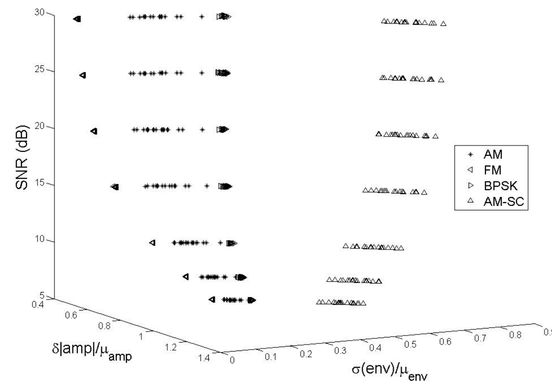

Figure 5. Envelope and Amplitude Feature Space

4.3 Feature Pattern Classification

Since the features used here are only two dimensional, the classifier is also simplified from pattern recognition OCON-ANN [24] to feature slicer, which is a threshold grid separating different modulation signals apart. An example AM slicer for various incoming SNR is shown in **Figure 6**. Due to the noise suppression in feature extraction, the slicers are trained very easily, taking subseconds to train all four modulations in Matlab. The convergence curve is shown in **Figure 7**.

The classification correction rate directly depends on processing gain from the block averaging feature

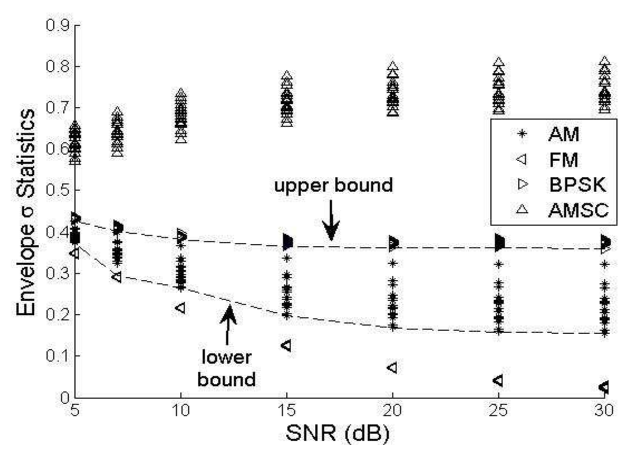

Figure 6. Modulation Feature Slicer Separating AM Signal from Others

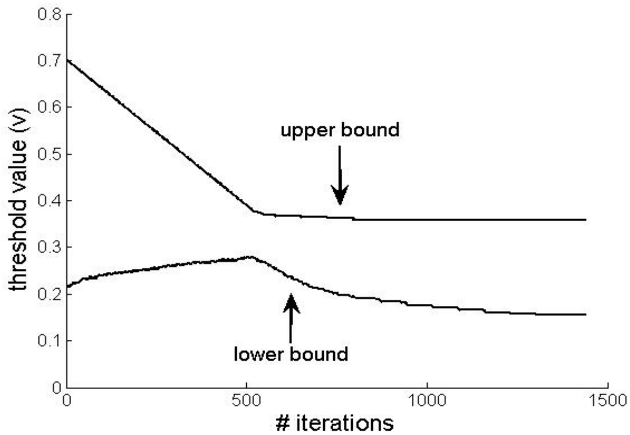

Figure 7. AM Signal Slicer Training Convergence

extraction block. The main tradeoff is between processing delay and accuracy for different incoming signal quality. The feature extraction processing is currently configured to carry block-based accumulating averaging; therefore, as collection length extends, the classification result is more accurate. With in-lab collected public safety air waveforms (15~20 kHz bandwidth) with SNR varying between 5 dB and 30 dB, and with a unit block size of 100 symbols, the modulation is always classified correctly within 10 ~ 20 blocks, which is less than 0.1 seconds.

5. TEST BED IMPLEMENATION

The signal classification testbed system consists of two parts: a GNU Radio with USRP as the signal transmitter and an Anritsu™ Signature vector signal analyzer as the receiver and classifier.

5.1. GNU Radio and USRP

The GNU Radio project is an open source project to build a software defined radio. GNU Radio uses a RF board called universal software radio peripheral (USRP) as the air interface adaptor. Front-ends with different RF frequency range can be connected to the USRP; together with the GNU Radio software package, they form a flexible multi-band SDR platform.

5.2. Public Safety Waveform Implementation

CWT is currently developing a cognitive radio platform for the public safety community. The radio needs to be able to recognize different public safety waveforms with different frequency bands and different modulations. The modulation signals generated in this paper are compliant with public safety modulation signals, such as AM large carrier and suppressed carrier (12 kHz ~ 15 kHz), FM narrowband (15 kHz ~ 20 kHz), and possible digital modulations such as narrowband DBPSK (10 kbps ~ 20 kbps). They are all within 25 kHz public safety channel bandwidth. The future plan is to integrate the P25 [25] standard waveform into this testbed. This signal classification testbed will be demonstrated at SDR06.

5.2. Waveform Measurement Platform

The Anritsu™ Signature vector signal classifier is a multi-functional signal analyzer. It has built-in Matlab to seamlessly connect signal acquisition with signal processing.

6. CONCLUSTION

In this paper, we demonstrated a system design of signal recognition for cognitive radios. Design challenges are analyzed in detail, and classification results with real public safety air waveform are presented. The next step is to combine this pre-sync signal recognition module with post-sync module [24] and integrate both into a GNU Radio testbed to form a complete cognitive receiver.

7. ACKNOWLEDGEMENTS

This work was supported by the National Science Foundation under grants 9983463, DGE-9987586, and CNS-0519959 and by the National Institute of Justice, Office of Justice Programs, US Department of Justice under Award No. 2005-IJ-CX-K017. The opinions, findings, and conclusions or recommendations expressed are those of the author(s) and do not necessarily reflect the views of the National Science Foundation or the Department of Justice.

8. REFERENCES

[1] T. W. Rondeau, B. Le, D. Maldonado, D. Scaperoth, and C. W. Bostian, "Cognitive radio formulation and implementation," in *IEEE Proc. CROWNCOM*, Mykonos, Greece, 2006, pp. pp 1-10.

[2] T. W. Rondeau, C. J. Rieser, C. W. Bostian, W. Cyre, and T. Gallagher, "Cognitive Radio Engine Based on Genetic Algorithms in a Network." vol. PCT Number US04/020,400, 2004.

[3] J. G. Proakis, *Digital Communications*, 4 ed. New York: McGraw Hill, 2000.

[4] L. W. Couch, *Digital and Analog Communication Systems*, 6 ed.: Prentice Hall, 2001.

[5] W. A. Gardner, "Signal Interception: A Unifying Theoretical Framework for Feature Detection," *IEEE Trans. Communications*, vol. 36, pp. 897 - 906, Aug. 1988.

[6] D. Cabric, S. M. Mishra, and R. W. Brodersen, "Implementation Issues in Spectrum Sensingfor Cognitive

Radios," in *IEEE Proc. Signals, Systems and Computers*, 2004, pp. 772 - 776

[7] L. E. Franks, "Carrier and Bit Synchronization in Data Communication - A Tutorial Review," *IEEE Trans. Communications,* vol. COM-28, No. 8, pp. 1107-1120, 1980.

[8] H. Meyr, M. Moeneclaey, and S. A. Fechtel, *Digital Communication Receivers - Synchronization, Channel Estimation, And Signal Processing*: John Wiley & Sons, 1998.

[9] P. A. J. Nagy, "Modulation classification - a unified view," in *EUSIPCO'96*, 1996.

[10] C.-Y. Huang, "Likelihood methods for MPSK modulation classification," *IEEE Trans. Communications,* vol. 43, Feb/Mar/Apr 1995.

[11] A. Polydoros, "On the detection and classification of quadrature digital modulations in broad-band noise," *IEEE Trans. Communications,* vol. 38, Aug. 1990.

[12] B. F. Beidas, "Higher order correlation-based approach to modulation classification of digital frequency modulated signals," *IEEE Journal on Selected Areas In Communications,* vol. 13, Jan 1995.

[13] B. F. Beidas, "Asynchronous Classification of MFSK signals using higher-order correlation domain," *IEEE Trans. Communications,* vol. 46, Apr. 1998.

[14] S.-Z. Hsue and S. S. Soliman, "Automatic modulation classification using zero crossing," *IEEE Proc. Radar and Signal Processing,* vol. 137, pp. 459-464, Dec. 1990 1990.

[15] F. F. Liedtke, "Computer simulation of an automatic classification procedure for digitally modulated communication signals with unknown parameters," *Signal Processing,* vol. 6, pp. 311-323, Aug 1984.

[16] F. Jondral, "Automatic classification of high frequency signals," *Signal Processing,* vol. 9, pp. 177-190, Oct. 1985.

[17] R. J. Mammone, R. J. Rothaker, C. I. Podilchuk, S. Davidovici, and D. L. Schilling, "Estimation of carrier frequency, modulation type and bit rate of an unknown modulated signal," in *International Communications Conference (ICC),* 1987.

[18] L. V. Dominguez, J. M. P. Borrallo, and J. P. Garcia, "A general approach to the automatic classification of radiocommunication signals," *Signal Processing,* vol. 22, pp. 239-250, Mar. 1991.

[19] E. E. Azzouz and A. K. Nandi, "Procedure for automatic recognition of analogue and digital modulations," *IEE Proc. Communications,* vol. 143, pp. 259 - 266, Oct. 1996

[20] Z. Yaqin, R. Guanghui, W. Xuexia, W. Zhilu, and G. Xuemai, "Automatic digital modulation recognition using artificial neural networks" in *IEEE Proc. Neural Networks and Signal Processing*, 2003 pp. 257 - 260.

[21] G. Arulampalam, V. Ramakonar, A. Bouzerdoum, and D. Habibi, "Classification of Digital Modulation Schemes Using Nerual Networks," in *International Symposium Signal Processing and its Applications*, Brisbane, Australia, 1999, pp. 649 - 652.

[22] C. Louis and P. Sehier, "Automatic modulation recognition with a hierarchical neural network" in *IEEE Proc. MILCOM,* 1994 pp. 713 - 717.

[23] N. Kim, N. Kehtarnavaz, M. B. Yeary, and S. Thornton, "DSP-based hierarchical neural network modulation signal classification," *IEEE Trans. Neural Networks,* vol. 14, pp. 1065 - 1071, Sept. 2003

[24] B. Le, T. W. Rondeau, D. Maldonado, and C. W. Bostian, "Modulation Identification Using Neural Network for Cognitive Radios," in *Software Defined Radio Forum Technical Conference*, Anaheim, CA, 2005.

[25] http://www.project25.org/

