

Primary User Transmit Mode Classification Based Spectrum Sensing in Cognitive Radio Network

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Abstract—Machine learning (ML) aided spectrum sensing is viewed as an alternative promising solution for cognitive radio (CR) systems in recent years. In this paper, a novel spectrum sensing scheme is proposed on the basis of various machine learning algorithms. Driven by the large number of spectrum observations collected from secondary user equipments (SUEs) in the cellular cognitive radio networks (CCRN), the proposed scheme first identify, by means of various ML classification algorithms, the transmit mode (TM) of the primary user (PU) transmitters in the CCRN to gain a coarse knowledge of the PU behaviors over the licensed spectrum. With the TM of the primary user transmitters (PUTs) ascertained, geo-location oriented spectrum opportunities can be subsequently pinpointed for SUEs in the CCRN. Simulations verify that the proposed scheme increases the spectrum access opportunity under the premise of minimizing the interference to the PUs.

Index Terms—Machine learning, spectrum sensing, classification, convolutional neural network, cognitive radio.

I. INTRODUCTION

Aiming to identify the status of the licensed spectrum and enable secondary access, spectrum sensing techniques have been extensively investigated for cognitive radio (CR) systems in recent years [1]. In order to guarantee that as less interference is generated to the primary user (PU) as possible, secondary user equipments (SUEs) in the cellular cognitive radio network (CCRN) can only gain opportunistic access to the licensed frequency band (LFB) when they detect no PU activity over it. However, the task of ascertaining the PU behavior with satisfactory accuracy is practically challenging if conventional spectrum sensing methods, e.g. energy detection (ED), are concerned, due to complicated radio propagation effects and the limited number of signal samples captured within a stringently short sensing interval.

In recent years, machine learning (ML) aided spectrum sensing is viewed as an alternative promising solution for cognitive radio (CR) systems [2]–[5]. For the purpose of strengthening the capability in squeezing the spectrum opportunities and suppressing the nuisance interference generated by the SUEs to the PU receivers, we propose in this paper a novel spectrum sensing scheme on the basis of ML algorithms, where the primary user transmitters' (PUTs') transmit mode (TM) is identified through classification. Based on the knowledge of the TM and the locations of the PUTs, the SUEs can easily assure themselves whether they can access the LFB or not.

Analysis and simulations verify that the proposed scheme increases the spectrum access opportunity under the premise of minimizing the interference to the PU.

II. SYSTEM MODEL

We consider a CCRN which dynamically shares the LFB with a number of PUs. It is assumed that N PUTs are serving their corresponding PU receivers in their proximity. The operating status of the PUTs can alternate between active and inactive states. Therefore, there are totally 2^N TMs for the N PUTs in the CCRN. Let s_n indicate the operating state (a.k.a transmit mode) of the n -th PUT. We have $s_n = 1$ if the n -th PUT is in the active state (i.e. the n -th PUT is transmitting over the LFB) and $s_n = 0$, otherwise. It is worth noting that once the PUTs' TM is identified by the SUEs, it is thus simple for the SUEs to know the radio transmission pattern over the LFB in the CCRN area.

Unlike the conventional spectrum sensing schemes merely relying on the currently received signal energy to make the decision on whether the LFB is accessible, the spectrum sensing scheme proposed in this paper tackles the problem in an entirely different mechanism. Specifically, the spectrum access opportunities of the LFB is identified based on the locations of the SUEs and the active PUTs, where the philosophical idea behind the proposed scheme is that if one SUE is sufficiently far away from the active PUTs, the probability of accessing the LFB with limited interference to the PU receivers is practically high.

Correspondingly, the target geographic area of the CCRN is initially divided into Q grids with the same acreage. Meanwhile, for any active PUT in the CCRN, the target geographic area can also be categorized into three kinds of regions according to the literature [6]: the PUT communication area (PCA) with a radius of D_u indicating the maximum communicating range that an active PUT can support, the PU receiver protection area (PRA) with a radius of D_p , and the SUE communication area (SCA) with a radius of D_s . For any SUE located in the PCA, the LFB is strictly forbidden to be used. If the SUEs are located within the PRA, access to the LFB in overlay mode is allowed, meaning that it is required for the SUEs to detect whether the PU signal actually exists in the LFB or not. When the SUEs are outside the PRA, the underlay mode is adopted for accessing the LFB, because the SUEs are in sufficiently large distance from the PU receivers,

and the interference generated to them is therefore sufficiently small or even negligible. In this sense, the SUEs can gain free and safe access to the LFB in the SCA region. The task of spectrum sensing now become the one of identifying the TM of the PUTs in the CCRN.

When the PUTs are operating under the l -th TM $S_l = \{s_1^{(l)}, s_2^{(l)}, \dots, s_N^{(l)}\}$ where $l \in \{0, 1, \dots, 2^N - 1\}$, the signal received by the SUEs in the q -th grid can be expressed as:

$$z_q(i) = \sum_{n=1}^N \sqrt{P_{TX}} s_n^{(l)} h_{n,q} X_n(i) + N_q(i), \quad q = 1, 2, \dots, Q \quad (1)$$

where i is the time index, P_{TX} refers to the identical transmit power of the PUTs, $X_n(i)$ is the transmit symbol of the n -th PUT, $N_q(i)$ denotes the additive white Gaussian noise (AWGN) with zero mean and variance of σ_0^2 , and $h_{n,q}$ represents the channel gain from the n -th PU to the q -th SUE¹, expressed as:

$$h_{n,q} = \sqrt{\text{PL}(\|\mathbf{C}_n^{\text{PUT}} - \mathbf{C}_q^{\text{SUE}}\|)} \cdot \nu_n, \quad (2)$$

where $\mathbf{C}_n^{\text{PUT}} = [C_{n,x}^{\text{PUT}} \ C_{n,y}^{\text{PUT}}]^T$ stands for the position of the n -th PUT, $\mathbf{C}_q^{\text{SUE}} = [C_{q,x}^{\text{SUE}} \ C_{q,y}^{\text{SUE}}]^T$ gives the position of the SUEs in the q -th grid, $\|\cdot\|$ is the Euclidean distance, $\text{PL}(d) = d^{-\alpha}$ is the path-loss component for relative distance d with the path-loss exponent α , and ν_n is the multipath fading component in accordance with Rayleigh distribution.

The energy sample obtained at the q -th SUE can be expressed as:

$$Z_q = \sum_{i=1}^{2w\tau} |z_q(i)|^2, \quad q = 1, 2, \dots, Q \quad (3)$$

where w is the LFB bandwidth and τ is the sensing interval². The energy samples Z_q obtained from all the grids can be organized in an $O \times P$ aggregate matrix:

$$\mathbf{Y}_k = \begin{pmatrix} Z_{11}^{(k)} & Z_{12}^{(k)} & \dots & Z_{1P}^{(k)} \\ Z_{21}^{(k)} & Z_{22}^{(k)} & \dots & Z_{2P}^{(k)} \\ \vdots & \vdots & \ddots & \vdots \\ Z_{O1}^{(k)} & Z_{O2}^{(k)} & \dots & Z_{OP}^{(k)} \end{pmatrix}, \quad O \times P = Q \quad (4)$$

where the entry $Z_{op}^{(k)}$ denotes the energy sample obtained in the k -th sensing operation from the (o, p) -th grid geographically indexed in the CCRN.

Since machine learning algorithms are employed to classify the current TM among the possible 2^N TMs, the CCRN is able to obtain the training set $\{\mathbf{Y}_1, \mathbf{Y}_2, \dots, \mathbf{Y}_K\}$ and the corresponding training label set $\{C_1, C_2, \dots, C_K\}$, where

¹In this paper the q -th SUE means anyone of the SUEs in the q -th grid. Since the grid is set small enough, the SUEs in the q -th grid would have almost the same radio propagation effects in the received signal and hence we just use the q -th SUE for simplicity.

²It is assumed that within the practically short sensing interval τ , the PUTs' TM is not varying.

$C_k \in \{0, 1, \dots, 2^N - 1\}$ denotes the PUTs' TM in the k -th sensing interval.

III. PUT TRANSMIT MODE CLASSIFICATION

Unlike the conventional energy detection based spectrum sensing schemes that do not care about the TM of the PUTs at all, but make the sensing decision directly based on the received signal energy, in this section, we introduce the transmit mode classification (TMC) algorithms in detail. Gaining awareness of the PUTs' TM in the CCRN is the first step in the proposed scheme towards identifying the spectrum access opportunity over the LFB for the SUEs eventually.

A. Energy-based TM Classification

In PUTs' transmit mode classification, the input of the proposed scheme is a matrix of currently obtained spectrum observation $\mathbf{Y}_k^*$ and the training energy matrix set $\hat{\mathbf{Y}} = \{\mathbf{Y}_1, \mathbf{Y}_2, \dots, \mathbf{Y}_{K \cdot 2^N}\}$ has been collected under all the PUT modes with the same signal-to-noise ratio (SNR)³. After the energy values are arranged in descending order, we can obtain the G -largest energy samples which may correspond to the grids of the active PUTs in the CCRN. If it is found that any two or more of the G energy values are within g neighboring grids, we only keep the larger value among them and then set the other samples to be zeros. In this way, the approximate positions of the active PUTs are obtained. Because the signal energy samples based PUTs' positions are inaccurate, in order to improve the accuracy of the PUTs' TM classification, the index rows and columns corresponding to the energy values are grouped into two sets $\mathbf{h}_1$ and $\mathbf{h}_2$. The TM for which the energy value of $\mathbf{Y}_k^*$ belongs to is selected from $\hat{\mathbf{Y}}$ with the smallest difference. Specific algorithm description is given in Algorithm 1.

B. K-means Clustering based TM Classification

In the proposed scheme, the unsupervised K-means clustering algorithm classifies the energy matrices in the training set into 2^N classes, where it is assumed that there are K energy matrices for each TM. Different from the ordinary K-means clustering algorithm that operates on vectors, we organize the test data in an $O \times P$ matrix as $\mathbf{Y}_k^*$. Supposing that Cluster l has a centroid $\mathbf{\Lambda}_l$, we can obtain the TM that the test data $\mathbf{Y}_k^*$ belongs to via the following formulas:

$$l_{\text{opt}} = \arg \min_{l=0,1,\dots,2^N-1} \sum_{i=1}^O \sum_{j=1}^P |\mathbf{Y}_k^*(i,j) - \mathbf{\Lambda}_l(i,j)| \quad (5)$$

and

$$\hat{S}_k = S_{l_{\text{opt}}} = \{\hat{s}_1^{(l_{\text{opt}})}, \hat{s}_2^{(l_{\text{opt}})}, \dots, \hat{s}_N^{(l_{\text{opt}})}\} \quad (6)$$

where $\mathbf{\Lambda}_l(i,j)$ denotes the l -th cluster's centroid indexed by the (i,j) -th element.

³It is assumed for simplicity that the transmit power P_{TX} is constant over time for any active PUT.

Algorithm 1 Energy-based TM classification**Input:** $\mathbf{Y}_k^*, \hat{\mathbf{Y}} = \{\mathbf{Y}_1, \mathbf{Y}_2, \dots, \mathbf{Y}_{K2^N}\}$, threshold φ **Output:** the PUTs' TM in the k -th sensing operation, $\hat{S}_k$

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1: Sort the input energy values in  $\mathbf{Y}^*$  in descending order
   to obtain  $\{Z_{x_1, y_1}, Z_{x_2, y_2}, \dots, Z_{x_Q, y_Q}\}$  and the corre-
   sponding position vector, row  $\mathbf{x} = \{x_1, x_2, \dots, x_Q\}$  and
   column  $\mathbf{y} = \{y_1, y_2, \dots, y_Q\}$ 
2: if  $(Z_{x_1, y_1} < \varphi)(Z_{x_2, y_2} < \varphi), \dots, (Z_{x_Q, y_Q} < \varphi)$  then
3:    $\hat{S}_k = S_0$  % TM  $S_0$  indicates all PUTs are inactive
4: else
5:   for  $i = 1 : G$ 
6:     for  $j = i + 1 : G$ 
7:       if  $(|\mathbf{x}(i) - \mathbf{x}(j)| < g) \& (|\mathbf{y}(i) - \mathbf{y}(j)| < g)$ 
8:          $Z_{x_j, y_j} = 0$ 
9:       end if
10:    end for
11:  end for
12:  The index rows and columns corresponding to the
   energy values of the spectrum observation matrix are
   grouped into sets  $\mathbf{h}_1$  and  $\mathbf{h}_2$ 
13:   $l_{\text{opt}} = \arg \min_{l=1,2,\dots,2^N-1} \left( \sum_{i=1}^{|\mathbf{h}_1|} |\mathbf{Y}_k^*(\mathbf{h}_1(i), \mathbf{h}_2(i))\right.$ 
14:     $\left. - \mathbf{Y}_l(\mathbf{h}_1(i), \mathbf{h}_2(i))\right|$ 
15:   $\hat{S} = S_{l_{\text{opt}}}$ 
16: end if
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C. HOG and SVM based TM classification

For classifying the PUTs' TM, the histograms of oriented gradient (HOG) and multi-classification methods can be combined together [7], [8]. In the proposed scheme, the HOG and support vector machine (SVM) based TM classification algorithm is implemented by using the HOG and the SVMs of the one-versus-all (OVA) coding scheme.

In obtaining HOG, a gradient in $g * g$ regions is used. In the OVA method, J binary SVM models are constructed for J classes where the j -th SVM, $\forall j \in \{1, 2, \dots, J\}$ is trained on any two classes of the labeled data set. The pair of classes are formed by assigning positive labels to all the data in the j -th class and assigning negative labels to the remaining training data not belong to the j -th class. It should be noted that the number of classes and the number of SVMs for the OVA method are equal. Table I shows a typical coding matrix for implementing the OVA scheme for the case $J = 8$.

D. Convolutional neural network based TM classification

The previously utilized algorithms belong to conventional machine learning based classification methods. In order to achieve high accuracy, more complicated algorithms can also be considered, e.g. convolutional neural networks (CNN) based classification algorithm [12]. The CNN structure we utilize hereby for TM classification consists of four transformation layers, starting with two consecutive convolution and pooling layers and followed by a dense and fully-connected layer. Table 2 gives details of the model structure and filter

TABLE I: Classification coding matrix in the OVA scheme

	l_1	l_2	l_3	l_4	l_5	l_6	l_7	l_8
j_1	+1	-1	-1	-1	-1	-1	-1	-1
j_2	-1	+1	-1	-1	-1	-1	-1	-1
j_3	-1	-1	+1	-1	-1	-1	-1	-1
j_4	-1	-1	-1	+1	-1	-1	-1	-1
j_5	-1	-1	-1	-1	+1	-1	-1	-1
j_6	-1	-1	-1	-1	-1	+1	-1	-1
j_7	-1	-1	-1	-1	-1	-1	+1	-1
j_8	-1	-1	-1	-1	-1	-1	-1	+1

TABLE II: CNN structure utilized in the proposed algorithm

Layer Type	Filter Size	Activation Function
Convolutional Layer (1)	3*3*32	ReLU
Convolutional Layer (2)	3*3*64	ReLU
Fully Connected Layer	1024 neurons	Softmax

size. The input is $\mathbf{Y}_k^*$ and the output is one classification label that determines the TM of $\mathbf{Y}_k^*$ among the possible 2^N TMs.

The convolutional layer and the pooling layer are feature extraction layers and they also serve as a core part of the CNN model. Accordingly, we obtain the output of the first convolution as:

$$\mathbf{O}_1(i, j) = \sigma((\mathbf{W}_1^v * \mathbf{Y}_k^*)(i, j) + b_1^v), v \in [1, \eta_1] \quad (7)$$

where η_1 is the number of convolutional filters in the first layer, $\sigma(\cdot)$ denotes the ReLU activation function, $\mathbf{W}_1^v$ and b_1^v are respectively the weighting matrix and the bias parameter utilized by the v -th filter of the first layer, and matrix convolution is defined as follows:

$$(\mathbf{W}_1^v * \mathbf{Y}_k^*)(i, j) = \sum_s \sum_t \mathbf{Y}_k^*(s + i, t + j) \mathbf{W}_1^v(s, t) \quad (8)$$

Similarly, the output of the second layer can be expressed as:

$$\mathbf{O}_2(i, j) = \sigma(\mathbf{W}_2^v * \mathbf{O}_1(i, j) + b_2^v), v \in [1, \eta_2] \quad (9)$$

where η_2 , $\mathbf{W}_2^v$ and b_2^v are, similar to Eq. (7), the parameters utilized by the second layer.

The output through the pooled and fully connected layers is:

$$\hat{S}_k = \sigma_1(\mathbf{W}_{\text{fu}} * f(\text{pool}(\mathbf{O}_2)) + b_{\text{fu}} I_F), \quad (10)$$

where $\mathbf{W}_{\text{fu}}$ and b_{fu} are respectively the weights and deviation of the fully connected layer, I_F is a column vector with its F elements all being one, pool represents the pooling layer, f is a flattening function, and σ_1 is the softmax activation function.

IV. SUE LOCATION BASED SPECTRUM OPPORTUNITY IDENTIFICATION

After obtaining the TM $\hat{S}_k = \{\hat{s}_1, \hat{s}_2, \dots, \hat{s}_N\}$ by means of any algorithm aforementioned, as shown in the following formula, the q -th SUE can obtain a flag A_q , which is equally a label of the LFB's availability for the q -th SUE, according to its distance to the nearest active PUT in the CCRN:

$$A_q = \begin{cases} 1 & \sum_{n=1}^N \|\mathbf{C}_n^{\text{PUT}} - \mathbf{C}_q^{\text{SUE}}\| \cdot \hat{s}_n < \|\hat{S}\|_0 \cdot D_u \\ 0 & \|\hat{S}\|_0 \cdot D_u \leq \sum_{n=1}^N \|\mathbf{C}_n^{\text{PUT}} - \mathbf{C}_q^{\text{SUE}}\| \cdot \hat{s}_n \leq \|\hat{S}\|_0 \cdot D_p \\ -1 & \sum_{n=1}^N \|\mathbf{C}_n^{\text{PUT}} - \mathbf{C}_q^{\text{SUE}}\| \cdot \hat{s}_n > \|\hat{S}\|_0 \cdot D_p \end{cases} \quad (11)$$

where $\|\cdot\|_0$ is the l_0 -norm. As for the label A_q , $A_q = 1$ means that the q -th SUE is strictly prohibited to access the LFB, $A_q = 0$ implies that the q -th SUE is located in the obscure area that the q -th SUE's transmission might cause interference to the potential PU receivers in its neighboring area, and $A_q = -1$ claims that the q -th SUE is sufficiently far away from any active PUT in the CCRN and hence it could freely gain access to the LFB without yielding any interference to the PU receivers in the proximity of the active PUTs.

V. SIMULATION AND ANALYSIS

Computer experiments are carried out to evaluate the algorithms employed for TM classification. As shown in Figure 1, we consider a CCRN covering $12\text{km} \times 12\text{km}$ area and consisting of 14400 grids, where each grid is with the size of $100\text{m} \times 100\text{m}$. The PU signal bandwidth w is 5 MHz, the sensing duration τ is 100 μs , and the path-loss exponent α is 4. As for the algorithm parameters, we have $G = 8$ and $g = 4$ for the energy based TM classification algorithm and $g = 8$ or 16 for the HOG algorithm. In computer simulations, the number of training data is the same with that of the test data. MATLAB (R2017a) is used in a 64-bit computer with an i5 processor (clock speed of 3 GHz) and 8 GB RAM.

Figure 2(a) shows the accuracy of PUTs' TM classification for the case of SUEs being uniformly distributed in the CCRN, where 11.1% of the total grids are under consideration for spectrum observation collection. Compared with the traditional Gaussian mixed model (GMM) [2] and AdaBoost (ada) algorithms [9]–[11], the proposed CNN algorithm performs better. Fig. 2(b) presents the performance of TM classification accuracy, where the spectrum observation data are collected from the SUEs normally distributed near their serving base stations and about 47.4% of the total grids are selected. Compared with the case of uniformly distributed SUEs, the performance of the proposed CNN algorithm with the case of normally distributed SUEs is better, and as straightforwardly expected, the classification accuracy is higher under large transmission power. Figure 2(c) shows the TM classification accuracy in the case that all SUEs in the CCRN contribute to providing sensing data. In this case, the CNN algorithm is slightly improved compared to the case shown in Fig. 2(b), and

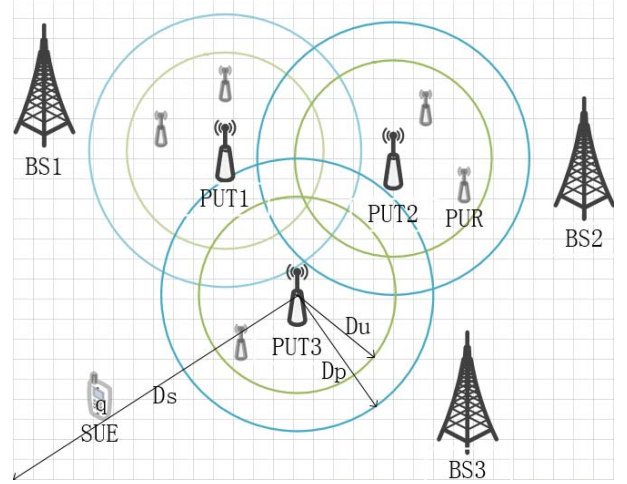


Fig. 1: BSs and PUTs position distribution

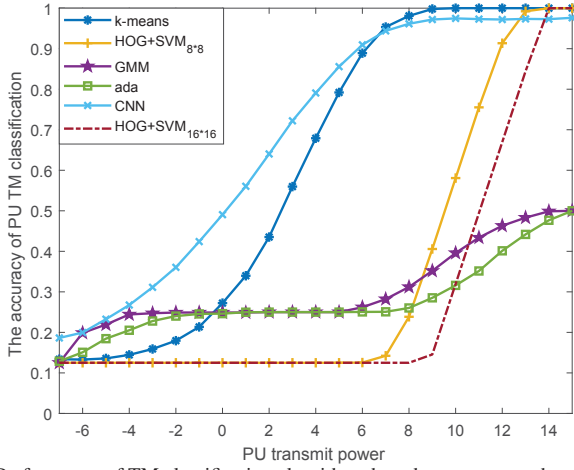
the classification accuracy is about 100% in the case of high transmission power. It can be easily seen from Figure 2 that as the number of SUEs participating in collecting spectrum data increases, the accuracy of PUTs' TM classification also increases. Therefore, the observation data obtained from the SUEs normally distributed near their serving base stations are selected to identify the PUT transmission mode.

Figure 3 gives the label diagram obtained on the basis of the SUEs-PUTs distance metric described in Eq. (11). The green region in Fig. 3 represents the grids obtaining label $A_q = 0$ in spectrum sensing, the yellow portion is for the grids with label $A_q = 1$, and the blue region is for the grids with label $A_q = -1$. In the traditional scheme, $A_q = -1$ is chosen only when the PUT transmission mode is S_0 , and $A_q = 1$ is set for any other. It can be seen from the figure that when there is any PUT active in the CCRN, the SUEs in TMs $\{S_1, S_2, \dots, S_{2N-1}\}$ still have the opportunity to access the LFB while protecting the PU receivers from being interfered as much as possible.

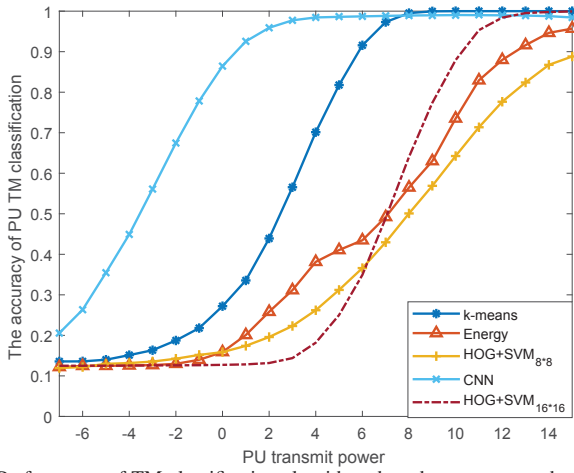
Figure 4 shows the capability of the proposed scheme in ameliorating the spectrum access opportunities. Since traditional spectrum sensing scheme enables the SUE to access the LFB only when all PUTs in the CCRN are decided in detection as inactive, which is equally the TM S_0 , a large number of spectrum opportunities under TMs $\{S_1, S_2, \dots, S_{2N-1}\}$ are unnecessarily wasted. However, the proposed scheme still has the opportunity to access the LFB when the PUTs are active in the CCRN, which improves the spectrum utilization efficiency.

VI. CONCLUSION

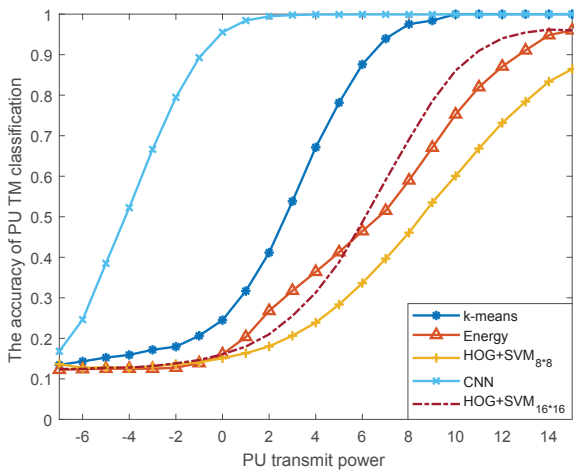
In this paper, we propose a novel spectrum sensing scheme based on the mechanism of PUTs' transmission mode classification. By means of partitioning the CCRN into multiple grids, the transmission mode of the PUTs is first determined via various machine learning based classifiers, and then the labels that control the SUEs to access the LFB in the CCRN are drawn through evaluation of the distances from the SUEs to the active PUTs. Simulation results show that the proposed scheme



(a) Performance of TM classification algorithms based on spectrum observations collected from uniformly distributed grid(11.1%)



(b) Performance of TM classification algorithms based on spectrum observations collected from normally distributed grid near the base stations(47.4%)



(c) Performance of TM classification algorithms based on spectrum observations collected from all grids (100%)

Fig. 2: PU state prediction accuracy

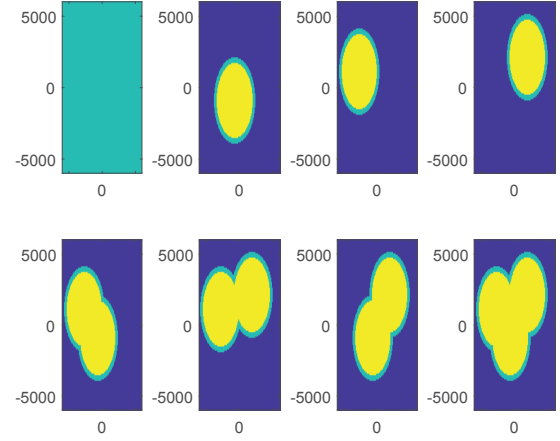
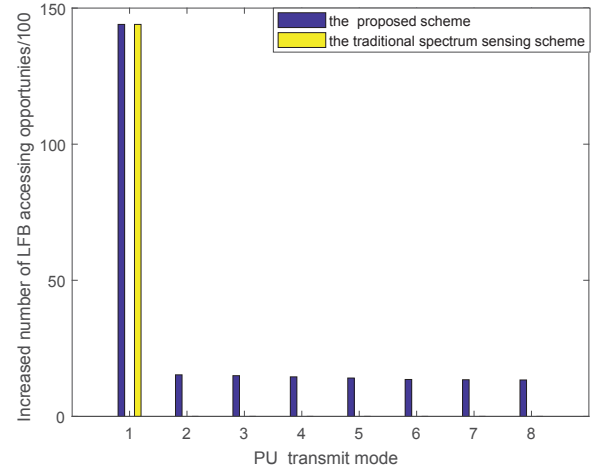

 Fig. 3: Label map with the transmit power $P_{TX} = 43$ dBm


Fig. 4: Increased number of LFB accessing opportunities in different PU transmission modes

achieves different levels of transmission mode classification accuracy with different machine learning based classification algorithms. Compared with the conventional energy detection based sensing scheme, the proposed scheme improves the spectrum utilization efficiency significantly under the premise of minimizing the interference to the PU.

VII. ACKNOWLEDGEMENT

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