ISI Effects in a Hybrid ICA-SVM Modulation Recognition Algorithm

David Boutte and Balu Santhanam

Department of Electrical and Computer Engineering
MSC01 1100 1 University of New Mexico
Albuquerque, NM: 87131-001
Email: dboutte,bsanthan@ece.unm.edu

***Abstract*—Automatic modulation recognition is a topic of interest in many fields including signal surveillance, multi-user detection and radio frequency spectrum monitoring. In this paper the effect of *inter symbol interference* (ISI) on the performance of a recently proposed hybrid ICA-SVM modulation recognition algorithm is studied. The algorithm combines elements of cyclo-spectral analysis, ICA and SVM algorithms to distinguish between different types of *continuous phase modulations* (CPM) and phase shift keying modulations. Although ISI decreases the achievable SVM margin, combining the ICA-SVM hybrid approach with feature equalization and a modified SVM kernel allows reliable classification to occur when ISI is present.**

I. Introduction

Automatic modulation identification plays an important role in signal surveillance and frequency spectrum monitoring. The presence of ISI significantly degrades the achievable performance of a recently proposed hybrid ICA-SVM recognition algorithm discussed in [1]. ISI skews the extracted feature statistics, mitigates the ICA gain, and acts as an independent feature noise source, thereby reducing the classifier margin in the SVM hypothesis space. The combination of these two reduce the recognition probabilities for lower SNR values. However, by modifying the algorithm to include equalization of the input features to the ICA and a more efficient kernel in the SVM, these ISI effects can be mitigated.

The purpose of an equalization system is to determine and apply a filter that results in an equalized impulse response having minimum ISI and channel distortion. In this case, the channel that the equalizer will be applied to is not the traditional open air communication channel, but a transformed version of it. To extract the features necessary to construct a modulation classifier using a ICA-SVM algorithm it is necessary to compute the *spectral coherence density function* (SCD) [2] of the received signal at baseband. The SCD can then be parameterized as feature vectors and passed on to the ICA-SVM system for classification. It is this modified channel that needs to be equalized with either a linear Viterbi equalizer [3] or one directly incorporating the ICA [4]. These two approaches to feature equalization are compared and their impact upon the classifier's performance is studied.

Research funded through Miratek Corporation, 8201 Lockheed Suite 218, El Paso TX. (915)772-2852 May 2007

SVM kernel selection dictates the SVM's capacity to classify the data set in hypothesis space [5]. Different kernels correspond to different capacities of the the machine or equivalently, different margins of separation between the support vectors in the hypothesis space. As the margin between the support vectors is increased so is the algorithm's recognition rate. Simulations are carried out using both a *radial basis function* (RBF) kernel and a kernel constructed using Chebychev polynomials [6]. Modifying the kernel allows higher recognition rates at lower SNRs and similarly higher recognition rates in the presence of ISI.

In this paper, the effect of ISI on the performance of a recently proposed hybrid ICA-SVM modulation recognition algorithm is studied. The presence of ISI in both CPM and phase shift keying modulations causes a significant decrease in the algorithm's ability to classify the received signal. However, introducing feature equalization and a Chebychev SVM kernel into the algorithm can mitigate these ISI effects. Several simulations are constructed which study these changes in the algorithm as well as the unmodified ICA-SVM's performance in ISI.

II. Algorithm

The ICA-SVM modulation recognition algorithm proposed in [1] is comprised of three main blocks. First the SCD of the received signal is estimated and parameterized in terms of the standard deviation, autocorrelation and kurtosis. Second, these feature vectors are sent to an ICA block which uses denoising [7] and separates the features into independent features by internally maximizing their negentropy [8]. These independent feature vectors are then sent to an SVM [9] where a classifier is constructed by transforming the features into a hypothesis space using a kernel. This algorithm performs better than previous algorithms [10], [11], [12] for many modulation types in very low receiver SNR regions. However, the presence of ISI degrades the algorithm's perforce requiring the addition of feature equalization and a kernel modification.

The hybrid ICA-SVM automatic modulation recognition algorithm in [1] operates in a sequential manner. A decision is reached after each incoming symbol, the classifier is then iteratively refined as more symbols are received. This allows the modulation of interest to be classified reliably within a few

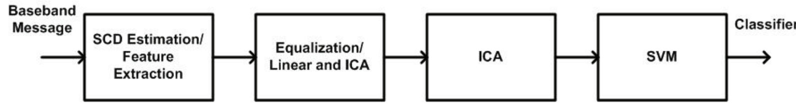
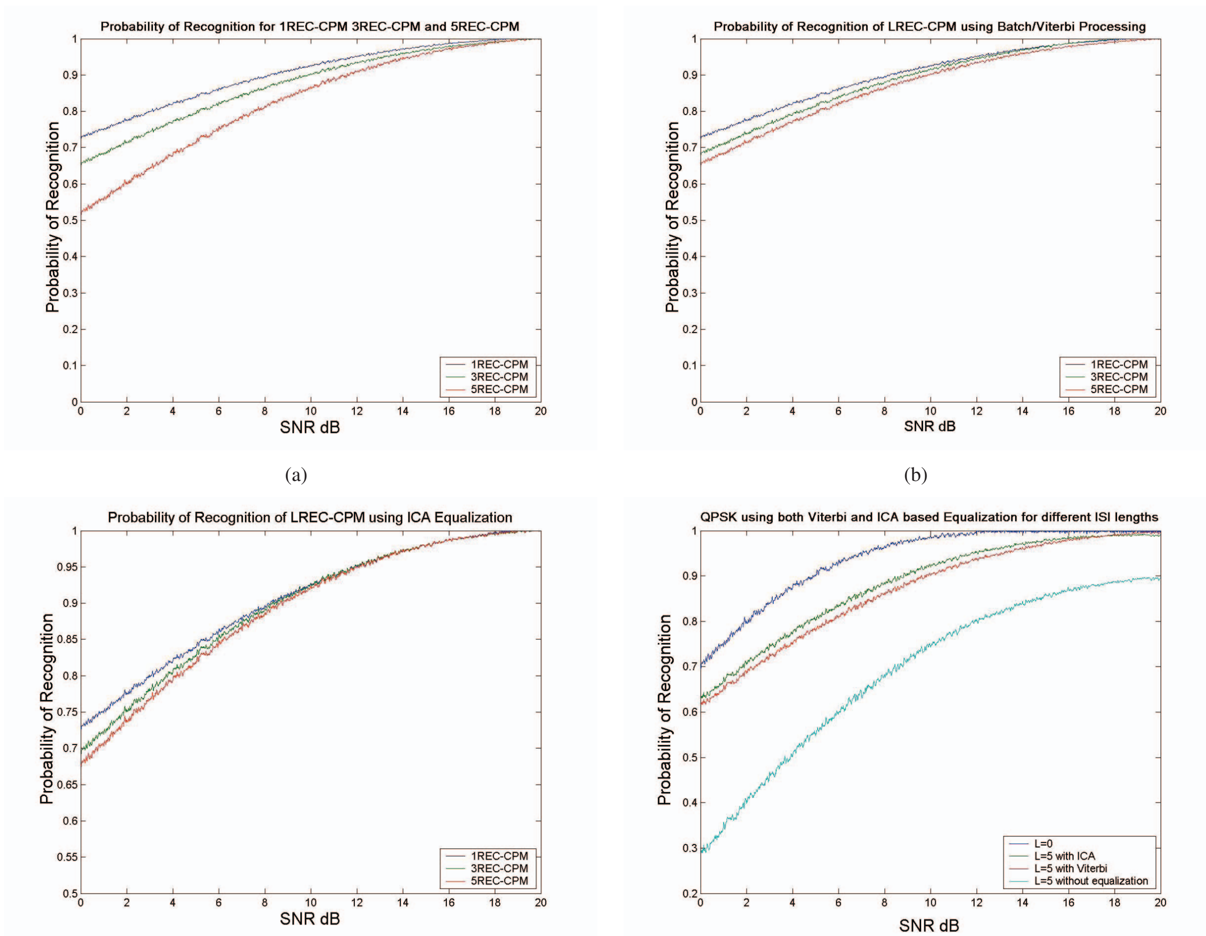


Fig. 1. Block diagram for the feature weighted hybrid ICA-SVM modulation recognition system presented in this paper.



(a) (b) (c) (d)

Fig. 2. Probability of recognition for LREC-CPM and QPSK using different amounts of channel memory.The probability of recognition is degraded when channel memory is increased. When equalization is used these ISI effects are mitigated. The performance is compared between a Viterbi based equalizer and an ICA based equalizer.

symbol intervals of reception. However, in channels where ISI is present this type of sequential processing does not perform well. The increased channel memory causes uncertainty in the symbol intervals which degrades performance. The proposed solution to this problem is the introduction of batch, rather than sequential, processing coupled with the use of equalization.

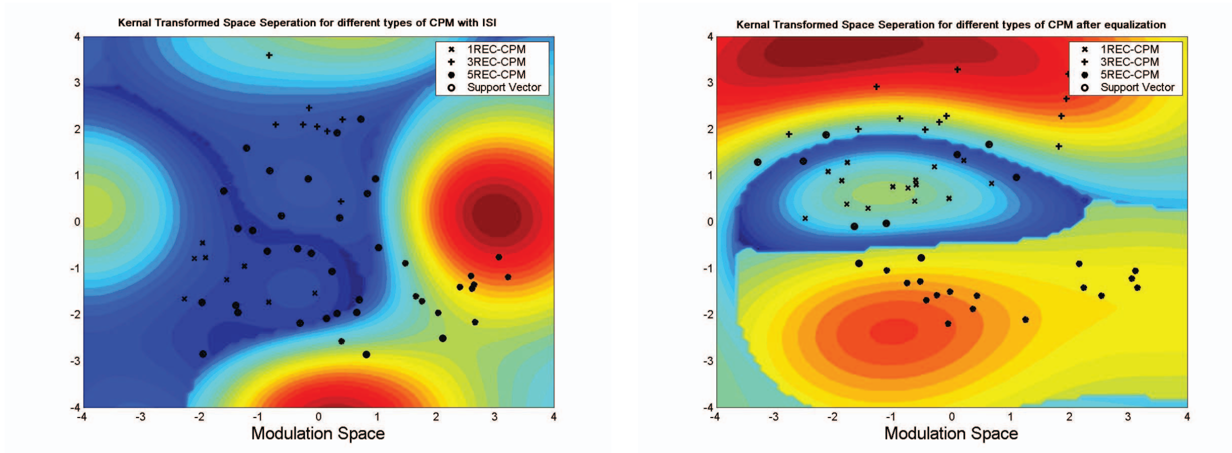
Using linear channel estimation for Viterbi equalization or nonlinear ICA estimation the output symbol sequence $\hat{S}(n)$ can be expressed as

$$\underline{\hat{S}}(n) = H^{\dagger}\underline{x}(n), \tag{1}$$

where H can be expressed in the MSE case as

$$H = E[\underline{x}(n)\underline{S}^{*}(n-l)] = \frac{1}{m-l+1}\sum_{l}^{m}\underline{x}(n)\underline{S}^{*}(n-l), \tag{2}$$

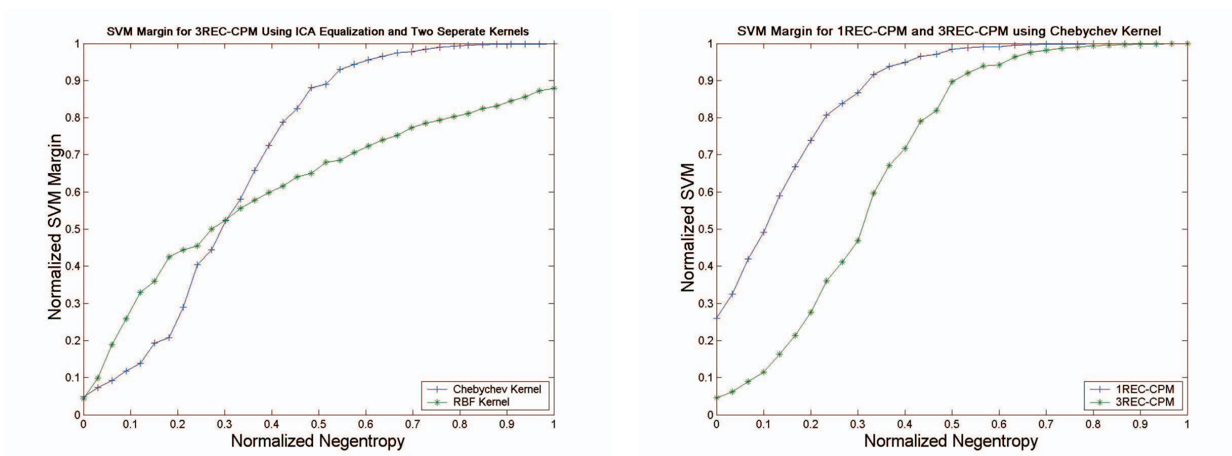
where l and m are the respective pre and postcursor tap positions. The procedure is similar when using the more complicated ICA estimator and is discussed in more detail in [13]. This equalization is performed in the transformed feature space; after feature extraction from the SCD of the received signal. Introducing ISI into the communication channel generates a corresponding ISI effect upon the features. Treating the feature vectors as separate received signals allows the equalization framework to be brought into the transformed



(a) Modulation separation in the presence of ISI

(b) Modulation separation after equalization

Fig. 3. Kernel transformed spaces for different types of CPM that contain ISI. Notice the large number of support vectors needed when ISI is present and the small separation between modulations. This lowers the probability of recognition for the various types of modulations. When feature equalization is applied the separation is increased and less support vectors are needed.



(a)

(b)

Fig. 4. Effects of SVM kernel changes on the separation between support vectors. A higher normalized separation corresponds to a higher recognition rate. The distance is computed at each ICA iteration and as the negentropy of the feature vectors is increased so is the SVM margin.

space.

Combining the use of feature equalization with a change in the SVM kernel is the final step in ISI mitigation. A radial basis function kernel described in [9] can be expressed as

$$K(x, y) = \exp\left(-\gamma \|x - y\|^2\right), \tag{3}$$

where γ is the RBF width factor. Similarly a Chebychev kernel which is constructed from Mercer's conditions as in [6] can be expressed as

$$K(x, y) = \sum_{i=1}^{\infty} \lambda_i \Phi_i(x) \Phi_i(y), \tag{4}$$

where $\lambda_i \geq 0$ and $\Phi_i(\cdot)$ is obtained through the eigenvalue decomposition of the Chebychev coefficients. Kernels of the form in Eq (4) are more complicated than their RBF counterparts, however they are more appropriate in some modulation recognition problems.

III. Results and Simulations

The algorithm described in Fig. (1) was simulated in MATLAB using several types of input modulations with and without ISI impairments. The overall effect of ISI is to skew both the feature statistics and increase the effective noise power seen by the SVM. Conversely this can be viewed as an overall loss in system SNR. As in any receiver system as the SNR is decreased the performance is impaired as seen in Fig. (2(a)) for one, three and five REC-CPM and as the bottom curve Fig. (2(d)) for QPSK with 5 symbols of channel memory.

As a solution to the ISI problem, feature equalization was implemented for both the CPM and PSK case. In Fig. (2(b)) the effect of a linear Viterbi equalizer is shown on one, three and five REC-CPM. Comparing this to Fig. (2(a)) shows an increase in the probability of recognition at 0dB SNR when an equalizer is employed. This is further refined in Fig. (2(c)) when a nonlinear ICA based equalizer is used on the same length REC-CPM schemes. The ICA based equalizer is able to more accurately estimate the transformed composite channel as seen in Fig. (2(d)) and consequently offers better ISI suppression. This is also demonstrated in the SVM hypothesis as seen in Fig. (3). Fig. (3(a)) describes the SVM hypothesis space for different length REC-CPM schemes without using any feature equalization. The margin is increased after ICA based equalization is applied as seen in Fig. (3(b)). This further confirms the assertion that introduction of feature equalization, particularly employing the ICA as a composite channel estimator, can largely mitigate the effects of ISI for the selected modulation schemes.

The second modification of the recognition algorithm is selecting a different kernel for use in the SVM. In Fig. (4), the output SVM margin is plotted versus input negentropy to the SVM. Fig. (4(a)) shows the SVM margin as a function of feature negentropy using ICA equalization on 3REC-CPM using both a Chebychev type kernel and a RBF type kernel. As the input negentropy is increased the Chebychev kernel attains a large SVM margin over the RBF kernel for the same amount of ISI. Conversely in the presence of ISI, the Chebychev kernel produces fewer recognition errors with sufficient input negentropy. Combining ICA based equalization, with sufficient training, and the Chebychev kernel further mitigates ISI effects upon the algorithm. This is further demonstrated in Fig. (4(b)) where different amounts of ISI are input into the SVM with a Chebychev kernel. As the ISI is increased, the corresponding SVM margin is decreased, however with sufficient ICA iterations, or sufficient input negentropy it is possible to achieve the same margin as the lower ISI case. PSK5 and PSK7 are known to be difficult to classify with significant miss classifications between them in [1]. Fig. (5) shows the effect of ISI on the SVM margin using both the Chebychev kernel and RBF kernel with two symbols of interference. Again the Chebychev kernel is better able to deal with the increased noise power presented in the ISI case, which is reflected as an increase in the normalized SVM margin over the RBF kernel.

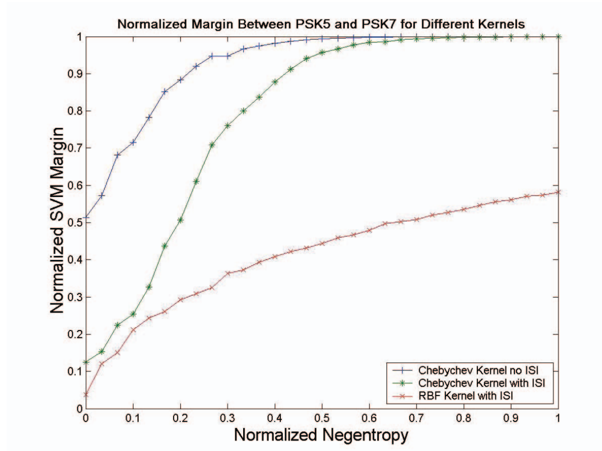


Fig. 5. Normalized SVM margin for two close modulation types, PSK5 and PSK7 in the presence of ISI. Using the Chebychev kernel over an RBF improves the margin of separation between these modulations in the presence of 2 symbols of interference.

IV. Conclusions

The effect of ISI on the performance of the recently proposed hybrid ICA-SVM algorithm was investigated. Combining feature equalization with a hybrid Chebychev kernel enables the hybrid ICA-SVM algorithm to mitigate the effects of ISI on classification performance. The improvement in classification performance when using a nonlinear ICA based feature channel estimate over a linear Viterbi based one is primarily due to the transformed nature of the feature channel that the ICA equalizer is better able to exploit with sufficient training. Similarly using a Chebychev kernel instead of a RBF based kernel allows increased SVM margins; and thus recognition rates, when CPM is being classified. Together these modifications make a hybrid ICA-SVM recognition system viable in the presence of strong ISI.

References

[1] D. Boutte and B. Santhanam, "A feature weighted hybrid ica-svm approach to automatic modulation recognition," To Appear in the Proceedings 13th IEEE Digital Signal Processing Workshop, 2009.

[2] W. A. Gardner, W. A. Brown, and C. K. Chen, "Spectral correlation of modulated signals: Part 2-digital modulation," *IEEE Trans. Commun.*, vol. 35, pp. 595–601, June 1987.

[3] J. Wu and A. H. Aghvami, "A new adaptive equalizer with channel estimator for mobile radio communication," *IEEE Trans. Veh. Technol.*, vol. 45, pp. 467–474, Aug. 1996.

[4] M. Gupta and B. Santhanam, "A general approach towards blind multiuser detection using higher-order statistics, vol. 3," IEEE WCNC, pp. 1585–1590, 2006.

[5] V. N. Vapnik, *Statistical Learning Theory*. New York, New York: John Wiley and Sons, 1998.

[6] Y. Tan and J. Wang, "A support vector machine with a hybrid kernel and minimal vapnik-chervonenkis dimension," *IEEE Trans. Knowledge Data Eng.*, vol. 16, pp. 385–395, 2004.

[7] D. Zhang and P. K. Rajan, "Supergaussian data denoising by semi-ica estimation," Proceedings of the Thirty-Seventh Southeastern Symposium on System Theory, vol. 3, pp. 485–490, 2005.

[8] A. Hyvarinen and E. Oja, "Independent component analysis: Algorithms and applications," *Neural Networks*, vol. 13, pp. 411–430, Feb. 2000.

[9] N. Cristianini and J. Shawe-Taylor, "An introduction to support vector machines and other kernel-based learning methods," Cambridge University Press, 2000.

[10] E. E. Azzouz and A. K. Nandi, *Automatic Modulation Recognition of Communication Signals*. 3300 AA Dordrect, The Netherlands: Kluwer, 1996.

[11] A. Swami and B. Sadler, "Hierarchical digital modulation classification using cumulants," *IEEE Trans. Commun.*, vol. 48, pp. 416–429, march 2000.

[12] W. A. Gardner and S. Venkataraman, "Performance of optimum and adaptive frequency-shift filters for cochannel interference and fading," Maple Press, 1990.

[13] A. Haghighat, "Ica-based signal equalization for digital receivers," Proccedings of the IEEE 64th Vehicular Technology Conference, pp. 1–5, 2006.

[14] C. M. Spooner and W. A. Gardner, "Estimation of cyclic polyspectra," Proceedings of the Twenty-fifth Asilomar Conference on Signals and Systems, vol. 2, pp. 370–376, 1991.