SECOND-ORDER STATISTICAL APPROACH FOR DIGITAL SIGNALS CLASSIFICATION IN COGNITIVE RADIO USING SUPPORT VECTOR MACHINE

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ABSTRACT

Cognitive radio systems require detection of different signals for communication. In this paper, an approach for multiclass signal classification based on second-order statistical features and multiclass Support Vector Machine (SVM) classifier is proposed. The proposed system is designed to recognize three different digital modulation schemes such as PAM, 32QAM and 64QAM. The signal classification is achieved by extracting the 2^{nd} order cumulants of the real and imaginary part of the complex envelope and these second-order statistical features are given to multiclass SVM classifier for classification. The modulated signals are passed through an Additive White Gaussian Noise (AWGN) channel before feature extraction. The evaluation of the system is carried on using 400 generated signals. Experimental results show that the proposed method produces an accurate classification rate with 65-89% for 1024 samples.

Key words: Cognitive radio, Second-order statistics, Support Vector Machine, Digital modulation.

I. INTRODUCTION

A number of definitions can be found to describe Software Defined Radio, also known as Software Radio or SDR. Software Defined Radio is defined as: "Radio in which some or all of the physical layer functions are software defined". A radio is any kind of device that wirelessly transmits or receives signals in the radio frequency (RF) part of the electromagnetic spectrum to facilitate the transfer of information. In today's world, radios exist in a multitude of items such as cell phones, computers, car door openers, vehicles, and televisions. A study of multi-class signal classification based on automatic modulation recognition through Support Vector Machines (SVM) is presented in [1].

Obviously SDR in Cognitive Radio should be configured not only to independent standards, protocols and services but also to the extensively dynamic nature of bandwidth allocation in [2]. Cognitive radio is envisioned as the ultimate system that can sense, adapt and learn from the environment in which it operates. A new robust Automatic Modulation Classification (AMC) algorithm, which applies higher-order statistics (HOS) in a generic framework for blind channel estimation and pattern recognition, is proposed in [3].

Feature based method for automatic classification and recognition of 7 digital modulations for Software Defined Radio is presented in [4]. The classification is conducted with artificial neural networks (ANN). Evaluates the performance of energy detection based spectrum sensing for several real-world primary signals of various radio technologies is presented in [5]. A method for the automatic classification using cumulants derived using fractional lower order statistics is proposed in [6]. The performance of the classifier is presented in the form of probability of correct classification under noisy and fading conditions.

A novel approach based on fuzzy logic to classify signals with respect to standards on the basis of known radio parameters is presented in [7]. Ideally it would like to classify the primary user systems with respect to existing "Known standards". A novel design of the Automatic modulation recognition (AMR) method with reduced computational complexity and fast processing speed is needed. A discrete likelihood-ratio test (DLRT)-based rapid-estimation approach to identifying the modulation schemes blindly for uninterrupted data demodulation in real time is described in [8].

Sensing of digitally modulated primary radio signals is described in [9]. In achieving this objective, a digital automatic modulation classifier was developed using an artificial neural network. A new framework for Cognitive Radio (CR) spectrum sensing based on linear and polynomial classifiers is proposed in [10]. A cooperative CR network is considered in this paper with CR nodes collaborating in making the decision about spectrum availability. The automatic modulation classification methods based on likelihood functions, studies various classification solutions derived from likelihood ratio test, and discusses the detailed characteristics associated with all major algorithms is presented in [11].

In this paper, an approach for the digital signals classification in cognitive radio based on cumulants and SVM is presented. The remainder of this paper is organized as follows. Sections 2 and 3 give brief description about the methodologies and the proposed system respectively. In section 4 the experimental results are explained in detail.

II. METHODOLOGY

The proposed system for the classification of digital signals in cognitive radio is built based on second-order statistics and multiclass SVM for classification. In this following section the theoretical background of all the approaches are introduced.

2.1 Second-order statistics

The autocorrelation function or sequence of a stationary process, $x(n)$ is defined by,

$$R_{xx}(m) = E\{ x^*(n)\, x(n+m) \} \qquad [1]$$

where E{•} denotes the ensemble expectation operator. The power spectrum is formally defined as the Fourier Transform (FT) of the autocorrelation sequence (the Wiener-Khintchine theorem) is given by,

$$P_{xx}(f) = \sum_{m=-\infty}^{\infty} R_{xx}(m) \exp(-j2\pi fm) \qquad [2]$$

Where f denotes the frequency. An equivalent definition is given by

$$P_{xx}(f) := E\{X(f)\, X^*(f)\} \qquad [3]$$

Where $X(f)$ is the Fourier Transform of $x(n)$

$$X(f) = \sum_{n=-\infty}^{\infty} x(n) \exp(-j2\pi fn) \qquad [4]$$

A sufficient, but not necessary, condition for the existence of the power spectrum is that the autocorrelation be absolutely summable. The power spectrum is real valued and nonnegative, that is, $P_{xx}(f) \geq 0$; if $x(n)$ is real valued, then the power spectrum is also symmetric, that is, $P_{xx}(f) = -P_{xx}(f)$

The higher-order moments are natural generalizations of the autocorrelation, and cumulants are specific nonlinear combinations of these moments. The first-order cumulant of a stationary process is the mean $C_{1x} := E\{ x(t) \}$. The higher-order cumulants are invariant to a shift of mean. Hence, it is convenient to define them under the assumption of zero mean. If the process has nonzero mean, then subtract the mean, apply the following definitions to the resulting process. The second-order cumulants of a zero-mean stationary process are defined by [4],

$$C_{2x}(k) = E\{ x^*(n)\, x(n+k) \} \qquad [5]$$

The first-order cumulant is the mean of the process; and the second-order cumulant is the auto covariance sequence. Note that for complex processes, there are several ways of defining cumulants depending upon which terms are conjugated. The zero-lag cumulants have special names: $C_{2x}(0)$ is the variance and is usually denoted by σ_x^2

2.2 Support Vector machine

Support vector machines (SVMs) are a set of related supervised learning methods that analyze data and recognize patterns, used for classification and regression analysis. The standard SVM is a non-probabilistic binary linear classifier, i.e. it predicts, for each given input, which of two possible classes the input is a member of. A classification task usually involves with training and testing data which consists of some data instances. Each instance in the training set contains one "target value" (class labels) and several "attributes" (features). SVM has an extra advantage of automatic model selection in the sense that both the optimal number and locations of the basis functions are automatically obtained during training. The performance of SVM largely depends on the kernel [12].

SVM is essentially a linear learning machine. For the input training sample set

$$(x_i, y_i),\ t = 1 \ldots n,\ x \in R^n,\ y \in \{-1, +1\} \qquad [6]$$

the classification hyperplane equation is let to be

$$(\omega, x) + b = 0 \qquad [7]$$

thus the classification margin is $2/|\omega|$. To maximize the margin, that is to minimize $|\omega|$, the optimal hyperplane problem is transformed to quadratic programming problem as follows,

$$\begin{cases} \min \phi(\omega) = \frac{1}{2}(\omega, \omega) \\ s \cdot t \cdot y_1((\omega, x) + b) \geq 1, t = 1, 2 \ldots t \end{cases} \quad [8]$$

After introduction of Lagrange multiplier, the dual problem is given by,

$$\begin{cases} \max Q(a) = \sum_{t=1}^{n} a_i - \frac{1}{2}\sum_{t=j=1}^{n}\sum^{n} y_i y_j a_i a_j K(x_i \cdot x_j) \\ s \cdot t \sum_{i=1}^{n} y_i a_i = 0, a_i \geq 0, i = 1, 2 \ldots, n \end{cases} \quad [9]$$

According to Kuhn-Tucker rules, the optimal solution must satisfy

$$a_i(y_i((w \cdot x_i) + b) - 1 = 0, i = 1, 2 \ldots n \quad [10]$$

That is to say if the option solution is

$$a^* = (a_1^*, a_2^*, \ldots, a_i^*)^T, i = 1, 2, \ldots n \quad [11]$$

Then

$$w^* = \sum_{i=1}^{n} a_i^* y_i x_i$$

$$b^* = y_i - \sum_{i=1}^{n} y_i a_i^* (x_i \cdot x_j), j \in \{ f / a_i > 0 \} \quad [12]$$

Then

For every training sample point x_i, there is a corresponding Lagrange multiplier. And the sample points that are corresponding to $a_i = 0$ don't contribute to solve the classification hyperplane while the other points that are corresponding to $a_i > 0$ do, so it is called support vectors. Hence the optimal hyperplane equation is given by,

$$\sum_{x_i \in SV} a_i y_i (x_i \cdot x_j) + b = 0 \quad [13]$$

The hard classifier is then,

$$y = sgn\left[\sum_{x_i \in SV} a_i y_i (x_i \cdot x_j) + b\right] \quad [14]$$

For nonlinear situation, SVM constructs an optimal separating hyperplane in the high dimensional space by introducing kernel function $K(x, y) = \phi(x) \cdot \phi(y)$, hence the nonlinear SVM is given by,

And its dual problem is given by,

$$\begin{cases} \min \phi(\omega) = \frac{1}{2}(\omega, \omega) \\ x, t, y_i((\omega, \phi(x_i)) + b) \geq 1, i = 1, 2, \ldots t \end{cases} \quad [15]$$

And its dual problem is given by,

$$\begin{cases} \max(a) = \sum_{i=1}^{i} a_i - \frac{1}{2}\sum_{i=j=1}^{i}\sum^{i} y_i, y_j, a_i a_j K(x_i \cdot x_j) \\ s \cdot t \cdot \sum_{i=1}^{n} y_i a_i = 0, 0 \leq a_i \leq c, i = 1, 2, \ldots, t \end{cases} \quad [16]$$

Thus the optimal hyperplane equation is determined by the solution to the optimal problem. A SVM classifier can predict the input data into two distinct classes. However, it can be used as multiclass classifiers by treating a K-class classification problem as K two-class problems. This is known as one vs. rest or one vs. all classification.

The SVM classifier implementation is standard implementation. In the MATLAB environment the LIBSVM software is used. LIBSVM is integrated software for support vector classification, regression and distribution estimation. It also supports multi-class classification.

III. PROPOSED SYSTEM

The proposed system for the classification of digital signals in cognitive radio mainly consists of two different phases which include the training phase and classification phase. All the phases are explained in detail in the following sub sections. Three different types of digital modulation schemes are considered for the classification (PAM, 32QAM and 64QAM).

3.1 Training Phase

Feature extraction is a fundamental pre-processing step for pattern recognition and all machine learning problems. In the proposed method,

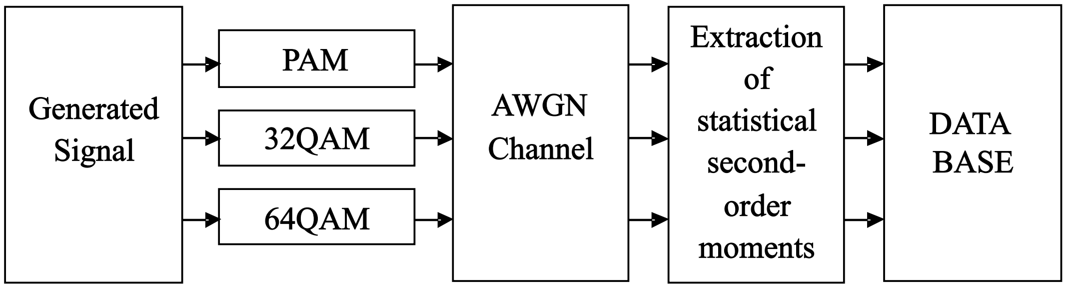

Fig. 1. Block diagram of feature extraction phase

2^{nd} order cumulants of real and imaginary part of the complex envelope are used as features for the classification of digital signals. The training phase is shown in Fig 1.

The generated signal is first modulated by using PAM, 32QAM and 64QAM modulation schemes. These modulated signals are passed through an AWGN channel with a predefined SNR level. The second-order statistical features extracted from the received signals and stored in the database for the classification purpose. The SVM classifier is trained by using the database generated in the training phase. The algorithm is as follows.

Algorithm I: Training Phase

[Input] Generated signals

[Output] the feature vector of all modulated signal with noise as database (DB)

1. Modulate the signal by using PAM modulation scheme.

2. Pass the modulated signal through an AWGN channel with predefined SNR level.

3. Calculate the 2^{nd} order cumulants by eqn. (5)

4. Step 3 is repeated for real and imaginary part of the complex envelope.

5. Insert this feature vector and the known class into the database.

6. Repeat the above steps for 32QAM and 64QAM modulation schemes.

3.2 Classification Phase

In the classification phase, the unknown signal is classified as any one of the three modulation types. The second order statistical features are extracted from the unknown signal and this feature vector is processed with the features in the database by using the SVM classifier. The algorithm is as follows.

Algorithm II: Identification Algorithm

[Input] unknown signal and the database

[Output] the class of the signal to which this unknown signal is assigned

1. Calculate the 2^{nd} order cumulants by eqn. (5)

2. Step 1 is repeated for real and imaginary part of the unknown signal

3. Test with the trained SVM classifier and find the class of the unknown signal.

IV. EXPERIMENTAL RESULTS

In this section, the performance of the proposed system based on the higher-order statistical feature discussed in Section 3 is verified. A set of 400 signals with segment size of 1024samples are generated. These 400 signals are modulated by using PAM, 32QAM and 64QAM modulation schemes and passed through an AWGN channel of predefined SNR level. Among these 400 signals per modulation scheme are separated into two set and 300 signals per modulation scheme are randomly selected as training set and the remaining 100 signals per modulation scheme as testing set. The SNR level used in the proposed system are 0, 1, 5 and 10 dB. For each modulated scheme, there the 1600 modulated signal corrupted by AWGN per each segments.

The performance metric used to evaluate the accuracy of the proposed system is the confusion matrix. A confusion matrix represents information about actual and classified cases produced by a classification system. Performance of such system is commonly evaluated by demonstrating the correct and incorrect patterns. From Table 1 to Table 4 shows the results obtained from the SVM classifier for 1024 samples at SNR level 0, 1, 5 and 10 dB respectively and positive predictive value (PPV) also shown. From the results it is concluded that the classification accuracy increases as SNR increases. Figure 2 shows the overall classification accuracy of the proposed system. In table 1, Among the 400 signals generated per each modulation scheme for 0 dB, the true positive value for PAM, 64QAM and 32QAM are 116, 400 and 267 respectively. The overall classification rate for 1024 samples at 0, 1, 5 and 10 dB is 65.25, 73.33, 88.83 and 88.91.

Table 1
SVM Classification accuracy for 1024 samples at 0 dB SNR

Modulation Type	PAM	64QAM	32QAM	PPV
PAM	**116**	0	133	46.59
64 QAM	0	**400**	0	100
32 QAM	284	0	**267**	48.46
Accuracy (%)	29	100	66.75	**65.25**

Table 2
SVM Classification accuracy for 1024 samples at 1 dB SNR

Modulation Type	PAM	64QAM	32QAM	PPV
PAM	**213**	0	133	61.56
64 QAM	0	**400**	0	100.00
32 QAM	187	0	**267**	58.81
Accuracy (%)	53.25	100	66.75	**73.33**

Table 3
SVM Classification accuracy for 1024 samples at 5 dB SNR

Modulation Type	PAM	64QAM	32QAM	PPV
PAM	**399**	0	133	75.00
64 QAM	0	**400**	0	100.00
32 QAM	1	0	**267**	99.63
Accuracy (%)	99.75	100	66.75	**88.83**

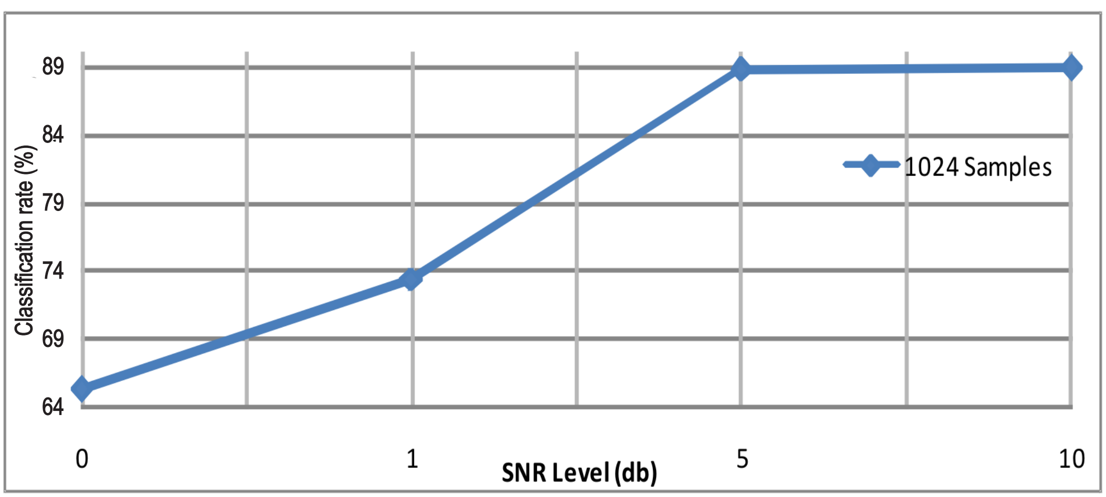

Fig. 2. Overall classification rates (%) for 1024 samples

Table 4
SVM Classification accuracy for 1024 samples at 10 dB SNR

Modulation Type	PAM	64QAM	32QAM	PPV
PAM	**400**	0	133	75.05
64 QAM	0	**400**	0	100.00
32 QAM	0	0	**267**	100.00
Accuracy (%)	100	100	66.75	**88.92**

V. CONCLUSION

In this paper, an approach for multiclass signal classification based on second-order statistical features and multiclass SVM classifier is presented. The 2nd order cumulants of the real and imaginary part of the complex envelope are used as features for multi signal classification. The proposed system tested on three different modulation schemes PAM, 32QAM and 64QAM. From the results, it is observed that the classification accuracy of the PAM scheme for 0 dB is much lesser than all other schemes used. Confusion matrix is used to evaluate the performance of the proposed system and the experimental results prove that the proposed system provides satisfactory performance for the multi signal classification.

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