Machine Learning Techniques Based Spectrum Sensing In Crn

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Abstract: Cognitive radio technology can mitigate the problems that faced during the spectrum allocation such as depletion of spectrum due to the advancement in new technologies like IoT and 5G technology. The hidden primary user problem is a serious issue faced by cognitive networks, since the secondary user can misclassify the spectrum occupancy. Thus, this problem stated using cooperative spectrum sensing based on machine learning techniques. The machine learning techniques includes Gaussian Mixture Model (GMM) and Support Vector Machine(SVM) where GMM technique is an unsupervised learning technique and SVM is a supervised learning technique. The above techniques have two phases(classification and training phase), which decides the channel available and channel unavailable class. Gaussian Mixture Model is used to determining the training features with the mixture of gaussian density distribution. Support Vector Machine has subset of training vectors with which the decision surface is made. It is done by maximizing the margin between separating hyperplane and training vectors. The receiver operative curve for above gaussian model is obtained. The obtained results verifiesthe factors of hidden primary user as overlap of data distribution and transmit power level .

Keywords : Cognitive radio, Cooperative spectrum sensing, Gaussian Mixture Model, Support vector machine, hidden primary user detection

I. INTRODUCTION

As the bandwidth of frequency spectrum employed in modern wireless communication systems is fixed and on the other side the number of wireless devices is increasing rapidly. To overcome the spectrum scarcity, the unused frequency bands are accessed by secondary users (SU's) without interfering with primary users (PUs). These unused licensed frequency bands of primary users (PUs) or primary systems technically known as white spaces or spectrum holes. The only innovative approach to access these white spaces without creating any interference to the primary users (PUs) is cognitive radio (CR). While coordinating to access the frequency channel, the transmitting parameters should be changed in order to overcome the interference with the PUs. Spectrum sensing (SS) is the important task to enable dynamic spectrum access without interfering with PUs. Cognitive radio (CR) is an intelligent radio of wireless communication in which a transceiver identifies which communication channels are busy and which are free, and immediately move into empty channels while avoiding occupied frequency channels [7]. This optimizes the utilization of available radio frequency (RF) spectrum while mitigating the interference to other PUs by identifying and utilizing only the white spaces [1]. CR is a modern technology that is developed on SDR platform.Functions of cognitive radio includes the ability of a transceiver to decide its geographic location, Identify and authorize its user, Encrypt or decrypt signals , to Sense adjacent wireless devices in operation and Adjusts its output power and modulation characteristics. There are two categories of cognitive radio (CR). They are Full cognitive radio(Full CR) considers all parameters that a wireless network or node can be aware off and Spectrum sensing cognitive radio (Spectrum sensing CR) is used to identify channels in the radio frequency (RF) spectrum. There is a provision for accessing the unutilized parts of the Radio Frequency (RF) spectrum for public use as per the decision made by the Federal Communications Commission (FCC). There is a requirement of white space devices which should contain advanced technologies to block interference. The proposal for CR was enhanced by J.Mitola at the DARPA in US. Full CR can be called as "Mitola radio."Cooperative Spectrum Sensing (CSS) can be used in distributed cooperative radios. The reliability of CSS technique is higher than individual spectrum sensing technique. When a single secondary user accesses the spectrum, it cannot the solve the hidden primary user.hence to handle this CSS scheme share the received power among the secondary users. To determine the channel availability with changing transmit power level of primary user machine learning techniques are incorporated with the CSS technique. The machine learning has more flexibility towards the decision boundary

In this paper, Machine based cooperative spectrum algorithm is performed to find the decision boundary sot that channel states can be classified based on it. This proposed system determines the channel states as channel available and channel unavailable states. The following techniques has two phases one is training phase and classification phase. In this paper we use both the supervised and unsupervised learning methods. Under unsupervised learning we use Gaussian Mixture Model and in supervised we use Support Vector MachineThe rest of the model is organized as follows. In Section II,we propose the system model and the design. The machinelearning-based cooperative spectrum sensing frameworkis presented in Section III. Then, we describe proposed framework andexperimental results algorithms in Sections IV and V, respectively.

II. SYSTEM MODEL AND PROBLEM DESIGN

We consider a cognitive radio network with primary users and secondary users. Secondary users in cognitive network share the unused frequency channels of primary user. The received power of each secondary user is calculated by each user and the energy level is reported to the fusion center for cooperatively sensing the spectrum.And the fusion center decides the channel availability basedon decision boundary which is calculated from different energy level of secondary user. In this paper we classify primary user between the active and inactive states. There areM primary users, each of which is indexed by m = 1, . . ., M.Let c_m^{PU}denote the coordinate of PU m in the two-dimensionalspace. Let $S_m$indicate the state of PU m. We have S_m= 1 ifPU m is inthe active state (i.e., PU m transmits a signal); andS_m= 0 otherwise. Let S = (S_1, . . ., S_M) T be the vector ofthe states of all PUs, where the superscript T denotes thetranspose operation. The probabilitythat S = s for givens = (S_1, . . .,S_M) Tis denoted by v(s) =P_R[S = s]. (1)

The channel is considered to unavailable and the secondary users in the CR network cannot access to it if there is a presnce of primary user.let A denote the channel availability, we have

$$A = \begin{cases} -1, & S_m = 1 \, for \, some \, m \\ 1, & S_m = 0 \, for \, all \, m \end{cases} \quad (2)$$

ENERGY DETECTION

Let Zn (i) denote the ith signal sample takenby SU n. The signal samples consist of the summation of thesignals from all PUs in the active state and the thermal noiseis,

$$Z_n(i) = \sum_{m=1}^{M} s_m h_{m,n} x_m(i) + N_n(i) \quad (3)$$

Where $x_m(i)$ is the signal transmittedby PUm , $h_{m,n}$is the channel gain obtained from PUm to SU , $N_n(i)$ is the thermal noise at SU $and\ S_m$is the channel availability which isdetermined by primary user state. The transmission power of PU m isassumed to be fixed to $\sum_{i=1}^{BT} \mathrm{E}[|Xm(i)|2]/T$ and thenoise spectral density is denoted by η = E[|N_n(i)|^2]. WhereB isthe total bandwidth of the spectrum and T is the time duration of the samples.energy detector of SU n estimates the energy level normalizedby the noise spectral density,

$$Y_n = \frac{2}{\eta} \sum_{i=1}^{BT} \mathrm{E}[|Zn(i)|2] \quad (4)$$

Under the condition S=s the Y_n follows noncentral chi-square distribution with degree of freedom q=2BT and no centrality parameter

$$\zeta_n = \frac{2\tau}{\eta} \sum_{m=1}^{M} s_m g_{m,n} p_m \quad (5)$$

where $g_{m,n}$is the power attenuation from PU m to SU n suchthat $g_{m,n}$ = |$h_{m,n}$|^2 The power attenuation $g_{m,n}$is given as

$$g_{m,n} = P_L(\|C_m^{PU} - C_n^{SU}\|) \,.\, \Psi_{m,n}.\, v_{m,n} \quad (6)$$

Where $\Psi_{m,n}$ is the shadow fading component and $v_{m,n}$ is the multipath fading component.

III. COOPERATIVE SPECTRUM SENSING WITH MACHINE LEARNING TECHNIQUE

Operation of cooperative spectrum sensing technique

The received energy vectors Y of all the secondary user are estimated by the each secondary user. The data of energy vector is passed on to the fusion center and fusion center shares the information to all other secondary user so that sensing of spectrum happens cooperatively .The training energy vectors are collected for all the samples. The classifier is trained using the training energy vectors. The training energy vectors differs for different machine learning techniques. Toreceive the test energy vector for classificationthe classifier is successfully trained. The classifier classifies the channel class as channel available and channel unavailable class. The channel available class determine that there is no primary user accessing the spectrum currently and channel unavailable class state shows that the primary user is currently accessing the spectrum and the secondary user cannot access the spectrum. The proposed system of cooperative spectrum, can adaptively change according to changing environment. The proposed training vector is fully autonomous hence does not require any prior information.

IV. PROPOSED FRAMEWORK

We consider a primary and two secondary userin the cognitive networks

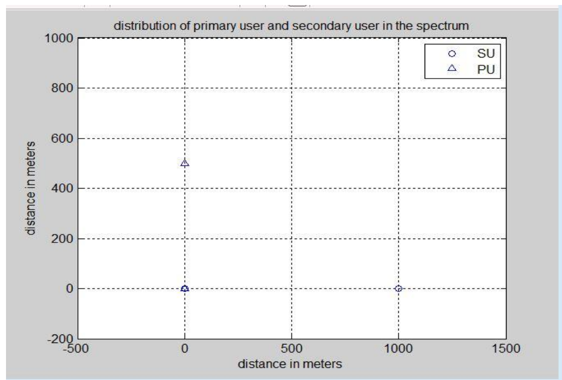


***Fig 1** Represents the distribution of primary and secondary user in the spectrum*

A. Unsupervised learning algorithm
(Gaussian Mixture Model)

- The gaussian mixture model is needed forDetecting channel availability more promptly ,Higher primary user detection capabilityand lower training and classification delay.A Gaussian Mixture Model (GMM) is a parametric representation of a probability density function, based on a weighted sum of multi-variate Gaussian distributions. GMMs are commonly used as a parametric model of the probability distribution of continuous measurements. GMM parameters are estimated from training data using the iterative Expectation-Maximization (EM) algorithm estimation.An Expectation–Maximization (EM) algorithm is an iterative method for finding Maximum Likelihood estimation parameters in statistical models, where the model depends on unobserved latent variables.EM Algorithm consists of two major steps: one is the E (Expectation) step and other isM (Maximization) step
- E (Expectation) step

In the E-step, the expected value of the log-likelihood function is calculated using the observed data and current estimate of the model parameters

- M (Maximization) step:

The M-step computes the parameters which maximize the expected log-likelihood found on the E-step. These parameters are then used to determine the distribution of the latent variables in the next E-step until the algorithm has converged.

EM ALGORITHM

Mean and covariance of cluster 1 are set to zero

$$\mu_1(1) \leftarrow \mu_{Y|S=0}$$
$$\sum_1 1 \leftarrow \sum Y|S = 0 \quad (7)$$

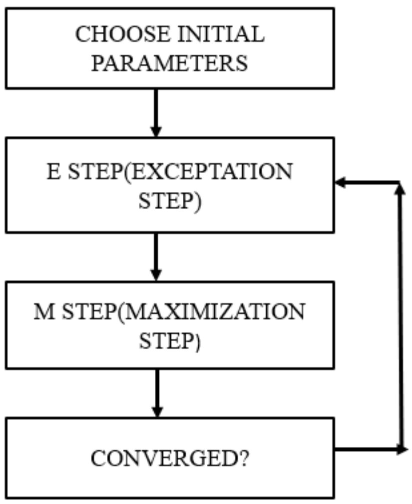
Initialize $v_k(1)$ for k = 1, . . .,Kand $\mu_k(1)$ and $\sum_k(1)$for k = 2, . . .,K.When j tends to 1 repeat the process. The Expectation Step is as follows

$$\mu_k^{(l)} \leftarrow \frac{v_k(j).\emptyset(y^l|\mu_k(j),\Sigma_k(j))}{\sum_{i=1}^{K} v_i(j).\emptyset(y^{(l)}|\mu_i(j),\Sigma_i(j))} \qquad (8)$$

For l=1,,.,L and k=1,…,K and l training energy vector.Maximization step is done next

$\mu_k(j+1) \leftarrow \frac{\sum_{l=1}^{L}\mu_k^{(l)}y^{(l)}}{\sum_{l=1}^{L}\mu_k^{(l)}}$ for k=2,….,K (9) . The process is continued until θj converges to j= j+1 .

EM ALGORITHM FLOW



SUPERVISED LEARNING ALGORITHM

Support Vector Machine

Support Vector Machine (SVM) is a supervised machine learning algorithm which can be used for both classification or regression challenges.It is mostly used in classification problems.We plot each data item as a point in n-dimensional space (where n is number of features you have) with the value of each feature being the value of a particular coordinate. Then, we perform classification by finding the hyper-plane that differentiate the two classes very well.

V. EXPERIMENTAL RESULTS

In this section to show feasibility of proposed schemes the bandwidthBis 5 MHz, the sensing duration Tis 100 μs, the noise spectral density η is−174 dBm, and the path-loss exponent α is 4. We assume that the shadowfading and the multi-path fading components are fixed as $\psi_{m,n}$= 1 and$N_{m,n}$= 1. The primary user is located in the sensing coverage of secondary user 1 and secondary user 2. The transmit power of primary are assumed to be 220 mW and 80mW

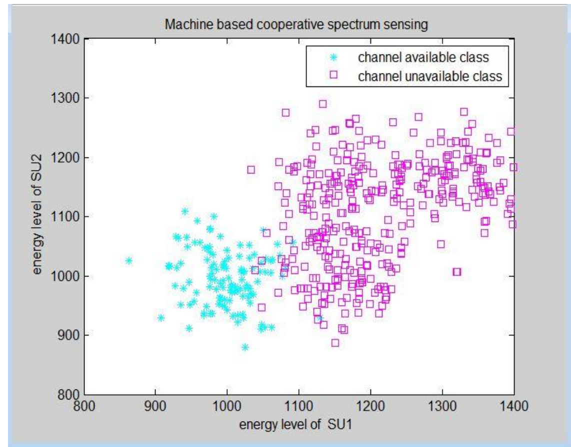


Fig 2 *When the transmit level of primary user is 220mW*

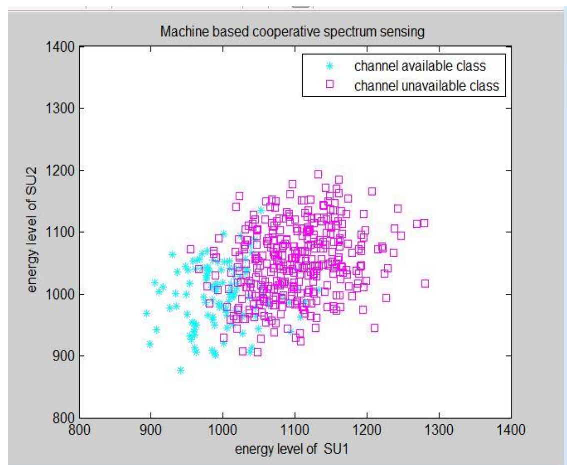


Fig 3 *When the transmit level of primary user is 80mW*

The above two figure states that the data distributions of secondary user 1 and secondary user 2 depends upon the transmit level of primary user . If the primary user is within the coverage limit of secondary user and it has higher transmit power then there will be less overlap of data distribution and if it is of lower transmit power overlap of data distribution occurs and causes the secondary user to misclassify the spectrum occupancy

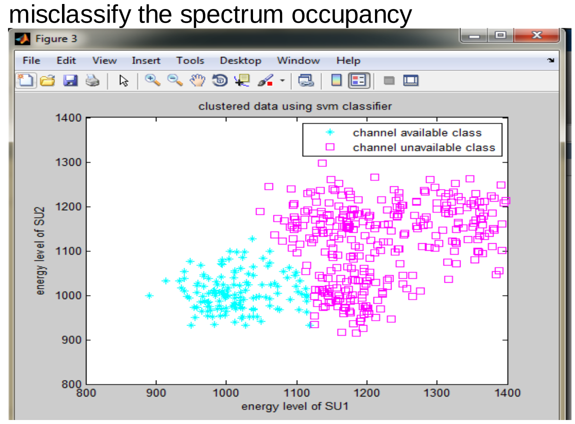


Fig 4 *Clustered channel classes after drawing decision boundary using SVM classifier when transmit power level of PU is 220mW*

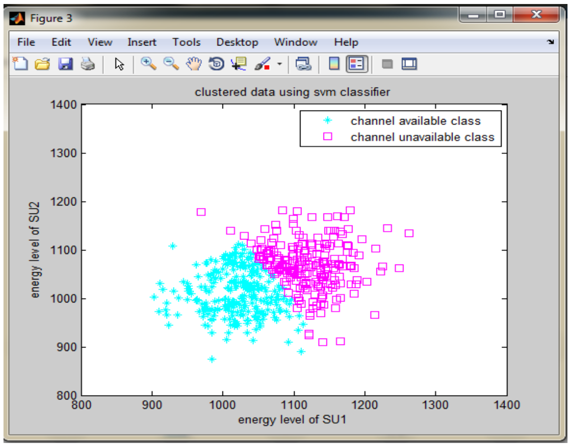


***Fig 5** Clustered channel classes after drawing decision boundary using SVM classifier when transmit power level of PU is 80mW*

In the above two figure the channel are classified into channel available and channel unavailable class which determines the state of primary user . The channel available states and unavailable are clearly classified and it is easy determine the channel class .This separation of channel class is done using gaussian mixture model .

VI. CONCLUSION

In this paper, we investigate the hidden primary user problem and it is solved using the machine learning based cooperative spectrum sensing in cognitive radio networks. It is verified that hidden primary user causes overlap of data distribution which causes the secondary user misclassify the spectrum occupancy Experimental results shows that the hidden primary user can be found by using the machine learning based cooperative spectrum sensing

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