

ROBUST AUTOMATIC MODULATION CLASSIFICATION AND BLIND EQUALIZATION: A NOVEL COGNITIVE

Barathram
Tamal Bose
Miloje Radenkovich
Kay Thamvichai



Wireless @ Virginia
Tech

Contents

- Introduction
- Problem Statement
- Cumulant Based AMC
- Channel Model and Assumptions
- Effect of Multipath
- Proposed Receiver
- Results
- Conclusion



AMC

- Automatic Modulation Classification (AMC) as the name suggests is the **automatic recognition of the modulation** format of a detected signal.
- Application: Civilian, military, spectrum management, and interference identification.
- In military application AMC identifies the modulation format used in the intercepted enemy signals.
- In civilian application AMC aids interoperability between various standards.



AMC

- ▶ AMC is broadly classified into two categories
 - Likelihood Based (LB)
 - Feature Based (FB)
- ▶ LB method is based on the likelihood function of the received signal and the decision is made by comparing the likelihood ratio against a threshold.
- ▶ FB-AMC uses several features of the received signal in order to make a decision.
- ▶ FB-AMC are simple to implement and less computationally intensive.



Blind Equalizer

- ▶ A CR uses blind equalizers due to the absence of training or pilot sequences.
- ▶ Blind equalization is a process by which a transmitted input sequence is recovered using only the received signal.
- ▶ Blind equalization algorithms adapt the weights of the equalizer by minimizing cost functions that exploit the higher order statistics (HOS) of the received signal.

SISO Blind equalizer in literature can be broadly classified into

Equalizer Structure

- Feed Forward Equalizer(FFE)
- Differential Feedback Equalizer(DFE)
- Fractionally Spaced Equalizer (FSE)

Update Mechanism

- Sato Algorithm [4]
- BGR [5]
- Godard [6]



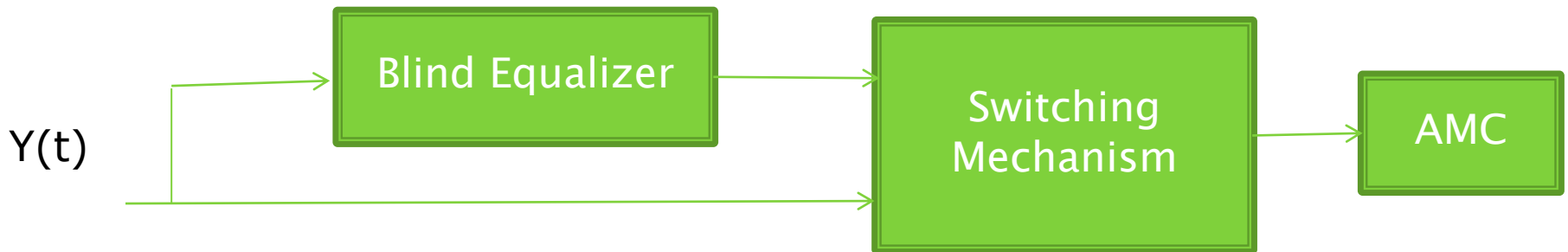
Problem Statement

- ▶ Multipath fading not only affects the performance of symbol detection but also affects the performance of the AMC.
- ▶ The weights of the blind equalizer are adapted by minimizing cost functions that are non quadratic.
- ▶ If not properly initialized, 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.
- ▶ Robust blind equalizers can be designed if the performance of the AMC is also considered while adapting equalizer parameters.



SISO Blind Equalizer and AMC

- ▶ Multipath channel not only affects symbol detection performance but also the performance of AMC.
- ▶ It is necessary to consider the performance of AMC while designing the blind equalizer.
- ▶ One of the important work in this direction is by Wu[3].
- ▶ In [3] a switching mechanism as shown below is proposed



SISO Blind Equalizer and AMC

- ▶ Robust AMC's can be built if the blind equalizer is designed by considering the performance of the AMC also
- ▶ We propose a novel cognitive receiver where performance of the AMC is also considered while designing the blind equalizer.
- ▶ This can be achieved by formulating the cost function that is related to the performance of the AMC
- ▶ The parameters of the blind equalizer are adapted by optimizing the cost function.
- ▶ Cumulant based AMC is considered to illustrate this concept.



Cumulants based classifier

Normalized fourth order cumulants are used for classification.

Second-order moments can be defined in two different ways i.e.

$$C_{20} = E[y^2(n)] \quad \hat{C}_{20} = \frac{1}{N} \sum_{n=1}^N y^2(n)$$

$$C_{21} = E[|y(n)|^2] \quad \hat{C}_{21} = \frac{1}{N} \sum_{n=1}^N |y(n)|^2$$

Similarly fourth order cumulants can be written in three ways

$$C_{40} = \text{cum}[y(n), y(n), y(n), y(n)] \quad \hat{C}_{40} = \frac{1}{N} \sum_{n=1}^N y^4(n) - 3\hat{C}_{20}^2$$

$$C_{41} = \text{cum}[y(n), y(n), y(n), y^*(n)] \quad \hat{C}_{41} = \frac{1}{N} \sum_{n=1}^N y^3(n)y^*(n) - 3\hat{C}_{20}\hat{C}_{21}$$

$$C_{42} = \text{cum}[y(n), y(n), y^*(n), y^*(n)] \quad \hat{C}_{42} = \frac{1}{N} \sum_{n=1}^N |y(n)|^4 - |\hat{C}_{20}|^2 - 2\hat{C}_{21}^2$$

Where

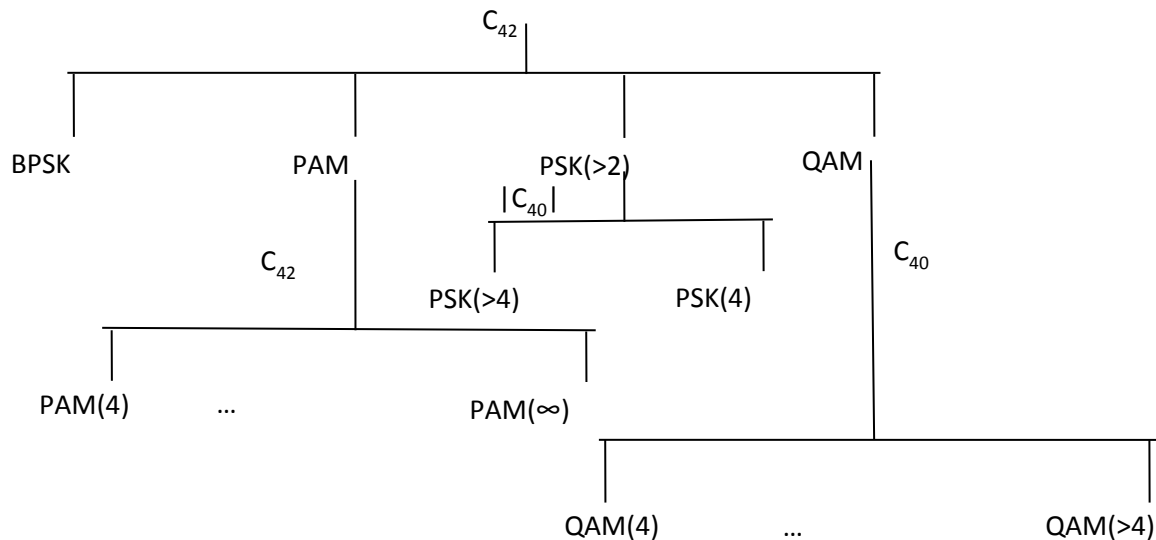
$$\text{cum}(w, x, y, z) = E(wxyz) - E(wx)E(yz) - E(wy)E(xz) - E(wz)E(xy)$$



Hierarchical Classification

Theoretical Cumulant Values [1]

| | BPSK | QPSK | PAM(4) | PSK(8) | QAM16 | QAM64 |
|----------|--------|--------|--------|--------|-------|--------|
| C_{40} | -2.000 | -1.000 | -1.36 | -1.000 | -0.68 | -0.619 |
| C_{42} | -2.000 | -1.000 | -1.36 | 0.000 | -0.68 | -0.619 |



Channel Model and Assumptions

$$x(i) = H(z^{-1})w(i) + n(i)$$

$x(i)$: Received Signal

$w(i)$: Transmitted Signal

$$H(z^{-1}) = 1 + h_1 z^{-1} + h_2 z^{-2} + \dots + h_{L-1} z^{-(L-1)}$$

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 transmitted sequence $w(i)$ is IID



Effect of Multipath Channel

$$x(i) = H(z^{-1})w(i)$$

$x(i)$: Received Signal

$$H(z^{-1}) = 1 + h_1 z^{-1} + h_2 z^{-2} + \dots + h_{L-1} z^{-(L-1)}$$

$w(i)$: Transmitted Signal

The cumulants of a received signal subjected to multipath fading is given by

$$C_{4k \times (i)} = \beta C_{4k w(i)}, \quad k = 1, 2$$

where

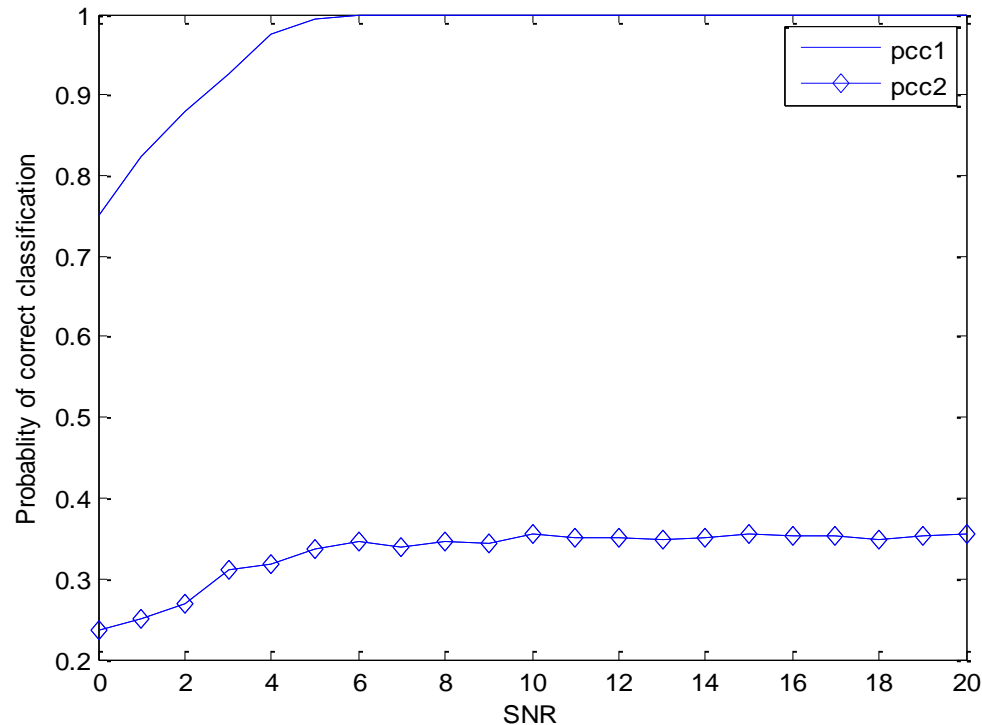
$$\beta = \frac{\sum_{l=0}^{L-1} |h_l|^4}{\left(\sum_{l=0}^{L-1} |h_l|^2 \right)^2} < 1$$

Since $\beta < 1$, the effect of the multipath channel is to drive the actual cumulant value of the transmitted signal toward zero.



Effect of Multipath Channel

{BPSK,QPSK,QAM(16), PSK(8)}



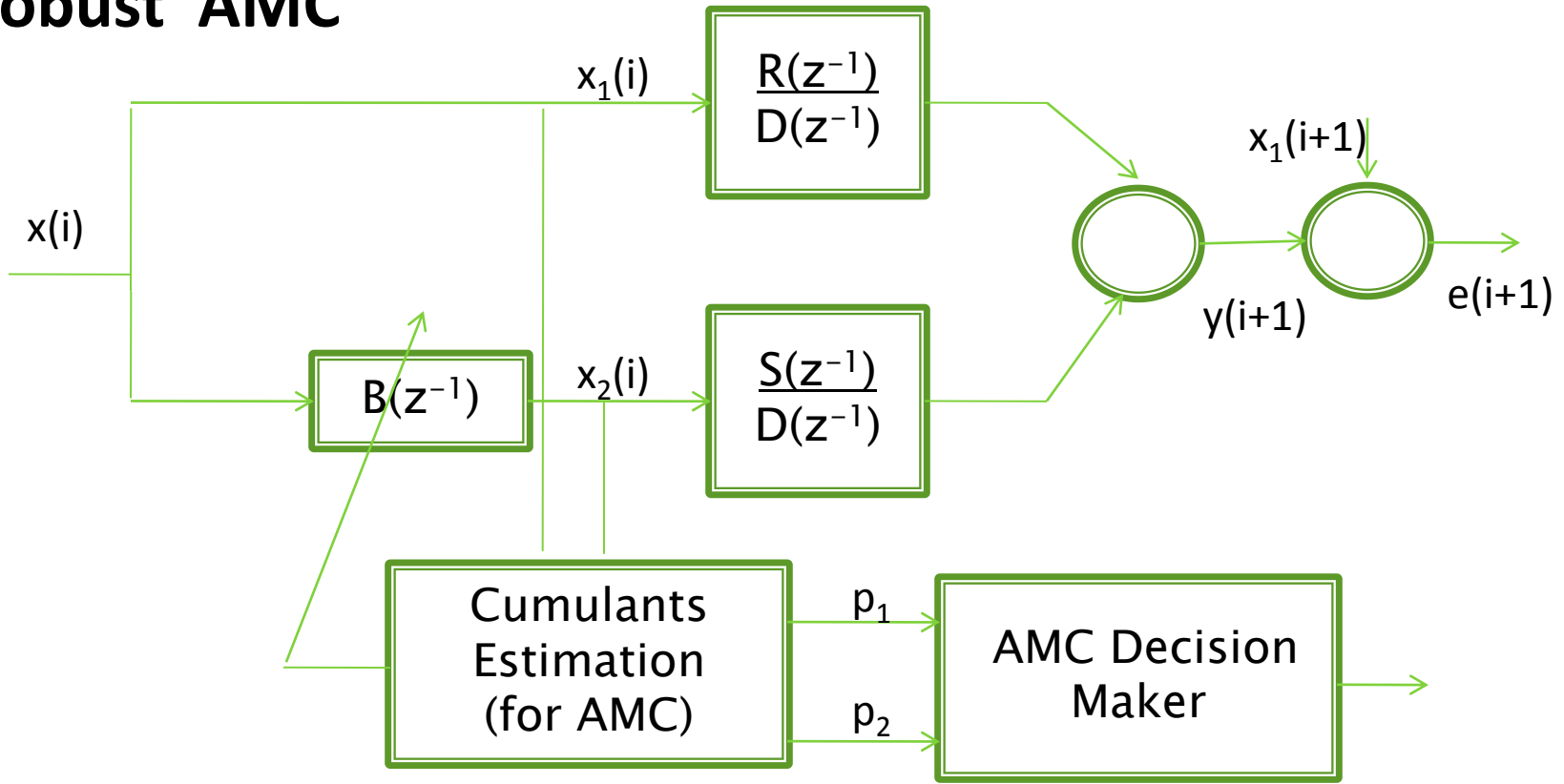
Pcc1- AWGN

Pcc2- Multipath

Four tap FIR Channel



Robust AMC



The above architecture is an adaptation of the blind equalizer presented in [8].

The equalizer consists of four polynomials $B(z^{-1})$, $R(z^{-1})$, $D(z^{-1})$ and $S(z^{-1})$.

$$x(i) = H(z^{-1})w(i) \quad w(i) = \text{Transmitted signal}$$

$$x_1(i) = x(i) \quad x(i) = \text{Received signal}$$

$$x_2(i) = B(z^{-1})x(i) \quad e(i+1) = \text{Equalized signal}$$

Robust AMC

- ▶ The equalizer structure offers two fold diversity for AMC decision making.
- ▶ The polynomial $B(z^{-1})$ can be any arbitrary polynomial such that $\text{degree}(B(z^{-1})) \geq 1$.
- ▶ The polynomial $B(z^{-1})$ basically induces unique zeros in one of the branches.
- ▶ Since $B(z^{-1})$ is an arbitrary polynomial, we adapt it in such a way that the performance of the AMC is improved.
- ▶ $R(z^{-1})$, $D(z^{-1})$ and $S(z^{-1})$ are adapted so that ISI is removed.



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

The polynomial $B(z^{-1})$ is adapted by minimizing the cost function related to the performance of the AMC.

For the cumulant based AMC the natural choice is

$$J_1 = -|C_{40 \times 2}| \quad \text{or} \quad J_1 = -(C_{40 \times 2})^2$$

Let $W_k = [b_0, b_1, \dots, b_{L1}]$ [Gradient search algorithm]

For $k = 0, 1, \dots$

Step 1: For $k = 0$ initialize W_0 to a random value.

Step 2: For $k = 1, 2, \dots$ calculate the output of the equalizer $x_2(n) = W_k \otimes x(n)$

Step 3: Update the coefficient vector using the following equation

$$W_k = W_{k-1} - \mu \frac{\partial J_1}{\partial W_{W_{k-1}}}$$

Step 4: Repeat Step 1 if termination criteria is not met

Step 5: Calculate the equalized output using W_k .

Adapting the predictor

The polynomials $R(z^{-1})$, $D(z^{-1})$ and $S(z^{-1})$ are adapted by minimizing the one step ahead prediction error.

$$J_2 = E(|x_1(i+1) - y(i+1)|^2)$$

The above cost function is minimum when

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

$$(R(z^{-1}) + S(z^{-1})B(z^{-1})) = z(H(z^{-1}) - 1).$$

Since $H(z^{-1})$ is not known, the predictor polynomials are estimated using a RELS algorithm.

Note: Estimation of $D(z^{-1})$, gives the estimate of $H(z^{-1})$



RELS Algorithm

The predictor is given by the equation is given by

$$D(q^{-1})y(i+1) = R(q^{-1})x_1(i) + S(q^{-1})x_2(i)$$

Let $\phi(i)^T = [x_1(i), \dots, x_1(i-N_1), x_2(i), \dots, x_2(i-N_2), -y(i), \dots, -y(i-N_3)], N_3 \geq L-1$

and $\hat{\theta}^H = [r_0, \dots, r_{N_1}, s_0, \dots, s_{N_2}, d_1, \dots, d_L, 0, \dots, 0]$

The number of inserted zeros depends is equal to (N_3-L)

Then $y(i+1) = \hat{\theta}^H \phi(i)$

The adaptive estimate of θ is given by

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

$$e(i+1) = x_1(i+1) - \hat{\theta}(i)^H \phi(i)$$

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

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

Recursive system

- ▶ The predictor polynomials are updated every sample.
- ▶ The forgetting factor in RELS is used to track the slowly varying $B(z^{-1})$ polynomial.

The AMC decision is made by fusing the two cumulant values i.e.,

$$p_1 = \frac{1}{\hat{\beta}} |C_{40x_1}| \quad p_2 = |C_{40x_2}|$$

Where $\hat{\beta}$ is the estimated value of β using $D(z^{-1})$

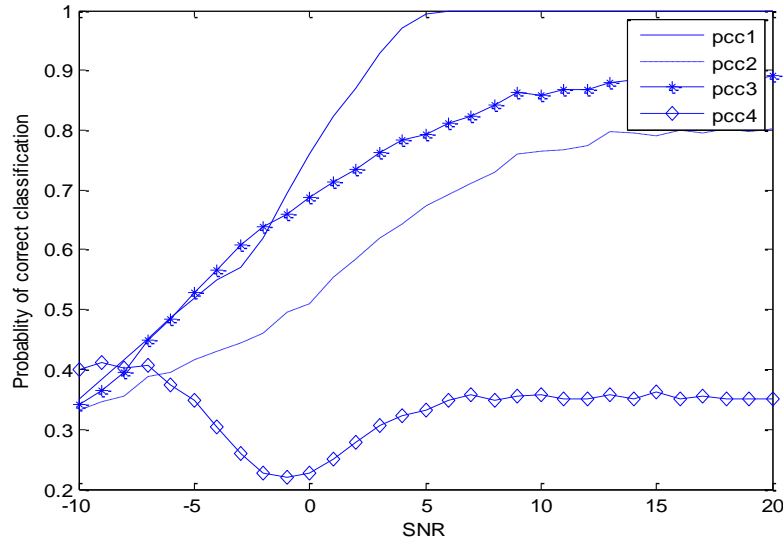
Since the channel tend to drive the cumulant value of a transmitted signal to zero, the natural choice for the fusion rule is

$$p_f = \max(p_1, p_2)$$



Simulation

{BPSK,QPSK,QAM(16), PSK(8)}

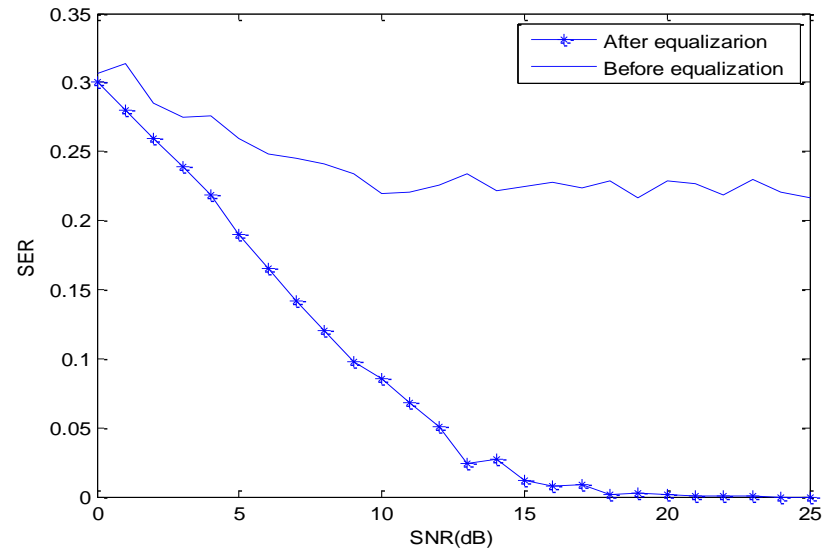


Pc1 = AWGN

Pc2 = Perfect Knowledge of Channel

Pc3 = Proposed method

Pc4 = Channel (no equalizer)



SER vs SNR(dB)

The reason for this improvement are,

- higher cumulant value of x_2 .
- Fusion of two cumulant values.

Future Work

- ▶ The above SISO BE will be extended to improve the performance of other feature AMC's.
- ▶ Some of the AMC's considered are cyclostationarity based AMC, cyclic cumulants based AMC, and higher order cumulants based AMC.
- ▶ This will involve formulating cost functions that are related to the performance of these above mentioned feature based AMC's.
- ▶ This concept will be generalized and extended to some of the other promising SISO blind equalizer architectures.
- ▶ Some of the SISO blind equalizer architectures considered are differential feedback equalizer (DFE), fractional spaced equalizer (FSE) and stop-and-go equalizer(SGE).
- ▶ A comparison of the performance of these different architectures will be done.



References

- [1] A. Swami and B. M. Sadler, "Hierarchical digital modulation classification using cumulants," IEEE Trans. Commun., vol. 48, no. 3, pp. 416-429, Mar. 2000.
- [2] K. Kim, I. A. Akbar, K. K. Bae, J.-S. Um, C. M. Spooner, and J. H. Reed, "Cyclostationary approaches to signal detection and classification in cognitive radio," IEEE DySpan, 2007, pp. 212-215.
- [3] 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.
- [4] Y. Sato "A method of self-recovering equalization for multi-level amplitude modulation," IEEE Trans. Commun., June 1975, vol. 23, pp. 639-682.
- [5] A. Benveniste, M. Goursat, and G. Ruget "Robust identification of a non minimum phase system: Blind adjustment of a linear equalizer in data communications," IEEE Trans. Automatic Control, vol. 25, pp. 385-399, June 1980.
- [6] D. N. Godart "Self-recovering equalization and carrier tracking in two dimensional data communication systems," IEEE Trans. Commun. vol. 28, pp. 1867-1875, Nov. 1980.
- [7] G. Picchi and G. Prati, "Blind equalization and carrier recovery using a 'stop-and-go' decision-directed algorithm," Proc. IEEE Trans. Commun. vol. 35, pp. 877-887, 1987.
- [8] M. Radenkovic and T. Bose, "Blind adaptive equalizer for IIR channels with common zeros," in Proc. IEEE International Symposium Circuits 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, Signal Processing, pp. 1-20, Jan 2009.

References

- [10] J. Tugnait, "FIR inverse to MIMO rational transfer functions with applications to blind equalization," in Proc. 13th Asilomar Conf. Signals, Systems Computers, 1996, vol. 1, pp. 295-299.
- [11] J. Tugnait, and B. Huang "On a whitening approach to partial channel estimation and blind equalization of FIR/IIR multiple-input multiple-output channels," IEEE Trans. Signal Process, vol. 48, no. 3, 2000.
- [12] J. Tugnait, and B. Huang "Blind estimation and equalization of MIMO channels via multidelay whitening," IEEE J. Select. Areas Commun., vol. 19, no. 8, 2001.
- [13] A. Hyvarinen, J. Karhunen, and E. Oja, Independent Component Analysis John Wiley and Sons, 2001.

Appendix



Lemma

Let $\{\omega(i)\}$ be a martingale difference sequence, and $g(i)$ be a nonanticipative function of $\{\omega(i)\}$, i.e., $g(i)$ is a function of only past $\omega(k)$, for $k \leq i$. If Assumption A2 holds, then

$$\left| \sum_{i=0}^n g(i-1)w(i) \right| = O(1) + O\left[\left(\sum_{i=0}^m g(i-1)^2 \right)^\beta \right]$$

Theorem 1

For $\lambda = 1$ and $\text{degree}(B(z^{-1})) > 1$ under assumption A1 and A2 the a'posteriori prediction error converges towards a scalar version of the symbol sequence, i.e.,

$$\lim_{n \rightarrow \infty} \sum_{i=1}^n [x_1(i+1) - y(i+1) + kw(i+1)]^2 = 0$$

