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LEARNING BASED COOPERATIVE SPECTRUM SENSING FOR PRIMARY USER DETECTION IN COGNITIVE RADIO NETWORKS

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Abstract

In Cognitive Radio Networks (CRN) spectrum sensing plays an important role in achieving spectrum utilization fast and accurately. Due to interference, power levels and hidden terminal problem, it becomes challenging to detect the presence of primary users accurately with better spectrum efficiency. Thus detection of primary users has become an important research problem in cognitive radio network. In this paper proposed a learning methods to detect the presence of primary user with high accuracy. The proposed classifiers has been trained using the extracted features to detect PU's signal in low SNR condition. The Support vector machine (SVM), wavelet transforms, K-Nearest-Neighbour (KNN) and Reinforcement Learning-based classification techniques are implemented for Cooperative Spectrum Sensing (CSS). This approach is based on training learning models with energy vectors in presence and absence of primary users. The results provides the analysis of the learning techniques in accordance with Receiver Operating Characteristics (ROC) and shown the finest learning model for accurate primary user detection.

Keywords:

Cooperative Spectrum Sensing, Support Vector Machine (SVM), Wavelet Transforms, K-nearest-Neighbour (KNN), Reinforcement Learning and Receiver Operating Characteristics

1. INTRODUCTION

Effective spectrum utilization is achieved in Cognitive Radio Networks (CRN) though the use of spectrum resources when they are not utilized. Though use of primary users (PU) resources when they are free is entertained in CRN, it is also necessary that primary users have the highest priority for the resources and use of spectrum by cognitive users or secondary users (SU) must be stopped as soon as the primary user becomes active. This necessitates high accuracy spectrum sensing scheme. Towards this different solutions have been proposed in literature survey. From physical layer view the spectrum sensing can be divided into three categories as

- Non – coherent detection
- Coherent detection
- Future detection

The received signal energy with a sampling period is compared with threshold to determining primary user presence in case of non- coherent detection. The non- coherent detection is the energy detection and well popular detection. It is a short sensing time and low complexity. It does not need any prior information of PU because of uncertainty of noise. Coherent detection is a Matched filter method compare the channel response of received signal with knowledge of the transmitted signal. The approach has higher computational complexity and performance degradation during rapid change in channel response. Future detection is the Cyclostationary feature extraction method utilizes the properties of PU. This approach is easily separate the signal and noise and has low accuracy due to timing error and frequency offset. Energy detection approaches are found to effective among all above discussed methods. Hidden terminal problem is most challenging problem pulling down the accuracy of energy detection approaches. Cooperative spectrum sensing mitigate the accuracy degrades due to hidden terminal problems. In case of Cooperative spectrum sensing scheme, a fusion center makes the decision of PU activity based on multiple cognitive radio users (CRU). Each CRU makes decision using energy based scheme. In the proposed paper, an attempt is made to ensemble machine learning model for PU detection and to provide an efficient spectrum sensing.

A new fusion algorithm with different features are used for each of the classifiers to detect the accuracy of each classifier as a part of hybrid classifier. The accuracy is increased by aggregation of distributed clustering than energy detection. The weights for each ensemble classifier are calculated through continues learning; because of this, the solution is able to adapt dynamically to the deployed environment and the solution is adaptive. The simulation results comparing with other techniques in terms of performance matrix and receiver operating characteristics (ROC). Instead of fusion rules, machine learning ensemble methods are used to make the final decision. Due to use of machine learning, the accuracy of primary user status detection is improved in presence of hidden terminal problem, multipath fading, background interference, randomness and uncertainty. The weight learning procedure for ensemble was not optimal to achieve the highest accuracy in spectrum sensing. In addition to this Reinforcement learning approaches are found to have better adaptivety to environment. In this work, to replace the weighted ensemble with reinforcement learning based ensemble to have a better adaptivity to environment and have improved accuracy.

2. SURVEY

Authors in [21] presented an extensive review on application of reinforcement learning in context of cognitive radio networks. Multiple Q learning models are discussed and open issues on improving the performance of spectrum sensing with Q learning is discussed in the work. Q-Learning based reinforcement was proposed for detecting of primary user in [3]. The objective function of Q-Learning is defined based on signal strength to detect the presence of PU signals. Authors in [4] propose a new model based on reinforcement learning for cooperative sensing in cognitive radio adhoc networks. In the proposed work SUs to learn the optimal set of cooperating neighbours and their report sequence while minimizing total cooperative sensing delays and energy inefficiency. Since each SU has to do spectrum sensing the complexity is high in this approach. A novel spectrum sensing algorithm based on comparing the ratio of signal energy corresponding to maximum and minimum SNR to the received signal is proposed in [5]. It is a three step algorithm. At first it an over-sampled signal of total duration equal to the symbol period is combined linearly. Second, SNR maximization as Rayleigh quotient optimization is done on the combined signal. Third, by using the solutions of these problems, the ratio of the signal energy corresponding to the maximum and minimum SNRs are proposed as a test statistics. Though the solution is robust against noise variance uncertainty it fails in absence of knowledge on transmitter pulse shaping filter. The sensing delay in conventional cooperative sensing scheme is reduced in [6]. The reporting times of CRU and Cluster Heads (CH) are merged with the sensing time slots of CRU to sense the spectrum accurately. Sensing performance is improved due to this merger. Fusion based effective spectrum sensing scheme is proposed in [7]. Results from multiple CRU's are aligned using Smith–Waterman algorithm to detect any outlier or misbehaviour before making a decision on status of primary users.

Cooperative fusion using machine learning proposed in [8]. Energy statistics based training dataset is created. Using this dataset KNN, SVM. Naïve Baiyes and Decision tree classifier are trained. Machine learning based fusion is found to give better accuracy. Pattern classification based cooperative spectrum sensing is proposed in [9].The method used received signal strength as features. Monte Carlo simulation is done to collect training samples. The classifier trained using these samples were found to be accurate but the method must be tested against real time datasets. Cluster based sequential cooperative spectrum sensing (SCSS) schemes proposed in [10]. The approach reduces the network overhead in transmission of reports from CRU to fusion center without affecting sensing performance. The reduction of network overhead is made possible with clustering based aggregation and avoidance of transporting redundant information. Genetic algorithm (GA) based spectrum sensing in Cognitive Radio is proposed in [11]. GA finds the best value for bandwidth, signal to noise ratio and bit error probability. The sensing is done with the optimized parameters found using genetic optimization. A blind energy based spatial spectrum sensing algorithm is proposed in [12]. This approach can work without knowledge of noise power which is quite different from conventional energy based spectrum sensing schemes. Using the difference of received signal energies among sector, the presence or absence of PU signal is detected. This method is able to solve the noise uncertainty problem and able to achieved increased accuracy with low computational complexity. A spectrum sensing scheme based on cost function is proposed in [13]. This cost function uses test statistic a new cost-function that defines a new test statistic based on data from multiple CRU is proposed in the work. This function yields a binary decision on presence or absence of PU signals.

The performance of the solution degrades under hyper Rayleigh fading channels. An optimal threshold detection scheme for energy based sensing detection is proposed in [14]. The threshold is calculated using objective function which minimizes the error probability expressed in terms of missed detection and false alarm. A spectrum sensing scheme using the principles of matched filter is proposed in [15] [23]. This scheme works for PU operating at multiple transmit level. The SNR wall problem in energy detection approaches is solved in [16]. The cooperation of multiple receivers is used to detect the primary user activity. The detection threshold evaluation method proposed in the work is able to achieve a significant improvement on the probability of detection under the presence of noise uncertainty. A spectrum sensing scheme using principles of cooperation for the case of multiple PU and CRU is proposed [17]. At CRU energy detector based decision is made and send to AP, which analyses it to detect the presence of primary channels. In [18] a sequential sensing technique is adapted to reduce the sensing time to its minimum value while maintaining the desired detection performance. Due to the weak PU signal the sensing time could be still unacceptably long, particularly in non-Gaussian noise. A novel sequential sensing scheme based on supra-threshold stochastic resonance is proposed in [19]. Spectrum sensing using wavelet transform is proposed in [20]. The sampling is done using compressed sensing scheme and the result is transformed using wavelet. The transformed wavelet coefficients are thresholded to detect primary user. Adaptive thresholding with forward consecutive mean excision (FCME) algorithm is used for thresholding the energy levels. Cooperative Power spectral density Split Cancelation is proposed in [21]. Fourier transform is applied on the sensed signal to get the stochastic properties of the power spectral density. The primary user channels are detected by applying threshold on power spectral density.

3. PROPOSED METHODOLOGY

The proposed Methodology for spectrum sensing uses clustering architecture. Each of CRUs are grouped into clusters using low energy adaptive clustering hierarchy centralized (LEACH-C) protocol. Each of K cluster has a cluster head. The K cluster heads report their decision to centralized Fusion Center (FC) where the decision of primary channel is made. The topology of the proposed solution is given in Fig.1). The architecture of the proposed methodology is given in Fig.1. Each CRU makes multiple parameter measurements using different mechanism about the PU signal and these measurements are sent to the CH. CH aggregates the parameter measurements from its CRUs and send to the Fusion center. At Fusion center, multiple classifiers are trained to classify the PU status. The results of multiple classifiers are fused using weighted ensemble to classify the PU status.

3.1 ED FEATURES AND DECISION TREE CLASSIFIER

Each CRU does local spectrum sensing independently to detect the PU activity. The spectrum sensing is a binary hypothesis test given as

$$H_0: y_i(t) = \eta_i(t), \text{ when PU is absent}$$
$$H_1: y_i(t) = h_i x(t)+\eta_i(t), \text{ when PU is present} \quad (1)$$

where t=1,2,…N_x is the sample index, N_x is the total number of samples of received signal.

$$N_x = 2BT_s$$

where B is the predefined bandwidth and T_s is the sensing time. $y_i(t)$ is the received signal at the CRU_i. $x(t)$ is the transmitted signal by PU. The PU transmitted signal is assumed to be Gaussian random process with zero mean and variance. $\eta_i(t)$ is the additive white Gaussian noise at the i^{th} channel. h_i is the channel gain and assumed to be constant over each sensing period. Each CRU sends it measurements $y_i(t)$ to its CH through a dedicated channel in a sequential manner.

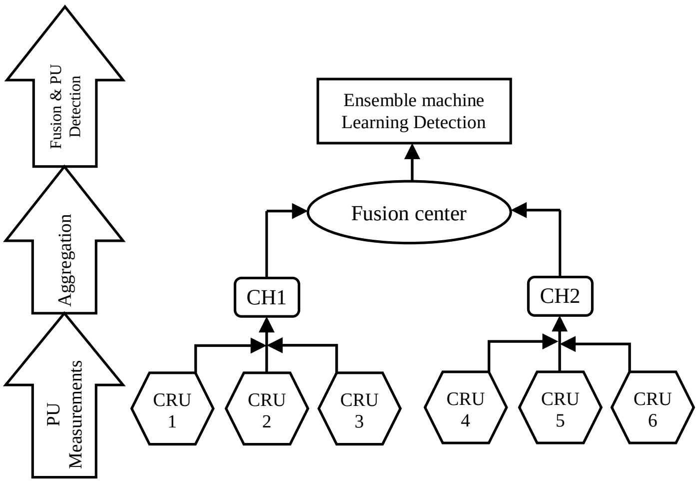

Fig.1. PU Detection Topology

The signal is received at CH as:

$$z_i(t) = \sqrt{PT_i} g_i y_i(t) + \Phi(t) \tag{2}$$

where PT_i is the transmit power of the CRU and g_i is the amplitude gain. $\Phi_i(t)$ is the white Gaussian noise introduced in the transmission. The received signal at kth CH is written as

$$z_i(t|H_0) = \sqrt{PT_i} g_i y_i(t) + \Phi(t)$$

$$z_i(t|H_1) = \sqrt{PT_i} g_i h_i x(t) + \sqrt{PT_i} g_i \eta_i(t) + \Phi(t) \tag{3}$$

At each of the CH, CRUs signals are averaged and squared to estimate the energy as:

$$Z_i = \frac{1}{N_x} \sum_{t=0}^{N_x - 1} |z_i(t)|^2 \tag{4}$$

The estimated energy at CH is sent to the Fusion center. Fusion center create an energy vector with energy measurement of each of the Cluster heads. Training set is created with energy vector and the status of PU (present -1 or absent - 0). The training set is used to train a Decision tree classifier using Random Forest method.

3.2 WAVELET FEATURES AND SVM CLASSIFIER

The PU signals acquired using compressive sampling using basic pursuit. Wavelet packet transform (WPT) is executed on the acquired signal to get the wavelet features at each of the CRU. The wavelet packet transform recursively decomposes the received signal spectrum into different subcarriers, and provides time frequency resolution. The received signal in terms of WPT transform is represented as:

$$r(n) = \sum_j \sum_k a_{j,k}[n] \varphi_{j,k}[n] + \sum_j \sum_k d_{j,k}[n] \varnothing_{j,k}[n] \tag{5}$$

where $a_{j,k}$ is the scaling coefficient, $d_{j,k}$ is the wavelet packet coefficient and j shows the level of transform. The wavelet features measured at each of the CRU is sent to cluster head. The wavelet features are then fused using average fusion rule at the CH and sent to the Fusion center. The training set of wavelet features vs the status of PU is created and an SVM classifier is trained using the dataset.

3.3 SNR FEATURES AND KNN CLASSIFIER

If the channel remains unchanged during the observation interval and that a sufficient number of samples are observed, the received signal can be represented as:

$$Y_i = \begin{cases} \left(\sigma_{ij}^2, \dfrac{2\sigma_{ij}^4}{N}\right) & H_0 \\ \sigma_{ij}^2(1+\gamma_{ij}), \dfrac{2\sigma_{ij}^4(1+\gamma_{ij})}{N} & H_1 \end{cases} \tag{6}$$

where σ_{ij}^2, γ_{ij} are the standard deviation of noise samples and the observed signal to noise ratio of the frame sensed at the CRU. Each CRU send the σ_{ij}^2, γ_{ij} to the CH. At CH, the average value of σ_{ij}^2, γ_{ij} is calculated and sent to Fusion center.

A training set of σ_{ij}^2, γ_{ij} values and the status of PU signals is created and a KNN classifier is trained to classify the PU status based on the σ_{ij}^2, γ_{ij} values.

3.4 WEIGHTED ENSEMBLE

A Ensemble of the results of DT, SVM and KNN classifier is done using Weighted Ensemble to classify the status of the PU. The weight of the classifier is calculated as:

$$w(C_i) = \log \frac{1 - error(C_i)}{error(C_i)}, 1 \le C_i \le 3 \tag{7}$$

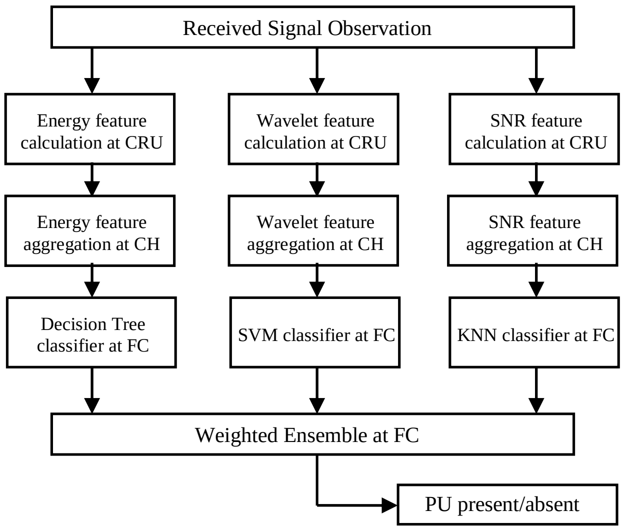

Fig.2. Ensemble Model

The error rate for each classifier is measured by a trail run. The results of DT, SVM and KNN are used in ensemble model. Suppose that the classifier training is performed on the training data and the error rate is calculated for each base classifier as 0.25 for DT, 0.14 for SVM, and 0.30 for KNN. For the error rate above the weights is calculated using weight equation. 0.47 is assigned to DT, 0.78 to SVM, and 0.36 to KNN; suppose that the three base classifiers generate the following results: DT predicts 0, SVM predicts 1 and KNN predicts 0 (1- indicated PU is present, 0 - indicated PU is absent). The ensemble classifier will use the weighted vote to generate the following prediction results

PU Absent: DT+KNN = 0.47+0.36 = 0.83

PU Present: SVM = 0.78.

According to the weighted vote, the PU Absent class has a higher value than PU Present class. Therefore, the ensemble classifier will classify as PU Absent.

3.5 REINFORCEMENT LEARNING

At fusion center, reinforcement learning based decision is made to detect PU status. Reinforcement learning is an unsupervised machine learning technique to learn knowledge about the operating environment by itself. The advantage is that it can learn knowledge on fly while carrying out its normal operation. A simple RL model is illustrated in Fig.3.

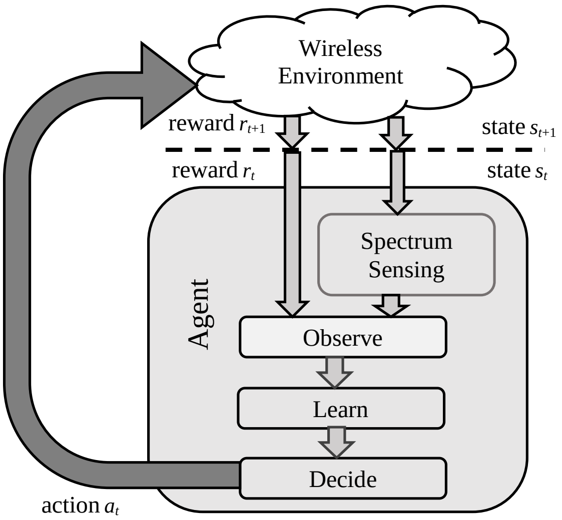

Fig.3. Reinforcement Learning (RL) Model

They are three important concepts in a RL model as state, action and reward. All these three concepts of state, action and reward are controlled by an agent. Agent makes decisions and continuously observer the output channels, based on the output it corrects itself to make better decision next time. State represent the decision making factors which affect the reward as observed by the agent. Actions are taken by agent which change state and reward. As the result of learning process, agent learn to take best actions. Reward is the positive or negative effect of agent's action on operating environment. The knowledge is represented in form of reward for each state action pair. At any time instant, an agent's action may affect the state and reward for better or for worse or maintain the status quo, and this in turn affects the agent's next choice of action. As time progresses, the agent learns to carry out a proper action given a particular state.

In ensemble method each CRU does a local spectrum sensing independently send the measurements to CH for analysis in a sequential manner. At CH, the received signals are averaged to estimate the energy and this estimation at each CH is sent to the fusion center creating an energy vector of observation.

At each of the CH, CRUs signals are averaged and squared to estimate the energy with Eq.(4). The estimated energy at CH is sent to the Fusion center, which creates an energy vector with energy measurement of each of the Cluster heads. The decision of PU present is made with reinforcement learning based on the energy vector observation. In this model, the fusion center is the agent which does the reinforcement learning as shown in Fig.4. The fusion center (FC) makes it decision based on the energy observation from the CH. The number of states in this reinforcement model is number of CH+ 3 (states for start, stop and No PU).

$$N = \text{number of CH} + 3$$

In each state S_t, FC selects action A_t, based on selection strategy and awaits a response from the environment. The response is the energy vector from the CH after a delay t_r. This response is used for reward calculation. The state changes from S_t to S_{t+1} after the FC obtains the reward r_{t+1}.

At each of the state agent makes one of the N-1 actions. Action selection strategy is designed to select the actions. Number of states and actions is directly proportional to number of CH in our proposed model.

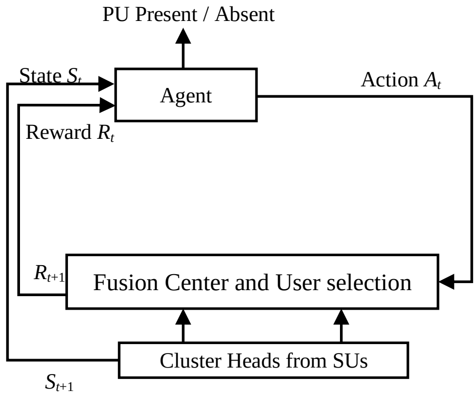

Fig.4. RL Model at Fusion Center

A reward function is designed to map the state action state transition to numeric rewards as

$$f_p{:}S\times A\times S\to R$$

The FC calculates the reward based on arrival of local decision from a CH as the result of action in that state for CH. An example state transition diagram is shown in Fig.5.

The FC starts at state S_0. After choosing first action A_0 = 2 it waits for the first reward r_1. The CH responsible for state S_1 reports it sensing result after a time delay. Upon the receipt of reward r_1 from SU_2, the state changes to S_1. We use Boltzmann distribution function for action selection. In this the probability of selecting action a_i in the state s_k is given by:

$$p\left(s_k, a_k = i\right) = \frac{e^{\frac{Q(s_k, a_k)}{t_n}}}{\sum_{j=1}^{N_a} e^{\frac{Q(k, a_j)}{t_n}}} \quad i = 1, 2, \ldots, N_a \tag{8}$$

where

$Q(s_k, a_k{=}i)/t_n$ is the state-action value function that evaluates the quality of choosing action $a_k = i$ at state s_k.

N_a is the number of actions.

t_n is the time varying parameter controlling the degree of exploration versus exploitation. All the actions are equally probable for larger values of t_n. FC explores the opportunities of more CH to achieve potentially higher detection probability. In case of smaller value of t_n the action with maximum $Q(S,a)$ is favoured. FC exploits the current knowledge of best selections of CH to achieve the potentially highest detection probability in this case.

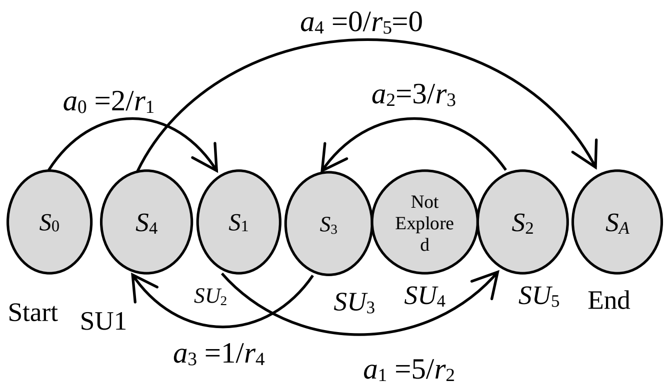

Fig.5. Sample State transition

As more episodes are devoted to sensing that changes the strategy from exploration toward exploitation, the value changes from large to small to assure that the convergence is achieved. The value of t_n is decremented using a linear function over the episode as follows:

$$t_n = -(t_0 - t_n)\cdot\frac{n}{N} = t_0 \tag{9}$$

where N is the total episodes.

The reward is a function of correlation incurred by the newly selected CH_i.

The cost associated with correlation is the cumulative correlation coefficients between the newly selected CH and all selected CH in previous states.

Given SU_j selected in the state s_m, m=0,1,…,k-1 and the correlation coefficient matrix $\sum = \{\rho_{ij}\}$, the cost can be expressed as:

$$C_p = \sum_{m=0}^{k-1}\rho_{ji}\left(s_m, a_m = j\right) \tag{10}$$

This reward function is given as:

$$r_{k+1}(s_k, a_k) = -C_p \tag{11}$$

The cumulative reward over the entire episode n is calculated as:

$$R_n = \sum_{i=1}^{K} r_i \tag{12}$$

where K states are selected in the episode n. The goal of reinforcement learning is to maximize the cumulative reward average over most recent N episodes.

Once the reinforcement learning is stabilized, each CRU makes energy measurement and send to CH. CH aggregates and send to Fusion center. At fusion center based on the energy vectors, state transition is triggered to know the state to which the RL transitions. If RL transitions to state of No PU, the result is PU is absent.

4. RESULTS

The performance evaluation of the proposed solution is simulated with following conditions in Table.1.

The performance of the proposed solution is compared against ensemble [1] [2] which is also a similar clustering based spectrum sensing techniques. The probability of detection for different SNR is shown in Fig.6.

In Reinforcement learning (RL) the performance of probability of false alarm is minimum, that is 0.2 at low SNR = -30dB.The probability of false alarm is less in the proposed solution compared to weighted ensemble [1] and [2]. This shows the capability of RL technique is adapting to user movement while maintaining detection performance.

Table.1. Performance evaluation conditions

Parameters	Values
No of CRU	12
No of Clusters	3
No of CRU per Cluster	4
Sensing, Reporting times	1ms (fixed interval)
Average SNR of each CRU	-17dB
Noise	White Gaussian Noise
No of samples collected for reinforcement learning	500
PU Signal	BPSK modulated
Signal Characteristics	Data a frequency = 1000Hz, carrier frequency = 2000Hz, and sampling frequency = 8000Hz
Dataset	A simulation run of 30 minutes is done with PU presence in every 5 minutes. Energy, wavelet, SNR features are extracted every 1 minute as manually labelled. The labelled dataset is used for training the KNN, SVM and decision tree (DT) classifiers used for comparison.
Solutions compared	The weighted ensemble of machine learning classifier to detect PU state as per [1] and solution [2] uses reinforcement learning to detect PU states. All the solution are compared at same power level.

The probability of detection is higher in the proposed solution compared to ensemble [1] and [2]. In Reinforcement learning the performance of probability detection is 0.85 at low SNR is -30dB is improved. The probability of false alarms is 0.03 at low SNR of -25dB. The probability of false alarms for different SNR is shown in Fig.7.

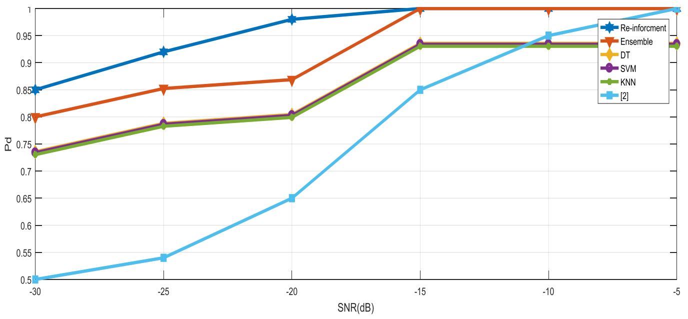

Fig.6. Probability of Detection with SNR

.Though the number of users considered for simulation is less, the area for simulation is only 100*100m and density is high. Instead of testing 100 CRU users in a bigger area, testing with lesser CRU in a small area will closely mimic the real deployment environment. Thus, simulation is done in way to mimic the real deployment.

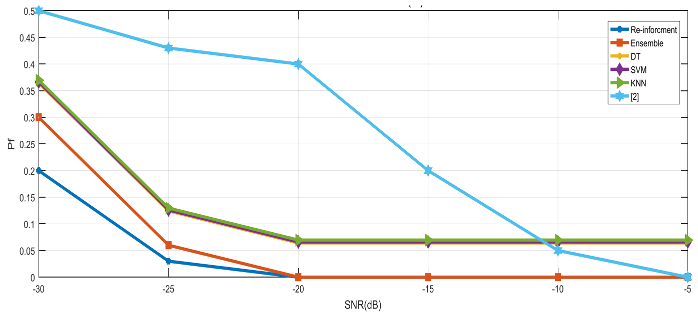

Fig.7. Probability of false alarm with SNR

The receiver operating characteristics (ROC) is plotted between probability of detection and probability of false alarm measured at SNR of -15dB is shown in Fig.8.

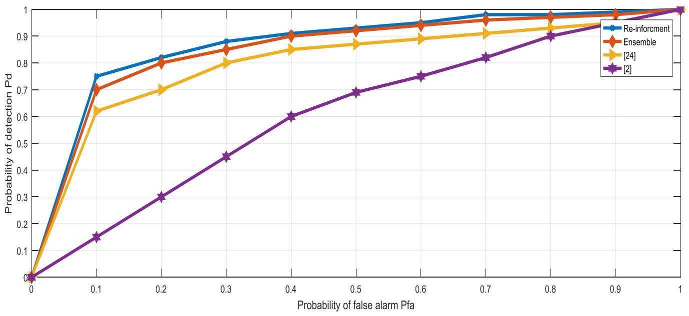

Fig.8. Receiver operating characteristics (ROC) at SNR = -15dB

The proposed reinforcement classifier is compared with weighted ensemble method [1] and proposed [24] for spectrum sensing in terms of the following parameters by using confusion matrix. In the field of statistical classification a confusion matrix is a table that is often used to describe the performance of a classification model.

1. Sensitivity
2. Specificity
3. Precision
4. Negative predictive value
5. Fall out
6. False discovery rate
7. Miss rate
8. Accuracy
9. Training time
10. Prediction speed

The proposed technique results are compared with the existing technique with different parameters are shown in Table.2. According to these performance measures, reinforcement classifier performs better results compared to ensemble classifier and [24].

Table.2. Results performance

Parameters	Reinforcement	Ensemble [1]	[24]
Sensitivity	0.966	0.956	0.932
Specificity	0.989	0.989	0.973
Precision	0.9919	0.9819	0.9718
Negative Predictive value	0.9551	0.9451	0.9347
Fall out	0.008	0.018	0.027
False discovery rate	0.029	0.019	0.0282
Miss rate	0.032	0.042	0.068
Accuracy	0.984	0.973	0.9525
Training time	1.8 s	2.2 s	2.2 s
Prediction speed	1.317μs	1.517μs	1.517μs

All the performance metrics are evaluated at same environment for all classifiers. From the results, the probability of detection is high in proposed Reinforcement based solution compared to ensemble [1] and [24]. The reason for increased probability of detection is attributed to the topology adopted in the proposed solution and two levels of aggregation as fusion and reinforcement learning at fusion center to detect PU.

5. CONCLUSION

A reinforcement learning based spectrum sensing scheme for detection of primary user status is proposed in this work. Energy measurements are done at each CRU and send to CH, from where the aggregated energy vector to the fusion center. At fusion center reinforcement learning based decision is made on the state of the PU. The reinforcement learning performance results are compared with other classifiers. The accuracy has improved by 5% at SNR of -15dB and 11% at SNR of -20dB when compared to ensemble model. Even at low SNR of -30dB they proposed solution is able to provide an 85% accuracy in PU detection compared to 80% in ensemble model. The probability of false alarm is 0.03 at low SNR of-25dB. The sensitivity, specificity and precision is improved compared to ensemble model.

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