Cooperative Spectrum Sensing Performance Assessment using Machine Learning in Cognitive Radio Sensor Networks

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ABSTRACT

The Cognitive Radio (CR) is an imminent technology, intended to make more effective use of the available spectrum by giving access to licensed frequency bands by unlicensed Secondary Users (SUs) without affecting Primary licensed Users (PUs). Depending on the region where the energy is being observed, each CR communicates local decisions or the seen energy to the Fusion Center (FC). This study presents the many plots that discuss an enhanced double threshold through the Cooperative Spectrum Sensing (CSS) approach. The FC then combines local decisions with the measured energy values to reach a final decision. The usage of several machine learning methods in spectrum decision with the myopic decision is estimated. The system seeks to enhance the long-term overall performance of the SU.

Keywords-cognitive radio; energy detection; GMM; support vector machine; double threshold; Smith-Waterman algorithm; spectrum sensing

I. INTRODUCTION

Today's demand for wireless communication services is increasing explosively with the advancement of wireless communication technology and the development of the global economy. Cognitive Radio (CR) has been suggested to cope with the problem of spectrum sparsity due to the ineffective use of spectrum resources [1-2]. For example, CR technology allows Wireless Sensor Networks (WSNs) to dynamically access frequency bands with improved propagation characteristics, such as the Ultra-High Frequency (UHF) bands used for television broadcasting. A spectral gap in the UHF band, also known as the TV void, can be used to operate this CR-based WSN. The lower the frequency in this band is, the greater are the transmission range and power efficiency. The association of CR technology with WSNs has led to the Cognitive Radio Sensor Network (CRSN) paradigm.

Fixed threshold techniques are comparatively easy to implement but are prone to making erroneous decisions due to the variability of the noise signal. This impact in higher false-alarm and false-positive rates. False alarms refer to situations where a noise signal is incorrectly identified as the primary signal. Additionally, false alarms can be more precisely defined as the result of false positives. As a result, this leads to underutilization of spectrum resources as transmission opportunities are lost. False detection can also occur when the primary signal is misidentification for a noise signal. [3-4]. It is a highly unwanted state as it leads to an interruption of the primary user's transmissions. Error detection is also a false negative. When the decision threshold is fixed at a static level on top of the noise floor, the Fixed Threshold Technique (FTT) runs into another issue. A weak primary signal goes undetected below the threshold and secondary transmissions can cause harmful interference to primary users. Additionally, some FTT techniques require empirical analysis of spectral measurement data, making the threshold selection process very difficult to automate [5]. This is very impractical, especially for CRSNs where nodes must be fully autonomous without human intervention. Additionally, it is not always possible to have a priori knowledge of the noise variance and spectrum. Therefore, adaptive and autonomous thresholding methods are preferred for CRSN applications. This article proposes a new CSS scheme using Machine Learning (ML) techniques. Generally, the ML techniques are used for pattern classification. ML divides patterns into distinct classes by using feature vectors that are extracted from the patterns and are fed as input into a classifier [6]. In CSS, we treat the feature vector as an "energy vector," whose components are the estimated energy levels of each CR device. Depending on the kind of the learning approach used, classification algorithms can be either unsupervised learning, such as Gaussian Mixture Models (GMMs) and K-means clustering or supervised, such as State Vector Machines (SVMs) and K-Nearest Neighbors (KNN).

II. BACKGROUND WORK

The proposed CSS scheme uses the quantized energy levels to train a classifier and the acquisition report to calculate distance, thus determining the class label of the current acquisition report. This is different from the spectrum acquisition technique [7]. Instead of majority voting, we opted to utilize the approach of SWA, an efficient distance measurement algorithm, to compute the harmony between the present capture report and the training report. Based on thresholds determined by various fusion rules, authors in [8] proposed various classification schemes. This article uses different fusion rules in the fusion center. It considers the weight of distinct CR users before making a global decision. Focus is given on finding thresholds for various schemes, where KNN is used as the classification scheme. Also, the fusion rule of the proposed method basically uses the distance between training and test reports at the CR user level, while Fusion Center (FC) considers the historical veracity of each CR user. Therefore, FC's global fusion rules use each CR user's training reports and performance history. Global merge rules are therefore more robust and reliable.

III. SYSTEM MODEL

To estimate the probability density of the input for the given N input vectors in $\Re^d$ and M linear combination of basic functions we have:

$$P(x) = \sum_{j=1}^{M} p(x/j)\,p(j) \tag{1}$$

where $P(x)$ is the x^{th} density point, $p(x/j)$ is the j^{th} density component, and mixing coefficients are denoted by $p(j)$ which is the earlier likelihood that a data vector was created from the j^{th} mixing component.

A. Main Property

We consider M is large enough and the model's parameters are properly adjusted. We will just talk about the situation of a mixture of Gaussians:

$$p(x/j) = \frac{1}{(2\pi\sigma_j^2)^{d/2}} \exp\left(-\frac{\left\|x-\mu_j\right\|^2}{2\sigma_j^2}\right) \tag{2}$$

B. Training

The maximum likelihood technique will be used to evaluate the parameters of the mixture model $p(j)$, μ_j, and σ_j:

$$\begin{aligned} E &= -\ln L = -\sum_{n=1}^{N} \ln P(x^n) \\ &- \sum_{n=1}^{N} \ln\{ \sum_{j=1}^{M} p(x^n/j)\,p(j) \} \end{aligned} \tag{3}$$

When E is minimal, maximum likelihood L is achieved. The analytical solution (using Bayes theorem and Gaussian definition) is:

$$\frac{\partial E}{\partial \mu_j} = \sum_{n=1}^{N} p(j/x^n)\frac{\mu_j - x^n}{\sigma_j^2} = 0 \tag{4}$$

$$\frac{\partial E}{\partial \sigma_j} = \sum_{n=1}^{N} p(j/x^n)\{\frac{d}{\sigma_j} - \frac{\left\|x^n-\mu_j\right\|^2}{\sigma_j^3}\} = 0 \tag{5}$$

By the definition of the mixing coefficients as the "SoftMax function" (also called Gibbs distribution or normalized exponential), we have:

$$\begin{aligned} p(j) &= \frac{\exp(\gamma_j)}{\sum_{k=1}^{M}\exp(\gamma_k)} \qquad (\forall j \quad \gamma_j \geq 0) \\ \frac{\partial E}{\partial \gamma_j} &= -\sum_{n=1}^{N} p(j/x^n) - p(j) = 0 \end{aligned} \tag{6}$$

This system model leads to the following solution:

$$\hat{\mu}_j = \frac{\sum_n p(j/x^n)\,x^n}{\sum_n p(j/x^n)} \tag{7}$$

$$\hat{\sigma}_j^2 = \frac{1}{d}\frac{\sum_n p(j/x^n)\left\|x^n-\hat{\mu}_j\right\|^2}{\sum_n p(j/x^n)} \tag{8}$$

$$\hat{p}(j) = \frac{1}{N}\sum_n p(j/x^n) \tag{9}$$

To find the values of these interdependent parameters, standard nonlinear optimization must be used. Another practical solution is the algorithm of Expectation-Maximization (EM):

1. Estimate initial values
2. Calculate new values
3. Back to step one, until convergence

A local minimum is reached by the EM algorithm. It is helpful in a variety of circumstances in addition to the one just mentioned. As an example, let us assume that $L(\mu, \sigma)$ represents the likelihood as a function of deviation σ and standard expectation μ. Under certain convexity assumptions, we can maximize L by repetitively estimating, determining, and freezing. Figure 1 shows the proposed CSS framework. Majorly, it consists of two modules, namely classification module and training module, both working independently.

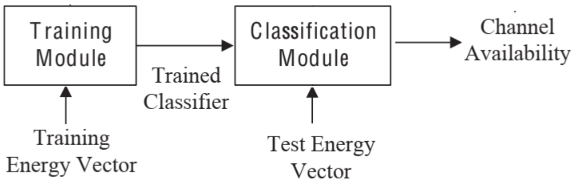

Fig. 1. The suggested CSS framework's structure.

When the classification module wants to determine the availability of a channel, the CRN constructs the test energy vector and provides it to it. The classification module resolves the channel availability using the classifier on the basis of the test energy vector. Finding a channel's availability in the CR network often takes just a few seconds. Due to their minimal complexity, the proposed CSS approaches' classification delays can satisfy these criteria [9]. The training module is important for providing the trained classifier in the classification module, as well as the training energy samples used to train the classifier. When the CRN first opens and when there are changes in the radio environment, the training module can be activated (for example, when the configuration of the PU network changes).

IV. THE PROPOSED CSS FRAMEWORK WITH ML TECHNIQUES

An enhanced adaptive double threshold scheme in energy detection that reduces the collision probability between PU and SU and improves spectrum utilization by reducing the false alarm probability is proposed [10]. This technique involves deciding the absence or presence of the PU using sub thresholds inside the uncertain region, between two thresholds. The uncertain region is the confused region, where no decision has taken about the availability of the PU. Repeated sensing is necessary, which increases the spectrum sensing cycles and hence the detection performance, which degrades. A suitable threshold determination procedure is employed in this module to reduce the spectrum sensing cycles and obtain better detection performance. Under a noise uncertainty environment, the thresholds determined in the above procedure are made adaptive based on the minimum and maximum noise variances to overcome noise uncertainty [11]. Furthermore, cooperative spectrum detection in CRN is expected to improve detection efficiency even in environments with fading and receiver uncertainty. A modified two-stage energy detector is used for local decision-making, while global decision-making is done by the coordinator. The proposed two-stage energy detection scheme alleviates the problem of spectral detection failure by using a single threshold in the first stage and an adaptive double threshold in the second stage. The performance of the improved two-stage energy detection scheme in cooperative spectrum acquisition is analyzed in terms of detection probability, error probability, and acquisition time.

CSS [12-13] is proposed to overcome node failure and fading problems. Each SU informs the FC of a local decision. The results of each CR are then combined by the FC using specific fusion rules H. The majority of the rules are OR and AND rules. The detection probability (Q_d) and false alarm probability (Q_f) of the OR rule linkage scheme are given in [14] as:

$$Q_d = 1 - \prod_{i=1}^{M} (1 - P_{di}) \quad (10)$$

$$Q_f = 1 - \prod_{i=1}^{M} (1 - P_{fi}) \quad (11)$$

where P_{fi} and P_{di} are the false alarm and detection probabilities of the i^{th} SU and M is the number of CR's participating in the CSS.

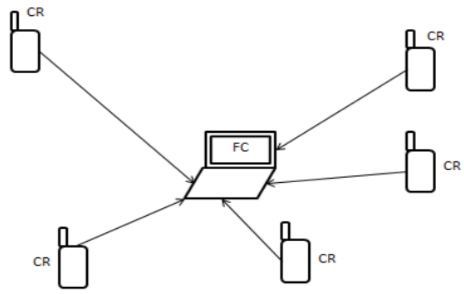

Fig. 2. CSS.

In conventional energy detectors each CR will makes local decisions based on a single threshold. The premise H_1 is correct if either the computed energy (X) or the measured energy (O_i) is higher than a certain threshold, otherwise the hypothesis H_0 stands. In the case of a double threshold energy detection approach, if the observed energy X is larger than 2, hypothesis H_1 holds true. If it is less than one, hypothesis H_0 holds true. No decision is made and CR will return to acknowledgment if the detected energy X falls between the two thresholds, i.e. $\lambda_1 < X < \lambda_2$. The threshold λ can be calculated by:

$$\lambda = Q^{-1}\left(P_{fa}\right)\sqrt{2N\sigma_w^4} + N\sigma_w^2 \quad (12)$$

Additionally, thresholds λ_1 and λ_2 are given by:

$$\lambda_1 = (1 - p)\,\lambda \quad (13)$$

$$\lambda_2 = (1 + p)\,\lambda \quad (14)$$

ML is typically used to achieve a solution to an optimization problem close to the optimal one, when the problem is too complex for conventional optimality analysis and it is unknown how to map the input data to the output (the answer to the problem). This kind of uncertainty in wireless communication systems results from noise (thermal, color, impulse, etc.) or other sorts of channel distortion or interference. In this article, we apply ML as a means of improving good sensing. ML-based detection techniques aim to detect frequency channel availability by developing the process as a classification problem. A classifier must determine its two states (empty or occupied) for each frequency channel, supervised or unsupervised. To determine channel availability, these classifiers make use of information like probability vectors and energy statistics.

V. SIMULATION RESULTS

Simulation research was conducted to assess the effectiveness of the ML energy detection method and the simulation results were used for evaluation. The classification error rate of the classifier is shown in Table I. The best weights obtained for SVM, KNN, and NB classifiers are 0.8873, 0.8691, and 0.2804 respectively. This shows that the SVM classifier has the most impact whereas the NB classifier has the least. Additionally, the outcomes demonstrate that the ensemble classifier minimizes the class 1 error as well as the overall error to 2.81%, thus reducing system risk [15]. Figure 3 shows the theoretical and simulation ROC (Q_d vs. Q_{fa} curves) performances for N=500 and 1000.

TABLE I. CLASSIFICATION ERROR RATE (%)

Classification methods	Total error rate	Channel unavailability class error rate
KNN	13.901	43.902
NB	14.347	28.206
SVM	12.182	85.365
Proposed	5.625	12.00

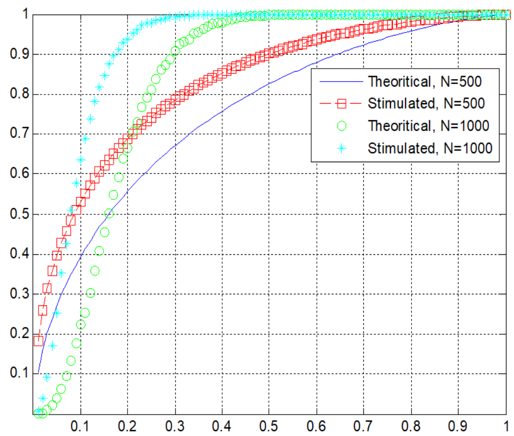

Fig. 3. Q_d vs Q_{fa} for a single energy detector.

Figure 4 shows the single-threshold and double-threshold ROCs (Q_d vs. Q_{fa} curves) at SNR = -5 dB for 200 samples. For this reason, the confusion area is not considered. For simplicity, we simulated that every CR used the same threshold λ and ρ = 0.1.

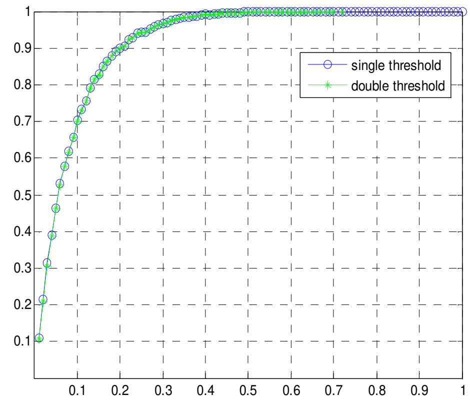

Fig. 4. Q_{fa} versus Q_d for a single energy detector.

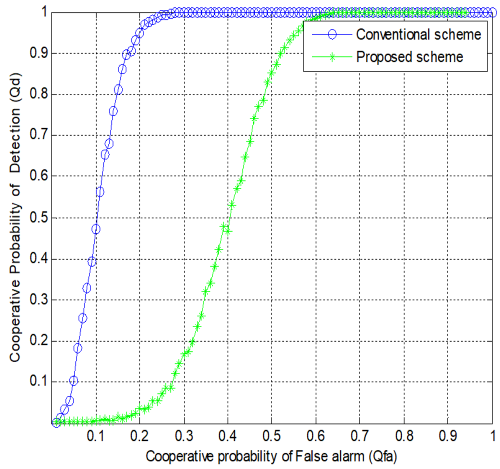

Fig. 5. Q_{fa} versus Q_d for a single energy detector.

We assumed M = 5 as the number of SUs involved in collaboration. Figure 5 clearly shows the advantages of the expected scheme over traditional CSS. The curve is drawn at SNR -8 dB with 100 samples. The proposed approach raises the detection probability for Q_{fa} = 0.1 by almost 10%.

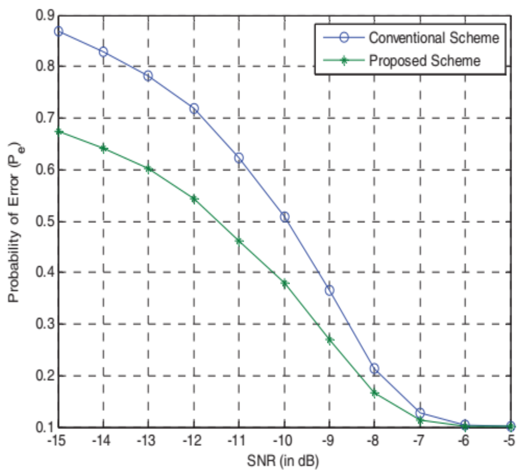

Fig. 6. P_e SNR (in dB).

Figure 6 shows the output waveform between the probability of decision error (P_e) and SNR by setting P_{fa}=0.1. It can be seen that the suggested technique minimizes the decision error in the low SNR range. Figure 7 shows the graph between P_e versus PU and SU positions. It can be seen that the designed scheme minimizes the decision error in the low SNR range.

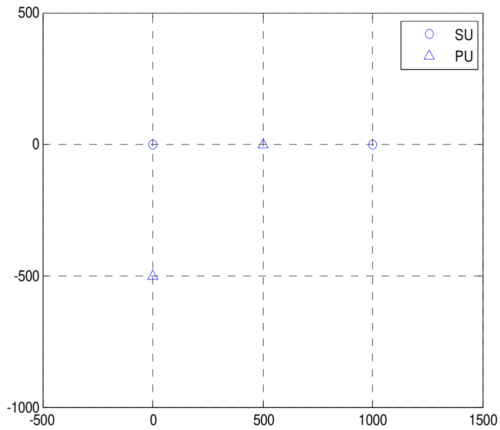

Fig. 7. PU and SU positions.

VI. CONCLUSION

CSS is an intelligent collaborative acquisition method. It has high measurement accuracy, is self-adaptive to the environment, and is more complex to operate than traditional joint measurement methods. The designed system learns from the situation the true state of the PU. The total error rates of KNN, NB, and SVM classifiers are 13.901, 14.347, and 12.182. Our proposed method reduced this metric to 5.625 and the channel unavailability class error rate (43.902, 28.206, 85.365) was also reduced to 12.00. Hence, the proposed system is able to make more effective use of the available spectrum, while seeking to enhance the long-term overall performance of the SUs.

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