ROBUST AUTOMATIC MODULATION CLASSIFICATION AND BLIND EQUALIZATION: A NOVEL COGNITIVE

Barathram Ramkumar (Wireless@VT, Bradley Department of Electrical and Computer Engineering, Virginia Tech, Blacksburg, VA-24060, bramkum@vt.edu);
Tamal Bose (Wireless@VT, Bradley Department of Electrical and Computer Engineering, Virginia Tech, Blacksburg, VA-24060, tbose@vt.edu);
Miloje S. Radenkovic (Electrical Engineering Department, University of Colorado, Denver, CO-80217, miloje.radenkovic@cudenver.edu); and
Ratchaneekorn Thamvichai (Wireless@VT, Bradley Department of Electrical and Computer Engineering, Virginia Tech, Blacksburg, VA-24060, tkay@vt.edu);

ABSTRACT

Automatic Modulation Classification (AMC) and blind equalization play important roles in an intelligent receiver when there is no information about the transmitted signal and channel. Apart from symbol detection, performance of the AMC is also affected by the presence of a multipath channel. In a cognitive radio (CR) set up it is preferable to design a blind equalizer which not only removes Inter Symbol Interference (ISI) but also improves the performance of the AMC. In this paper we propose a robust blind equalizer which not only eliminates ISI but also improves the performance of the fourth order cumulant based AMC. Computer simulations are given to illustrate the concept and yield promising results.

1. INTRODUCTION

One of the important aspects of cognitive radio is the ability to sense and characterize its RF environment and adapt accordingly [1], [2]. AMC is an important signal processing component that helps the CR in identifying the modulation format employed in the detected signal. AMC improves the spectral efficiency of a CR by adapting transmission and reception according to the spectral environment. The fourth order cumulants based AMC proposed in [3] is one of the widely used AMCs. In a typical wireless communication environment, the transmitted signals are subjected to noise and multipath fading. Multipath fading not only affects the performance of symbol detection by causing inter symbol interference (ISI), but also affects the performance of the AMC. Blind equalizers are used to recover the transmitted input sequence using only the output signal with no knowledge of the channel and transmitted sequence. Due to the lack of a training sequence, blind equalization algorithms adapt the parameters of the blind equalizer by minimizing cost functions that exploit the higher order statistics of the received signal. These cost functions are non convex and hence the blind equalizer has the potential to converge to a local minimum. Convergence to a local minimum not only affects symbol detection performance but also affects the performance of the AMC.

The objective of a blind equalizer is to remove ISI, but its impact on the AMC [7] has to be evaluated as well. In a cognitive radio scenario it is preferable to design a blind equalizer which not only removes ISI but also improves the performance of the AMC. Two approaches in this direction are found in the literature. The first method is proposed in [6], where performance of the cumulants based AMC is improved by estimating the channel using fourth order statistics. Also in [6], only the performance of the AMC is improved but there is no improvement in symbol detection. The other method proposed in [7] is the same as the one proposed in [6], except that a higher order statistics (HOS) based blind equalizer is added to the received signal and a switching mechanism is proposed based on which the AMC chooses between a raw signal and an equalized signal. There is no improvement in the performance of the AMC due to the switching mechanism and blind equalizer, but the switching mechanism makes sure that there is no performance degradation in the AMC due to the blind equalizer.

In this paper, we propose a novel cognitive receiver where performance of the AMC is also considered while designing the blind equalizer and thus eliminating the need for switching. The proposed system thus improves both signal detection and AMC performance. The proposed architecture is an adaptation of the blind equalizer presented in [9]. The reason for choosing this architecture is that it offers two fold diversity for AMC decision making, that is, the AMC makes a decision based on two estimated cumulant values. Because of this diversity, the performance of the AMC is better than those of [6] and [7]. Also, the proposed system is adaptive in order to accommodate time varying channels.

Even though an AMC based on fourth order cumulants is considered in this paper, this concept can be generalized to any feature based AMC. The paper is organized as follows. In Section II we provide a block diagram description of the proposed receiver architecture and also briefly describe cumulant based AMC. Detailed description of the algorithms and fusion rule are presented in Section III. Simulation results are presented in Section IV, followed by the conclusion.

Notation: $(.)^T$ denotes the usual transpose operation; $(.)^*$ or $(.)^H$ denotes the complex conjugate transpose; $|(.)|$ denotes the absolute value of the variable; $E(.)$ denotes the statistical expectation.

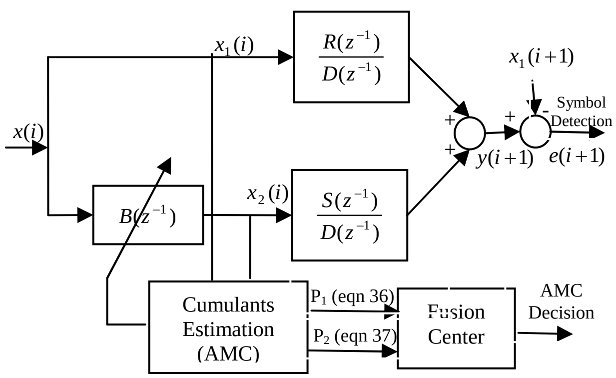

Fig. 1. Block diagram of the proposed cognitive receiver.

2. PROPOSED SYSTEM

The overall block diagram of the proposed receiver is shown in Fig. 1. In this section we explain each component of the block diagram in detail. Let $w(i)$ be the transmitted symbol sequence. The received signal $x(i)$ is given by

$$x(i) = H(z^{-1})w(i) + g(i) \tag{1}$$

where $g(i)$ is the additive white Gaussian noise and $H(z^{-1})$ is the channel impulse response. $H(z^{-1})$ is modeled as a FIR filter given by

$$H(z^{-1}) = 1 + h_1 z^{-1} + \ldots + h_K z^{-L}, \tag{2}$$

where z^{-1} is the unit delay operator, and h_i (for $i = 1,\ldots L$) are the fading coefficients of the corresponding multipaths.
The following assumptions are made about the channel and transmitted sequence.
Assumption A1 The channel $H(z^{-1})$ is a minimum phase polynomial, i.e., it has no zeros in $|z| \geq 1$.

Assumption A2 The symbol sequence $w(i)$ is uniformly bounded and is a Martingale difference sequence, i.e.,

$$E[w_R(i+1) \mid F_i] = 0, E[w_I(i+1) \mid F_i] = 0 \text{ (a.s.)} \tag{3}$$

where $F_i := \{w_R(0),\ldots,w_R(i), w_I(0),\ldots,w_I(i)\}$ and

$$E[w(i+1)w(i+1)^* \mid F_i] = \sigma_w^2 \quad \text{(a.s.)} \tag{4}$$

and $w(i) = w_R(i) + jw_I(i), j = \sqrt{-1}\}$. Assumption A1 implies that the energy in the direct component of the received signal is more when compared to the energy in the delayed multipath component. Assumption A2 implies that the current value of the transmitted sequence is independent of the past.

From Fig. 1 it can be seen that the received signal $x(i)$ is branched out into two signals $x_1(i)$ and $x_2(i)$ where

$$x_1(i) = x(i) \text{ and}$$
$$x_2(i) = B(z^{-1})x(i). \tag{5}$$

The polynomial $B(z^{-1})$ can be any arbitrary polynomial such that $\text{degree}(B(z^{-1})) \geq 1$. Let the polynomial $B(z^{-1})$ be defined as

$$B(z^{-1}) = b_0 + b_1 z^{-1} + \ldots + b_{(L_1-1)} z^{-(L_1-1)}. \tag{6}$$

The polynomial $B(z^{-1})$ basically induces a non common factor in the two branches, so that the Recursive Extended Least Square (RELS) algorithm from [9] can be applied. Even though $B(z^{-1})$ can be any arbitrary polynomial, it is a necessary polynomial required for the convergence of the RELS algorithm. The signals $x_1(i)$ and $x_2(i)$ are further passed through filter $F_1(z^{-1})$ and $F_2(z^{-1})$ respectively, where

$$F_1(z^{-1}) = \frac{R(z^{-1})}{D(z^{-1})} \text{ and } F_2(z^{-1}) = \frac{S(z^{-1})}{D(z^{-1})}. \tag{7}$$

The filters $F_1(z^{-1})$ and $F_2(z^{-1})$ are known as prediction error filters, whose coefficients are adjusted by minimizing the following one step ahead cost function

$$J_1 = E(|x_1(i+1) - y(i+1)|^2), \tag{8}$$

Where $y(i) = F_1(z^{-1})x_1(i) + F_2(z^{-1})x_2(i)$ and the prediction error $e(i+1)$ provides the equalized symbol sequence for symbol detection. The recursive algorithm for estimating $R(z^{-1})$, $S(z^{-1})$ and $D(z^{-1})$ is presented in the next section.

Another important component in Fig. 1 is the AMC. As mentioned earlier, the fourth order cumulants [3] of a received signal are used for classification. For a complex-valued random transmitted signal $w(n)$, second-order moments can be defined in two different ways as [3]

$$C_{20} = E[w^2(n)] \text{ and } C_{21} = E[|w(n)|^2]. \tag{9}$$

Similarly, fourth order cumulants can be written in three ways [3]

$$\begin{aligned} C_{40} &= cumm[w(n), w(n), w(n), w(n)] \\ C_{41} &= cumm[w(n), w(n), w(n), w^*(n)] \\ C_{42} &= cumm[w(n), w(n), w^*(n), w^*(n)] \end{aligned} \tag{10}$$

where

$$\begin{aligned} cumm[w,x,y,z] = {} & E(wxyz) - E(wx)E(yz) \\ & - E(wy)E(xz) - E(wz)E(xy). \end{aligned} \tag{11}$$

The cumulants in (9) and (10) can be estimated from the sample estimates of the corresponding moments [3]. By assuming zero mean, we have

$$\begin{aligned} \hat{C}_{20} &= \frac{1}{N}\sum_{n=1}^{N} w^2(n), \\ \hat{C}_{21} &= \frac{1}{N}\sum_{n=1}^{N} |w(n)|^2 . \end{aligned} \tag{12}$$

Similarly, for the fourth-order cumulants

$$\begin{aligned} \hat{C}_{40} &= \frac{1}{N}\sum_{n=1}^{N} w^4(n) - 3\hat{C}_{20}^2, \\ \hat{C}_{41} &= \frac{1}{N}\sum_{n=1}^{N} w^3(n)w^*(n) - 3\hat{C}_{20}\hat{C}_{21}, \\ \hat{C}_{42} &= \frac{1}{N}\sum_{n=1}^{N} |w(n)|^2 - |\hat{C}_{20}|^2 - 2\hat{C}_{21}^2 . \end{aligned} \tag{13}$$

The normalized value of the fourth order cumulants is defined by

$$\tilde{C}_{4k} = \hat{C}_{4k} \big/ \hat{C}_{21}^2 \qquad k = 0,1,2 \tag{14}$$

The theoretical values of cumulants for different modulation schemes are tabulated in [3]. In this paper we use $|\tilde{C}_{40}|$ and $|\tilde{C}_{42}|$ for classification. The normalized fourth order cumulant of a received signal which is subjected to multipath fading is given by

$$\tilde{C}_{4k_x} = \beta\tilde{C}_{4k_w} \qquad k = 0,1,2 \tag{15}$$

where $\tilde{C}_{4k_w}$ and $\tilde{C}_{4k_x}$ are the cumulant values of the signal before and after multipath fading, and

$$\beta = \frac{\sum_{l=0}^{L-1} |h_l|^4}{\{\sum_{l=0}^{L-1} |h_l|^2\}^2}. \tag{16}$$

Since $\beta < 1$ [3], the effect of the multipath channel is to drive the actual cumulant value of the transmitted signal toward zero and hence the classifier is unable to distinguish the modulation schemes based on the cumulant features. The performance of the cumulant based AMC in the presence of a multipath channel can be improved by estimating the value of β and multiplying the estimated cumulants by $1/\beta$. This approach is used in [6], where channel impulse response is estimated using HOS.

Since $B(z^{-1})$ is an arbitrary polynomial, we adapt it in such a way that the performance of the AMC is improved. For the AMC based on fourth order cumulants, we adapt $B(z^{-1})$ by minimizing the following cost function

$$J_2 = -|C_{4x_2}|. \tag{17}$$

The above cost function maximizes the cumulant value of $x_2(i)$ and hence the classifier will be able to distinguish the modulation schemes. For a different feature based AMC, an appropriate cost function must be chosen accordingly. From the figure it can seen that the AMC makes decisions by fusing p_1 and p_2, which are functions of C_{40x_1} and C_{40x_2} respectively. Appropriate functions for p_1 and p_2 and the fusion rule are derived in the following section.

3. RECURSIVE ALGORITHM

In this section, we provide a detailed description of algorithms used to update the polynomials. Also, we develop fusion rules for AMC decision making.

3.1. Estimation of $S(z^{-1})$, $R(z^{-1})$ and $D(z^{-1})$.

As mentioned in the previous section, the polynomials $S(z^{-1})$, $R(z^{-1})$ and $D(z^{-1})$ are adapted by minimizing (8). From Fig. 1 it can be seen that

$$x_2(i) = H(z^{-1})B(z^{-1})w(i) \tag{18}$$

$$x_1(i) = H(z^{-1})w(i). \tag{19}$$

The recursive algorithm for updating $B(z^{-1})$ is discussed in the next subsection. In this subsection we consider $B(z^{-1})$ to be an arbitrary polynomial with the condition $\text{degree}(B(z^{-1})) \geq 1$. Now

$$y(i+1) = \frac{R(z^{-1})H(z^{-1})}{D(z^{-1})}w(i) + \\ + \frac{S(z^{-1})B(z^{-1})H(z^{-1})}{D(z^{-1})}w(i) \quad (20)$$

and

$$x_1(i+1) = w(i+1) + [z(H(z^{-1}) - 1)]w(i). \quad (21)$$

It can shown from (20) and (21) that

$$x_1(i+1) - y(i+1) = Q(i) + w(i+1) \quad (22)$$

where

$$Q(i) = [\frac{(R(z^{-1}) + S(z^{-1})B(z^{-1}))H(z^{-1})}{D(z^{-1})} \\ - z(H(z^{-1}) - 1)]w(i). \quad (23)$$

From (22) and (23) it can be seen that the cost function (17) is minimum when $Q(i) = 0$. Therefore setting (23) to zero we get

$$D(z^{-1}) = H(z^{-1}) \quad (24)$$

and

$$(R(z^{-1}) + S(z^{-1})B(z^{-1})) = z(H(z^{-1}) - 1) \quad (25)$$

Note: It should be noted that the channel impulse response can be estimated from (24) . This information can be used to calculate β (refer to (16)).

Since the polynomial $H(z^{-1})$ is not known, it is not possible to solve the above equations. For $\text{degree}(B(z^{-1})) \geq 1$, the whole system can be viewed as a special case of the SIMO blind equalizer in [8]. Hence we can modify the recursive algorithm in [8] for estimating the unknown polynomials. Let

$$R(z^{-1}) = r_0 + r_1 z^{-1} + \ldots + r_{N_1} z^{-N_1}. \\ S(z^{-1}) = s_0 + s_1 z^{-1} + \ldots + s_{N_2} z^{-N_2}. \quad (26)$$

where $N_1, N_2 \geq \max(L1, L)$. Define

$$\phi(i)^T = [x_1(i), \ldots, x_1(i - N1), x_2(i), \ldots, \\ x_2(i - N2), -y(i), \ldots, -y(i - N3)], N3 \geq L \quad (27)$$

and

$$\theta = [r_0, r_1, \ldots, r_{N_1}, s_0, s_1, \ldots, s_{N_2}, r_0, h_0, \ldots, h_L, \\ 0, \ldots, 0] \quad (28)$$

where the number of zeros at the end is the difference between the chosen $N3$ and the unknown L. From (27) and (28) we have

$$y(i+1) = \theta^H \phi(i). \quad (29)$$

The value of θ is estimated using the following Recursive Extended Least Squares (RELS) algorithm:

$$\hat{\theta}(i+1) = \hat{\theta}(i) + p(i)\phi(i)e(i+1)^* \quad (30)$$

$$e(i+1) = x(i+1) - \theta(i)^H \phi(i) \quad (31)$$

$$p(i) = \frac{1}{\lambda} p(i-1) - \frac{1}{\lambda} \frac{p(i-1)\phi(i)\phi(i)^H p(i-1)}{\lambda + \phi(i)^H p(i-1)\phi(i)}, \\ 0 < \lambda \leq 1 \quad (33)$$

$$p(0) = p_0 I, p_0 > 0$$

Since the above algorithm is a special case of the algorithm in [8], the convergence property derived in [8] applies here. One of the important properties is that for $\lambda = 1$ under assumption A1 and A2 and $\text{degree}(B(z^{-1})) \geq 1$ the a'posteriori prediction error converges to a scalar version of the symbol sequence, i.e.,

$$\lim_{n \to \infty} \frac{1}{n} \sum_{i=1}^{n} [x_1(i+1) - y(i+1) - w(i+1)]^2 = 0. \quad (33)$$

The above equation indicates that the prediction error $e(i+1)$ (refer to Fig. 1) provides good symbol detection performance.

3.2. Adapting $B(z^{-1})$.

As mentioned earlier, $B(z^{-1})$ is adapted by minimizing (17). It can be seen that (17) is non quadratic and we use a gradient search method to find the coefficients of $B(z^{-1})$. Let $W = [b_0 + b_1 + \ldots + b_{L_1}]^T$ be the vector of coefficients of $B(z^{-1})$. The gradient search algorithm [5] for updating W is stated as follows. Let W_k denote the coefficient vector during the iteration $k = 1,2,\ldots$.

- For $k = 0$ initialize W_0 to a random value.
- For $k = 1,2,\ldots$ calculate the output of the equalizer

$$x_2(n) = \sum_{m=0}^{m=L1} W_{k-1}(m)x(n-m) \quad (34)$$

- Update the coefficient vector using the following equation

$$W_k = W_{k-1} - \mu \frac{\partial J_1}{\partial W_{W_{k-1}}} \quad (35)$$

where μ is the step size.

- If $\frac{|J_1(W_k) - J_1(W_{k-1})|}{J_1(W_{k-1})} < \zeta$ terminate the iteration and go to step 5. If not, repeat step 2, where ζ is chosen to be a small number less than one.

- Calculate the equalized output using W_k.

The equalized signal $x_2(n)$ has a higher cumulant value but does not guarantee good signal to interference noise ratio (SINR). The reason is that the cost function J_1 is non quadratic and the gradient decent algorithm converges to a local minimum [5]. The low SINR of $x_2(n)$ is not a concern because $x_2(n)$ is used only for the AMC and not for symbol detection. The coefficients of $B(z^{-1})$ are updated for every batch of data, whereas the other polynomials are updated for every sample. The forgetting factor in the recursion (30)-(33) is used to track the slowly varying $B(z^{-1})$ polynomial.

3.3. AMC decision making.

The decision about the modulation scheme is made by fusing the cumulant value calculated from two sources. From equations (24) and (28) it can be seen that the channel impulse response can be estimated using the recursion (30)-(32) apart from achieving equalization. From the estimated impulse response $D(z^{-1})$, the value of β can be estimated using (16). Let $\hat{\beta}$ be the estimated value of β, then

$$p_1 = \frac{1}{\hat{\beta}} |C_{4kx_1}|, \quad k = 0,2. \quad (36)$$

$$p_2 = |C_{4kx_1}|. \quad k = 0,2. \quad (37)$$

Since the channel tends to drive the cumulant value of a transmitted signal to zero, the natural choice for the fusion rule is

$$p_f = \max(p_1, p_2). \quad (38)$$

4. SIMULATIONS

In this section, the performance of both the AMC and symbol detection is examined. In order to analyze the performance of the AMC, the following AMC four class problem is considered

$$\Omega = \{BPSK, QPSK, QAM(16), PSK(8)\}. \quad (39)$$

The channel considered was a 4-tap FIR filter with AWGN. 1000 Monte Carlo trails were performed with a sample size of $N = 500$ for cumulant estimation. The probability of correct classification is used as a measure to analyze the performance of the AMC. Fig. 2 shows the probability of correct classification versus signal-to-noise ratio. In Fig. 2 $Pcc1$ is the performance of the AMC in the presence of an AWGN channel. $Pcc3$ is the performance of the proposed system and $Pcc2$ is the performance of the AMC when perfect knowledge about the channel is known. $Pcc4$ is the performance of the AMC in the presence of a multipath channel with no channel estimation or equalization. It can be seen from Fig. 2 that the proposed system shows improved performance when compared to $Pcc2$. The reasons for this improvement are, a higher cumulant value of x_2 and the fusion of two cumulant values.

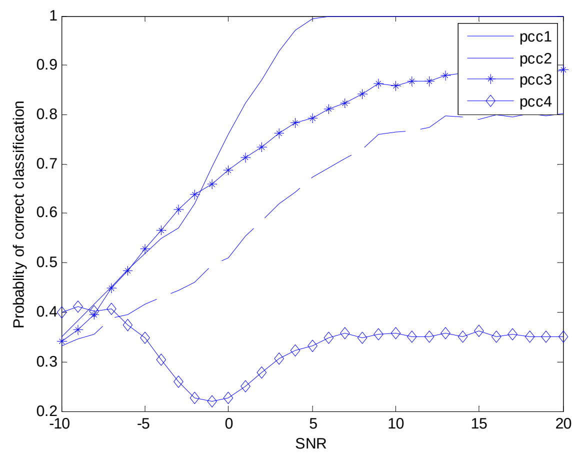

Fig. 2. Performance of the AMC

4.1. Symbol detection performance.

For analyzing the performance of symbol detection, the same 4-tap FIR channel was considered. The scatter plot of the received signal and equalized signal when using the PSK(8) modulation scheme for transmission is shown in Fig. 3 and Fig. 4. Symbol error rates (SER) before and after equalization are presented in Fig. 4. Simulation results illustrate that equalization is achieved using the proposed system. Also from the simulation results it can be seen that the performance of symbol detection and AMC are simultaneously improved.

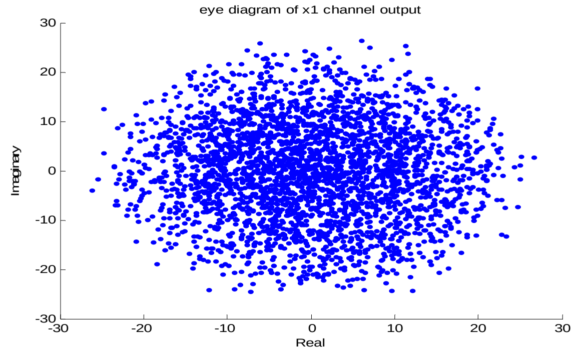

Fig. 3. Scatter plot of the received signal

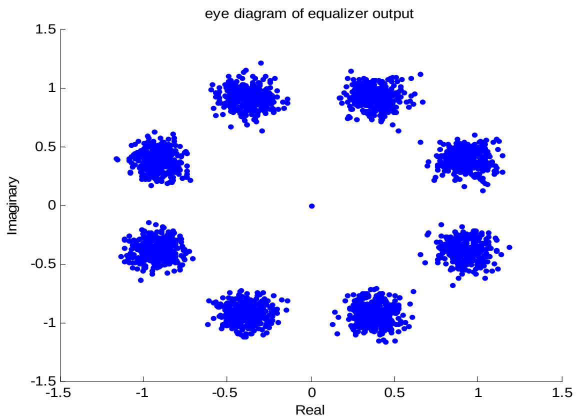

Fig. 4. Scatter plot of the signal after equalization

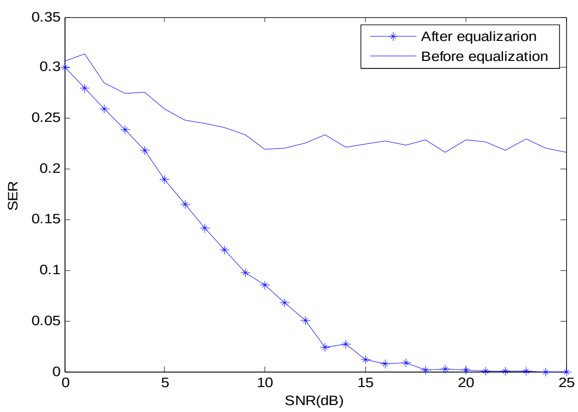

Fig. 5. Symbol error rate (SER) vs SNR (BPSK)

5. CONCLUSION

A novel receiver for cognitive radio is proposed. The proposed system enhances the performance of both the AMC and symbol detection. Simulation results also show good performance. Future work is to extend this concept to other feature based AMCs especially cyclostationarity and cyclic cumulants based AMC. Future work also includes extending this concept to MIMO communication systems and non minimum phase channels.

7. REFERENCE

[1] S. Haykin, *"Cognitive radio: Brain-empowered wireless communications,"* IEEE J. Select. Areas Commun., vol. 23, pp. 201-220, 2005.

[2] J. Polson, "Cognitive radio applications in software defined radio," in *Proc. of the SDR Forum Conference*, 2004.

[3] A. Swami and B. M. Sadler, "Hierarchical digital modulation classification using cumulants," *IEEE Trans. Commun.*, vol. 48, no. 3, pp. 416-429,Mar. 2000.

[4] S. Haykin, *Unsupervised Adaptive Filtering, Vol. II: Blind Deconvolution* JohnWiley & Sons, Inc, 2000.

[5] C. Y. Chi, C. C. Feng, C. H. Chen, and C. Y. Chen, *BlindEqualization and System Identification* Springer-Verlag, 2006.

[6] S. Xi and H.-C. Wu, "Robust automatic modulation classification using cumulant features in the presence of fading channels," in *Proc. IEEE Wireless Communications and Networking Conference*, Apr. 2006, vol. 4, pp. 2094-2099.

[7] H.-C. Wu, Y. Wu, J. C. Principe and X. Wang, "Robust switching blind equalizer for wireless cognitive receivers," *IEEE Trans. Wireless Commun*, vol. 7, no. 5, pp. 1461-1465,May 2008.

[8] M. Radenkovic and T. Bose, "Blind adaptive equalizer for IIR channels with common zeros," in *Proc. of the IEEE International Symposium on Circuits and Systems*, May 2006, pp. 4195-4198.

[9] M. Radenkovic and T. Bose, "A recursive blind adaptive equalizer for IIR channels with common zeros," *Circuits, Systems, and Signal Processing*, pp. 1-20, Jan 2009.