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Spectrum Sensing in Cognitive Radio Based on Adaptive Optimal SVM

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Abstract: Cognitive Radio (CR) is an efficient way to solve the problem of the lack of the spectrum resource. In a Cognitive Radio Network the unlicensed users (secondary users) must incessantly monitor the spectrum for the presence of the licensed users (primary users) to avoid the interference to primary users. In this study, a spectrum sensing scheme based on adaptive optimal SVM (support vector machine) is proposed. A prototype system and the simulation experiments show that in low SNR the algorithm can also get a reasonable probability of detection and a low probability of false alarm.

Key words: Cognitive radio, spectrum sensing, adaptive optimal SVM, PSO

INTRODUCTION

Recently there has been rapid development of wireless communication, so the electromagnetism spectrum resource is becoming more and more exiguity, but in actual most spectrum is not utilized completely. To solve this situation, Cognitive Radio is a efficient way. Mitola and Maguire (1999) and Haykin (2005) first introduced it by the numbers. CR is a radio that can learn from its environment, then choose the best way to serve its user. In a CR network the unlicensed (secondary) users are utilizing the licensed spectrum. They must detect the presence of the licensed (primary) users and quit the band as quick as possible to avoid the interference to licensed users. So the spectrum sensing is most significant to the implementation of a CR system (Tingrui *et al.*, 2011).

There has been several methods proposed for detecting the presence of Primary User (PU) by secondary user (SU) such as Energy detection based sensing (Ghurumuruhan and Li, 2005; Cabric *et al.*, 2006), Waveform Based Sensing (Tang, 2005), Cyclostationarity Based Sensing (Cabric *et al.*, 2004), Matched Filtering (Tandra and Sahai, 2005). They all have their own benefits and drawbacks. For example, energy detection based sensing is simple to implement and is not needed to know the prior knowledge of primary user. But the in energy detection based sensing algorithm choose the threshold of the sensing decision by estimating the noise variance. So, a small estimation error of noise power causes heavy performance drop (Zhao *et al.*, 2010). And the performance of energy detector degrades heavily under Rayleigh fading. Cyclostationarity Based Sensing

can get a good performance in low SNR but its computational complexity is very high.

Support Vector Machine (SVM) is a new way to statistical pattern recognition. It is based on structural risk minimization. Rather than the traditional methods based on empirical risk minimization like Neural Network (NN), it can give better generalization and better performance for small training samples (Liejun *et al.*, 2008).

In this study, a spectrum sensing scheme based on adaptive optimal SVM is proposed. In system of this paper cognitive node observe the information of the primary user and use an adaptive optimal SVM to make the sensing decision. The result of simulation shows that the spectrum sensing performance under AWGN channels is reasonable.

SYSTEM MODEL

Here, the detection problem f or secondary user and a system model throughout this study is introduced.

For simplification energy detection is selected as the feature of classification at the cognitive node which is based on the received signal energy E_i :

$$E_i = \sum_{n=1}^M |x(n)|^2, 1 \leq i \leq N \quad (1)$$

where, $x(n)$ is the n -th sample of the received signal at the SU, M is the size of the observation vector. Let us assume that the received signal form is such like this:

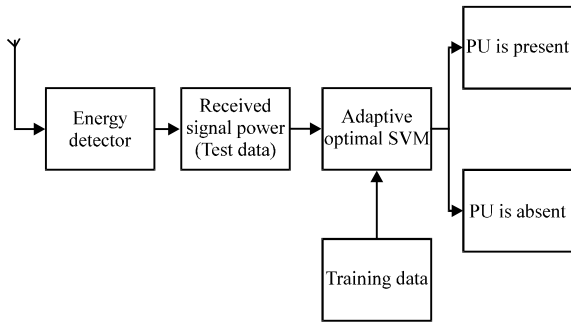


Fig. 1: Spectrum Sensing Scheme

$$x(n) = s(n) + w(n) \quad (2)$$

where, $s(n)$ is the signal of primary user, $w(n)$ is the additive white Gaussian noise (AWGN) sample. If $s(n) = 0$ there is no transmission of primary user. This is equivalent to classification between the following two hypotheses:

$$\begin{aligned} H_0 &: |x(n)|^2 = |w(n)|^2 \\ H_1 &: |x(n)|^2 = |s(n) + w(n)|^2 \end{aligned} \quad (3)$$

When H_0 is true PU is absent and When H_1 is true PU is present.

In system of this study, the spectrum scheme is illustrated as Fig. 1, "Training Data" is the power of signals such as the hypotheses shows in Eq. 3, they are the signal power of H_0 and H_1 under different SNR, they train SVM to be the classifier of spectrum sensing problem in this study and from energy detector the energy of the received signals will be gotten, they are "Test Data", the adaptive optimal SVM is employed to classify "Test Data" into two cases, one is the case that primary user is present and the other is case that primary user is absent.

Adaptive optimal SVM: According to section above, the detection of primary user can be solved as a binary classification problem. So in this study, an adaptive optimal SVM is selected as the fundamental tool to solve this problem.

Vapnik (1995) coined SVM on the foundation of statistical learning theory. it was designed for binary classification problem (Vapnik, 1995) first introduced the optimal solution of SVM for a linearly separable problem. Later extended it to non-linearly cases (Benhaddouche and Benyettou, 2010). The binary classification problem in this study is obvious non-linearly problem, so only the solution of this case will be discussed here.

A training group is supposed as:

$$(x_1, y_1), (x_2, y_2), \dots, (x_n, y_n), x \in \mathbb{R}^n, y_i \in \{1, -1\}, i = 1, 2, \dots, n$$

where, x_i is the input sample, y_i is the category index. Assumed that a hyperplane can classify these two groups such as:

$$W \cdot X + b = 0 \quad (4)$$

where, the position of the hyperplane is determined by W and b , $W \cdot X$ is the inner product. If a hyperplane is the optimal hyperplane, $\|W\|^2/2$ must be minimum. It can classify all of the training vectors correctly and the vectors of each class are separated with a maximum margin.

A quadratic optimization problem that can be formulated as follow can solve this problem:

$$\begin{aligned} \min_{w, b, \xi_i} & \frac{1}{2} \|W\|^2 + C \sum_{i=1}^n \xi_i \\ \text{s.t. } & y_i [(w \cdot x_i) + b] \geq 1 - \xi_i \\ & \xi_i \geq 0, i = 1, 2, \dots, n \end{aligned} \quad (5)$$

The boundary of different type of data is defined by vector W , b is a scalar threshold, C is the penalty parameter, it can control the training error rate by different values. For a non-linearly problem, Eq. 5 can be converted to:

$$\begin{aligned} \min_a & \frac{1}{2} \sum_{i=1}^n \sum_{j=1}^n y_i y_j a_i a_j K(x_i, x_j) - \sum_{i=1}^n a_i, (i = 1, 2, \dots, n) \\ \text{s.t. } & \sum_{i=1}^n y_i a_i = 0, 0 \leq a_i \leq C \end{aligned} \quad (6)$$

From Eq. 6 the decision function can be represented as follow:

$$f(x) = \text{sgn} \left\{ \sum_{i=1}^n a_i y_i K(x_i, x) + b \right\} \quad (7)$$

where, $K(x_i, x) = \phi(x_i) \phi(x)$ is the kernel function, it can change the input data to a higher dimensional space and change a non-linearly separable problem in low dimension to a linearly separable problem.

Generally there are four types of kernel function like polynomial, sigmoid, Radial Basis Function (RBF) and linear function used in SVM, in these kernel functions RBF kernel is widely used, no matter low dimensional, high dimensional, small samples or large samples RBF kernel can get a good result of classification (Qin *et al.*, 2009), so RBF is selected as kernel function.

$$K(x_i, x) = \exp\{-\gamma\|x - x_i\|^2\} \quad (8)$$

And optimal problem in Eq. 6 can be converted to:

$$\begin{aligned} \min_a & \frac{1}{2} \sum_{i=1}^n \sum_{j=1}^n y_i y_j a_i a_j \exp\{-\gamma\|x_i - x_j\|^2\} - \sum_{i=1}^n a_i \quad (i=1, 2, \dots, n) \\ \text{s.t.} & \sum_{i=1}^n y_i a_i = 0, 0 \leq a_i \leq C \end{aligned} \quad (9)$$

Equation 9 shows that the result of the minimization is determined by the selection of the parameters (C, γ) , the Breast-Cancer-Wisconsin (BCW) data from UCI database is used as the test data to show the influence of the parameters (C, γ) .

Figure 2a shows that when C is a small value error rate of classification is high, with C increases error rate of classification drops significantly, when C is bigger than a fixed value, error rate almost unchanged, but the bigger C will reduce the generalization ability of SVM, Fig. 2b shows that error rate of classification changes with γ , this parameter define the width of RBF kernel, if γ is too big the SVM will outfit the training data, else a too small γ will make SVM is not flexible enough for complex function approximation.

Figure 2 only shows the optimal area of (C, γ) for data from BCW of UCI database, in practical condition test data is almost random and the best (C, γ) is different from different classification, so they are always hard to be determined. In this study an adaptive optimal method based on PSO algorithm is employed to solve this problem.

Social behavior of birds motivated PSO, birds in a swarm preying on food and cooperation with each other to search for the optimal position (the position of food). In a PSO optimal problem, there exist a population of individuals, each individual is called a particle which

may be a potential solution. It can be supposed that the solution space of optimization problem is D dimensions. The i th particle is $X_i = (x_{i1}, x_{i2}, x_{i3}, \dots, x_{iD})$, the best position of itself is $P_i = (p_{i1}, p_{i2}, p_{i3}, \dots, p_{iD})$ and speed move to this position is $V_i = (v_{i1}, v_{i2}, v_{i3}, \dots, v_{iD})$ and the best global position is $P_g = (p_{g1}, p_{g2}, p_{g3}, \dots, p_{gD})$, the iteration can be represented as follows:

$$x_{id}^{t+1} = w \cdot v_{id}^t + c_1 \cdot r_1 \cdot (p_{id} - x_{id}^t) + c_2 \cdot r_2 \cdot (p_{gd} - x_{id}^t) \quad (10)$$

$$x_{id}^{t+1} = x_{id}^t + v_{id}^{t+1} \quad (11)$$

where, x_{id}^t and v_{id}^t are the d -th location component and speed component of i th particle, c_1 and c_2 are two positive coefficient, r_1 and r_2 are the random number selected from 0 to 1, w is the flexible coefficient of v_{id}^t , the second part of Eq. 11 is the ‘‘cognitive’’ part which is the optimization of the particle itself, the third part of Eq. 11 is the ‘‘swarm part’’ which is the cooperation between particles. In addition a limit range for each particle should be set such as $[-x_{id \max}, x_{id \max}]$ and $v_{id \max}$, in the process of the algorithm if the parameter of particle is out of the range, replace them by the boundary value.

In this study for the optimization of the error penalty parameter C and kernel parameter γ based on PSO, each particle is two dimensions of (C, γ) and a 3 cross validation is used to estimate the performance of each (C, γ) combination, first the training data is separated into 3 parts, one part is considered as the validation set and the rest 2 parts are for training. The average accuracy of the validation sets is the 3 cross validation accuracy.

EXPERIMENTS RESULT AND ANALYSIS

Here, the performance of proposed algorithm in this study is shown by simulation. The signal of primary user is DPSK, first adaptive optimal SVM at cognitive node is trained with signal power of two hypotheses such as (3), The SNR vary between -10dB and 20dB with interval of 5dB. There are 100 samples for each hypothesis at the each SNR, the SVM in the simulation is C-SVM, and the PSO parameters is set as bellow: $c_1 = 1.5$, $c_2 = 1.7$, population of the swarm is 20, generation of swarm is 100, the speed coefficient k is 0.6, w is 1, C is between 0.1 and 100, γ is between 0.1 and 100. Following that 10000 samples is chosen for each hypotheses at each SNR to test adaptive optimal SVM, the SNR vary between -10 and 20 dB with interval of 5dB. The spectrum sensing result of SVM with adaptive optimal parameter and the result of SVM with default parameter with $C = 3$, $\gamma = 1$ is compared. The comparison

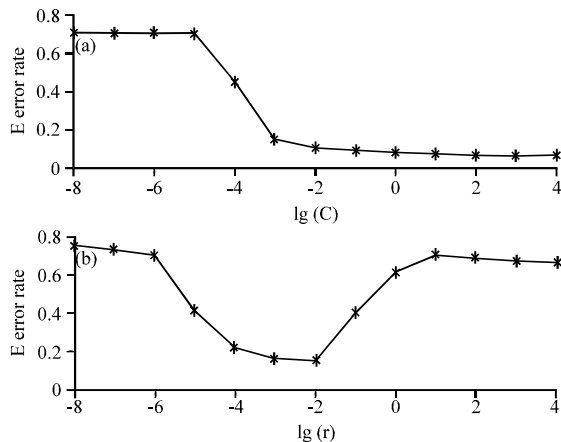


Fig. 2: Classification Error rate changes with (C, γ)

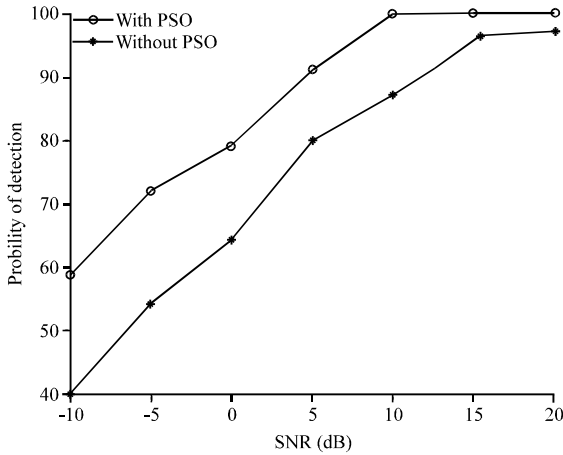


Fig. 3: Pd versus SNR

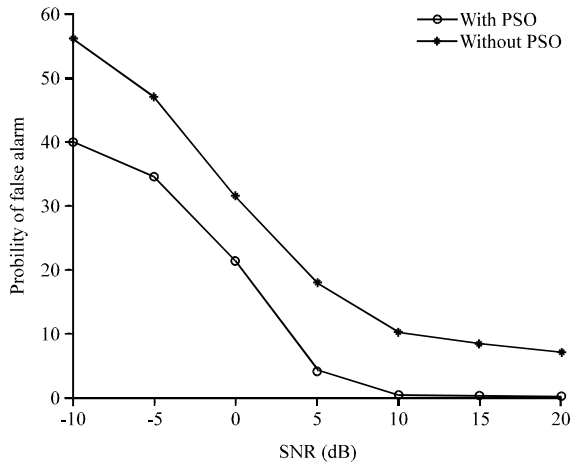


Fig. 4: Pf versus SNR

Table 1: Parameters Vs SNR in Fig. 3

Parameters	SNR						
	-10 dB	-5 dB	0 dB	5 dB	10 dB	15 dB	20 dB
C	72.8899	27.2776	15.789	5.1953	0.1	0.1	0.1
γ	69.5907	1.9501	9.8192	0.1	3.7621	0.22	2.561

Table 2: Parameters Vs SNR in Fig. 4

Parameters	SNR						
	-10 dB	-5 dB	0 dB	5 dB	10 dB	15 dB	20 dB
C	89.7623	73.8839	40.39	6.8684	0.1	0.1	0.1
γ	0.8059	5.7038	0.4119	0.9724	4.1593	1.283	0.529

is as Fig. 3 and 4, Table 1 and 2 show the optimal values of parameters.

Figure 3 and 4 show that the proposed adaptive optimal SVM performances better than traditional SVM with default parameters, it can get a higher probability of detection and a lower probability of false alarm than traditional SVM at same SNR.

Table 1 and 2 show that the parameters found by adaptive optimal algorithm proposed in this study, parameter C monotonically decreases with SNR increases and parameter γ changes with different SNR.

CONCLUSIONS

In this study, a Cognitive Radio spectrum sensing scheme based on adaptive optimal SVM has been proposed. At cognitive node the energy of the received signals was selected as the feature of the classification. And an adaptive optimal algorithm based on PSO is used to find the best parameters of SVM. Simulation results show that the proposed optimal algorithm outperforms the traditional SVM. And it does not need to estimate the variance of the noise in the traditional energy detection. But in practical condition the SNR of signal of primary user can not be known, so we can not to decide the training data at which SNR, this problem will be solved by a cooperative sensing scheme in our future work and with the adaptive optimal algorithm, the sensing time will be a little longer and it is also needed to be improved.

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