Primary User Signal Recognition Algorithm based on AL-ABM in Cognitive network

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Abstract—The cognitive users can use the spectrum holes which are vacant at some time or some frequency. Once the authorized users need to use the spectrum again, the cognitive users should stop using it to avoid interfering primary users. In this paper, a method based on active learning (AL) and AdaBoost machine (ABM) for the primary user signal modulation type recognition is proposed in low signal to noise ratio. A set of cyclic spectrum features are first calculated, and the training samples and testing samples are formed for classification. Then, active learning algorithm is applied to obtain samples improved classification through a number of iterations, and AdaBoost is formed. Finally, the formed SVM is utilized to recognize the primary user signal modulation type. The simulation results shows that the proposed AL-ABM Algorithm can improve the recognition accuracy of signal samples obviously.

Keywords-Cognitive network, Active Learning, Primary User Signal Recognition, AdaBoost Machine

I. INTRODUCTION

Recently radio spectrum resource has become increasingly scarce due to the development of communication. In order to improve the efficiency of the spectrum usage, cognitive radio is proposed and considered to be a promising technique to solve problems of increasing scarcity of spectrum [1,2]. The cognitive users can use the spectrum holes which are vacant at some time or some frequency. Once the authorized users need to use the spectrum again, the cognitive users should stop using it to avoid interfering primary users.

As one of the most important issues in cognitive radio networks[3,4], spectrum sensing is proposed to solve the shortage of vacant spectrum in recent. Spectrum sensing mainly includes follow three techniques: energy detection, cyclostationary feature detection and matched filtering[5]. In view of the radio channel complex environment, spectrum sensing technology focused on spectrum detection problem under low signal-to-noise ratio circumstances of channel multi-path fading and shadow fading. In [6], The authors proposed spectrum sensing algorithm based on the maximum - minimum eigenvalue (MME), but Spectrum sensing effect of the algorithm is not ideal, detection rate is low in the low SNR. The authors in [7] proposed spectrum sensing algorithm that using cyclic spectral energy(CSE) as the detecting statistic to obtain detection threshold, but due to an error cyclic spectrum estimation of eigenvalues, there was a shortage in testing performance in the low signal-to-noise ratio environment. The SVM, developed by Vapnik and others [8], has been used for many machine learning tasks such as pattern recognition and object classifications. A SVM-

based spectrum sensing algorithms proposed in [9] was applied to the field of cognitive radio, but SVM algorithm affects the classification effect directly due to the high computational complexity, to large-scale training samples, prone to overfitting and other reasons.In [10], a novel signal separation algorithm for spectrum sensing and signal separation which based on wavelet transform and blind source separation. In [11,12] a reliable scheme for cooperative spectrum sensing based on double threshold energy detection and Dempster-Shafer (D-S) theory was proposed.

In this article, spectrum sensing is studied from the machine learning and an primary user signal recognition method based on AL-ABM is proposed. A set of received signal spectrum features are extracted the important feature vector as training samples and testing samples for classification. Then, active learning algorithm is applied to obtain samples improved classification. Finally, we utilize the trained ABM to recognize the primary user signal modulation type.

The remainder of the paper is organized as follows. In section 2, the system model is described. The extraction of characteristic parameters is introduced in section 3. The proposed algorithm is investigated in section 4 and is well validated with computer simulation in section 5. The several concluding remarks are made in section 6.

II. THE SYSTEM MODEL

In this paper, we assume that a cognitive radio network with W primary users and M secondary users, for any one of the secondary user, the presence of the primary user can be summarized as a hypothesis test model of two elements

$$\begin{cases} H_0 : y(t) = n(t) \\ H_1 : y(t) = \sum_{w=1}^{W} s_w(t) + n(t) \end{cases} \qquad (1)$$

Where H_0 denotes that the primary user is not exist, H_1 denotes that the primary user exists. A process $s(t)$, that is any one of primary users, is said to be cyclostationary in building indoor environment if its mean and variance are periodic with a period T; $n(t)$ represents the additive white Gauss noise, the mean is zero, variance is σ_n^2.

On the basis of this model, We have extracted the cyclic spectrum characteristic parameters of the presence of the primary user or not, and obtain characteristic vector ,as adaboost machine training samples, thus we generate adaboost machine and spectrum sensing model. As we see from figure 1.
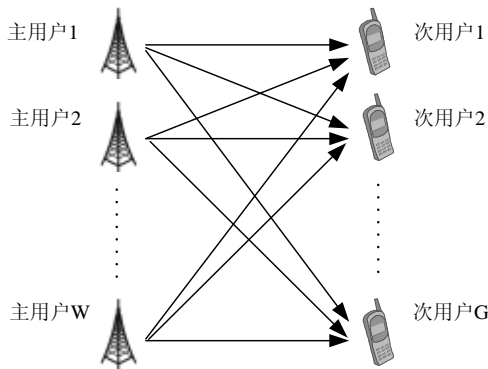

Figure 1. spectrum sensing model

III. SPECTRAL CORRELATION ANALYSIS AND SIGNAL FEATURE EXTRACTION

Many signals in communication system exhibit cyclostationarity property called spectral correlation features, these property can be used for signal detection and recognition..

The spectral correlation function (SCF)of the signal $y(t)$ is obtained from the Fourier transform of the cyclic autocorrelation in Equation (2).

$$S^\alpha(f) = \int_{-\infty}^{\infty} R^\alpha(\tau) \exp(-2\pi\alpha t j) dt \qquad (2)$$

Because the discrete Fourier transform $Y(k)$ of received signal $y(t)$ is Gauss process $y(t)$, s weighted linear combination, is still a Gauss process. The cyclic spectrum $S(k)$ is consist of L independent and identically distributed random variables, according to the central limit theorem, $S(k)$ obeys the Gauss distribution under $L \gg 1$.

Based on the calculation of the spectral correlation function, we can obtain three parameters as characteristic parameters of a signal modulation identification. The first one consists of the largest value of all spectral correlation function. The second feature to extract is the correlation coefficient for the SCF. The third feature of the set is the spectrum energy ε.

1. The largest value of all spectral correlation function

We assume that $S(k)$ is the largest value of all spectral correlation function $S^\alpha(f)$ as the first extracted characteristic parameter.

2. The correlation coefficient for the SCF

The correlation coefficient for the SCF between frequency components $f \pm 2\alpha$ can be calculated as

$$C_y^\alpha(f) = \frac{S^\alpha(f)}{[S(f + \alpha/2)S(f - \alpha/2)]^{\frac{1}{2}}} \qquad (4)$$

3. The spectrum energy ε

The largest energy spectrum is the spectrum energy ε, which is defined as

$$E = \frac{1}{K} \sum_{k=0}^{K-1} |S(k)|^2 \qquad (5)$$

The above characteristic parameters are formed characteristic vector as the input samples.

In this section, a novel approach to recognize the primary user signal modulation type is introduced based on the proposed system model.

We have extracted the cyclic spectrum characteristic parameters of the presence of the primary user or not $(a_1^q, a_2^q, \cdots, a_M^q)$, and obtain characteristic vector $y_q = (a_1^q, a_2^q, \cdots, a_M^q)^T, q = 1, 2, \cdots, M$ as ABM training samples, thus we generate ABM and using it to test input samples.

IV. SPECTRUM SENSING ALGORITHM BASED ON ACTIVE LEARNING AND ADABOOST

In this section, a novel approach to spectrum sensing is introduced based on the proposed system model. AL-ABM algorithm can be expressed as follow.

1. A few samples selected randomly from sampleset Uare marked manual tags and constitutes a training sample set L.

2. Training samples are randomly selected from the training set L to train the classifier, then establishing the initial classifer.

3.According to the standard Q query, A number of samples of the never marked samples in sample sets U are selected and annotated, then placed in a training set L.

4. Active learning classifier are re-training until the classifier reaches the final trainingstandards.

5. Repeat above steps, the primary user signal modulation type can be recognized by utilizing trained active learning.
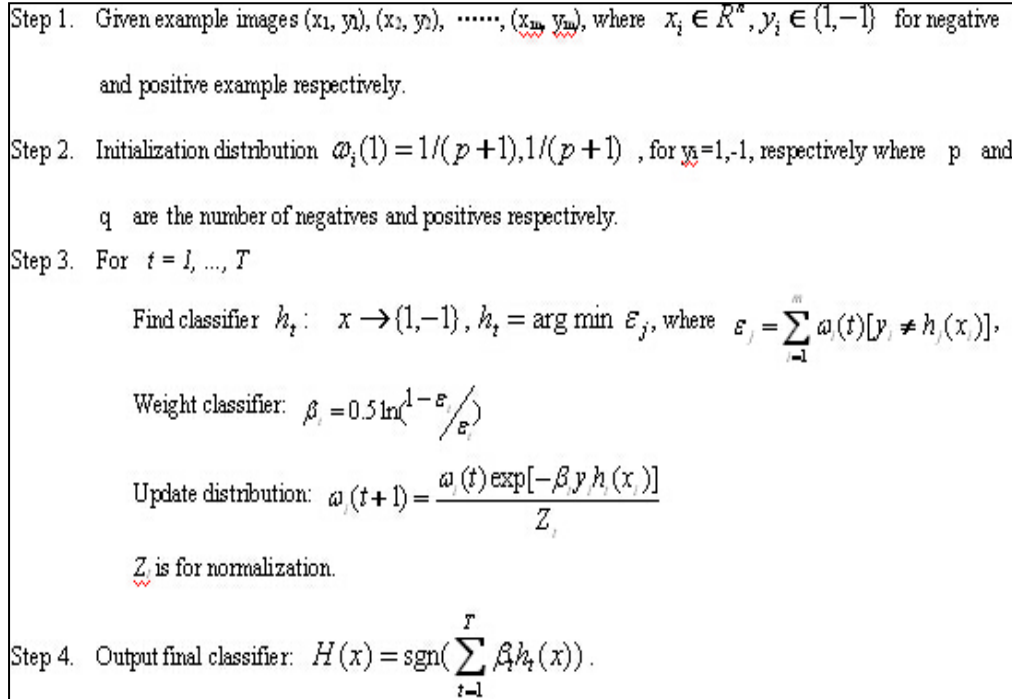
AdaBoost algorithm can be expressed as figure1.

Step 1. Given example images $(x_1, y_1), (x_2, y_2), \ldots\ldots, (x_m, y_m)$, where $x_i \in R^n, y_i \in \{1, -1\}$ for negative and positive example respectively.

Step 2. Initialization distribution $\omega_i(1) = 1/(p+1), 1/(p+1)$, for $y_i = 1, -1$, respectively where p and q are the number of negatives and positives respectively.

Step 3. For $t = 1, \ldots, T$

Find classifier $h_t: x \rightarrow \{1, -1\}$, $h_t = \arg\min \varepsilon_j$, where $\varepsilon_j = \sum_{i=1}^{m} \omega_i(t)[y_i \neq h_j(x_i)]$,

Weight classifier: $\beta_j = 0.5\ln\left(\frac{1-\varepsilon_j}{\varepsilon_j}\right)$

Update distribution: $\omega_j(t+1) = \frac{\omega_j(t)\exp[-\beta_j y_j h_j(x_j)]}{Z_j}$

Z_j is for normalization.

Step 4. Output final classifier: $H(x) = \text{sgn}(\sum_{t=1}^{T} \beta_t h_t(x))$.

Figure 2. Adaboost Algorithm

V. SIMULATION AND ANALYSIS

In order to verify that this algorithm in low signal-to-noise ratio environment quality, using Matlab7.0 to complete experiments for MSK, BPSK and AM. The simulations are carried out with 1000 samples at SNR ranging from -15 dB to 5dB, the length of DFT cyclic spectrum is 512.

Table 1 is for both cases of signal-to-noise ratio for the -5dB and -15dB , using MME, ANN and the article arithmetic on 3 types modulation classification of signals from the correct rate. Simulation results show that MME, ANN and this algorithm detects the correct rate have decreased for modulated signals when the signal-to-noise ratio gradually reduced. When the signal to noise ratio S/N=-15dB, AM signal detection algorithms in this article the right rates were higher than both ANN and MME algorithms with 12.5% and 63.8%, for MSK signal, this algorithm the algorithm detects the correct rate is significantly higher than the other two algorithms.

Figure3 shows the accuracy rate of the different algorithms for MSK, it is observed that the three algorithms have better detection accuracy rate. The accuracy decreases with decreases of signal-to-noise ratio, the accuracy rate of MME algorithm is 8.6%, ANN is 59.8%，the proposed algorithm accuracy rate is 80.0% in S/N=-15dB. Above results show that detection performance of the proposed algorithm is significantly higher than the other two algorithms, which demonstrates the feasibility of our algorithm.

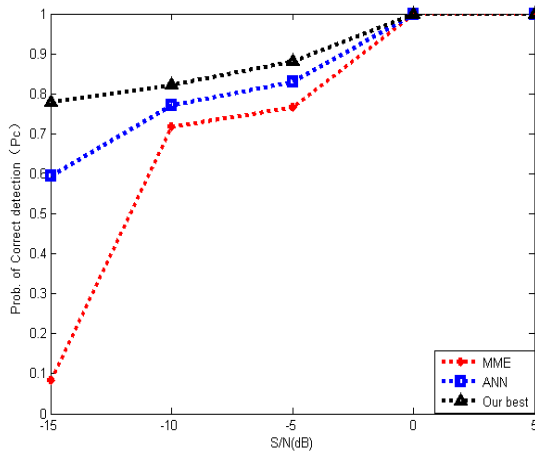| Signal Types	Correct rate%（S/N=-15dB）			Correct rate%（S/N=-5dB）		
	MME	ANN	Our Best	MME	ANN	Our Best
AM	18.3	69.6	82.1	82.3	85.4	93.2
BPSK	12.1	62.3	78.5	78.5	84.2	88.5
MSK	8.6	59.8	80.0	76.6	83.0	91.1

Fig 3. the accuracy rate of the different algorithms for MSK

VI. CONCLUSIONS

This paper focuses on the primary user signal detection issue in low SNR environment, presented primary user signal recognition method based on AL-ABM.The algorithm utilizes spectral correlation analysis in signal feature extraction and AdaBoost algorithm to treat primary user signal detection. Simulation results show that this algorithm can better improve the spectrum sensing performance of the primary user signal in low signal-to-noise ratio environment.

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