Signal Classification Based on Linear and RBF Classifier in Cognitive Radio

***Abstract*—In this paper we explore preliminary results of a linear classification schema designed to detect Primary Users (PU) in a Cognitive Radio Network (CRN). Higher-order moment characteristics of the signal are examined as features for a binary classifier of non-linearly separable signal statistics. The results of these findings may be used in full or in part in subsequent radio policy design.**

***Keywords*—M-PSK, Cognitive Radio, Machine Learning, Linear Classifier, Energy Detection, SNR.**

I. Introduction

With the drastic increase in the number of devices using the wireless spectrum, the challenge to optimize the underuse of the licensed spectrum becomes critical.

A theoretical solution is the Cognitive Radio (CR), a cognitive unit aware of its environment. As a conceptual model, CRs are capable of reasoning what characteristics (frequency, waveform, protocol, etc.) it should dynamically deploy to take advantage of its environment. This *agility* to opportunistically communicate on frequencies, across different radio platforms and across protocols depends on a CR's ability to **sense the spectrum**.

A typical exercise in spectrum sensing is detecting the presence of a licensed user. The least computationally expensive way of doing this is energy detection. Energy detection does not need a priori information about the the PU's transmission characteristics; but this method is not suitable for low-SNRs as the detection of PU deteriorates.

The rest of this paper is organized as follows: Section 2 is the problem formulation. Section 3 explores the computation, meaning and statical significance of these higher-order moments, and their relationship to low-SNRs. Section 4 identifies the features and SVM-kernels tested. Section 5 identfies results and Section 6 proposes future work.

II. Problem Formulation

Our detection is based on:

$H_0 : X(n) = S(n) + W(n)$, PU is present

$H_1 : X(n) = W(n)$, PU is absent

We choose Q-PSK+AWGN, AWGN as our signals for classification. The signal and noise are respectively sampled as training vectors for our classifier. The complex signals were generated using gnu-radio software at a sampling rate of 32ksps, where 64 samples were collected consecutively at a time. In our signal generation, the signal gain was held constant as the noise value was changed to generate signals at various SNRs.

III. Exploration of Higher-Order-Moments

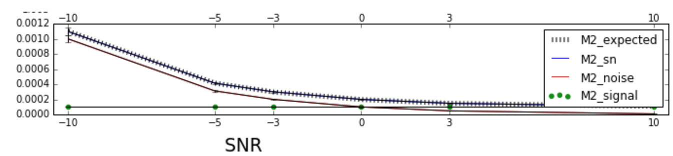
The derivation of the second and fourth moments for a M-ary PSK signal are given in [2].

M_2 is signal variance. Mathematically, M_2 of y_n reduces to:

$$M_2 = S + N$$

where S and N are the signal and noise power respectively. This theoretical calculation for M_2 was compared to our approximate computation of M_2 :

$$M_2 \approx \frac{1}{N_{sym}} \sum_{n=0}^{N_{sym}-1} \mid y_n \mid^2$$



The expected and computed values for M_2 for our noisy signal matched very well.

The fourth moment M_4 is kurtosis and relates to the pointedness of the signal. For any M-ary PSK signal, the kurtosis of the noise k_w is 2, while the kurtosis of the signal k_a is 1[2]. We observed that when we increased the size of the consecutive collection of samples (from 64 to 1024, for instance) our computed k_a and k_w showed less variance. Even at consecutive sampling of 64, k_a and k_w were practically 1 and 2, respectively.

Formally, they are computed:

$$k_a = \frac{E(\mid a_n \mid^4)}{(E \mid a_n \mid^2)^2}$$

$$k_w = \frac{E(\mid w_n \mid^4)}{(E \mid w_n \mid^2)^2}$$

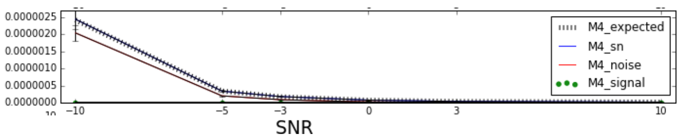
According to derivation in [2], M_4 of the noisy signal (for a M-ary PSK signal) is expected to be:

$$M_4 = S^2 + 4SN + 2N^2$$

We computed M_4 of y_n using

$$M_4 \approx \frac{1}{N_{sym}} \sum_{n=0}^{N_{sym}-1} \mid y_n \mid^4$$

Again, our computed values matched what we expected, albeit with higher variance.



We note that our signal behaves as expected, and note that we can observe the polynomial like change in M_4 of the noisy signal to changes in noise.

IV. Desiging Linear Classfiers on Moments

A Support Vector Machine (SVM) is a discriminative classifier that creates hyperplanes to separates class labels, here $H(0)$ and $H(1)$.

We test two kernels for our svm, linear and Radial Basis Function (RBF), which creates a function with respect to the origin. For the RBF kernel, the penalty, C, is set to 10.

A. Features

$$x_1 = M_2$$
$$x_2 = M_4$$

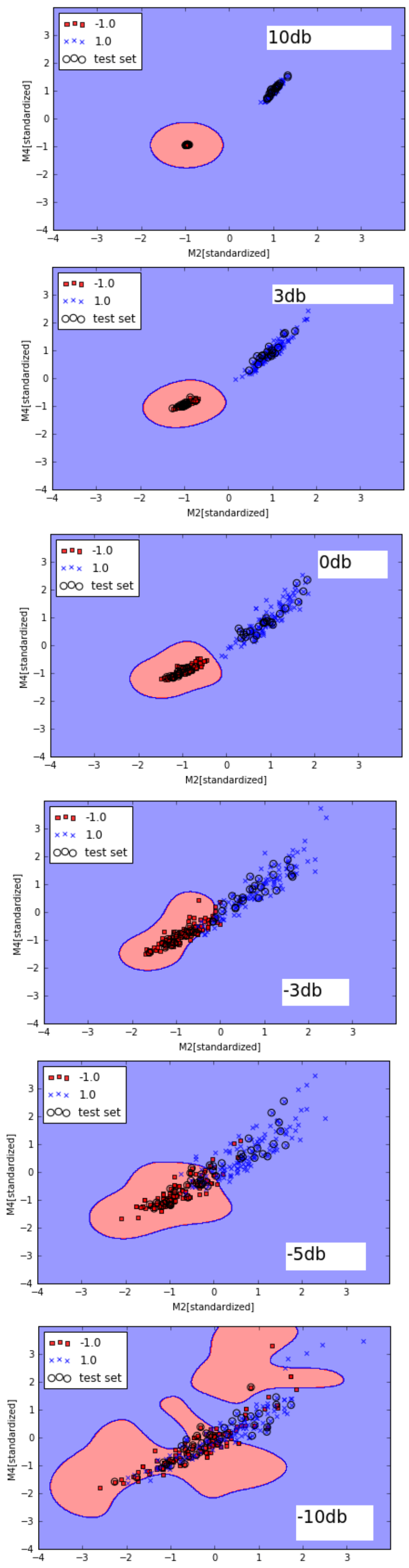
B. Features Sets

1.
$$x_1$$

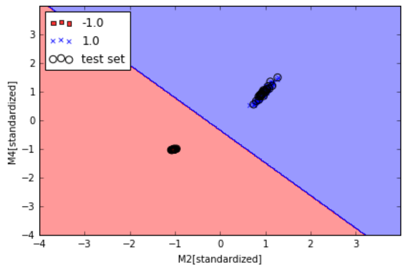
2.
$$x_2$$

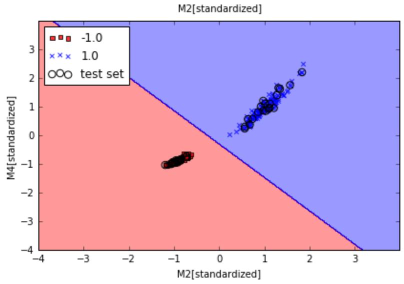
3.
$$x_1, x_2$$

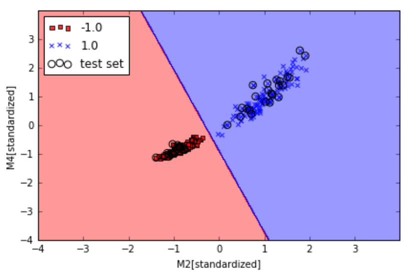
The hyperplanes are depicted for both kernels, when the feature set three is used. The following are the hyperplanes drawn for the RBF kernel

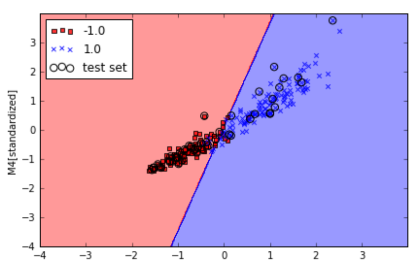


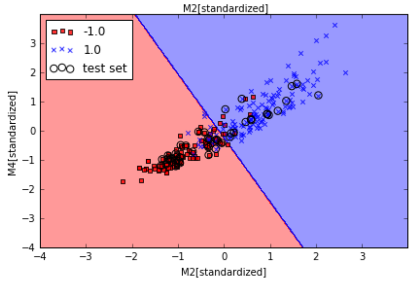
The following are the hyperplanes drawn for the linear kernel.

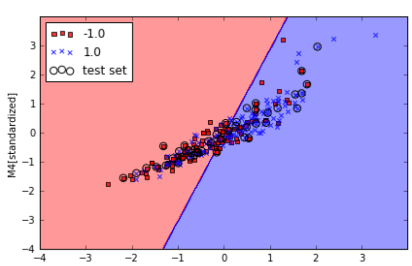












V. RESULTS

The prediction accuracy of the two kernels are presented. 100 experiments of training the classifier are performed.

ACCURACY WITH LINEAR KERNEL, 100 experiments conducted

	M2 and M4 (mean,var)	M4 (mean,var)	power (mean,var)
10db	(1.0, 0.0)	(1.0, 0.0)	(1.0, 0.0)
3db	(1.0, 0.0)	(1.0, 0.0)	(1.0, 0.0)
0db	(1.0, 0.0)	(0.99, 0.0001)	(1.0, 0.0)
-3db	(0.94, 0.0005)	(0.91, 0.0006)	(0.94, 0.0006)
-5db	(0.9, 0.0009)	(0.86, 0.0009)	(0.9, 0.0008)
-10db	(0.63, 0.0032)	(0.63, 0.0023)	(0.65, 0.0019)

ACCURACY WITH RBF KERNEL, 100 experiments conducted

	M2 and M4 (mean,var)	M4 (mean,var)	power (mean,var)
10db	(1.0, 0.0)	(1.0, 0.0)	(1.0, 0.0)
3db	(1.0, 0.0)	(1.0, 0.0)	(1.0, 0.0)
0db	(1.0, 0.0)	(0.99, 0.0001)	(1.0, 0.0)
-3db	(0.93, 0.0006)	(0.9, 0.0006)	(0.94, 0.0005)
-5db	(0.89, 0.0007)	(0.87, 0.001)	(0.9, 0.001)
-10db	(0.64, 0.0017)	(0.63, 0.0024)	(0.65, 0.0014)

Under either kernel, the similarity between accuracies is striking and suggests, counter-intuitively, that M_4 is not an asset as a feature.

VI. FUTURE WORK

Components of other SNR-estimators, such as the Signal-to-Variation SNR estimator will be examined for feature extraction.

REFERENCES

[1] Biglieri, Ezio, et al. Principles of cognitive radio. Cambridge University Press, 2012.

[2] Pauluzzi, David R., and Norman C. Beaulieu. "A comparison of SNR estimation techniques for the AWGN channel." IEEE Transactions on Communications 48.10 (2000): 1681-1691.