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Cooperative Spectrum Sensing in Cognitive Radios using Perceptron Learning for IEEE 802.22 WRAN

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Abstract

The primary objective of IEEE 802.22 standard is to determine vacant spectrum bands available in Digital Television channel (DTV) and to utilize them for wireless rural broadband connectivity. Cognitive Radio aims at maximizing the utilization of the limited radio bandwidth while accommodating the increasing number of services and applications in Wireless networks. For cognitive radio networks to operate efficiently, Secondary Users (SU) should be able to exploit radio spectrum that is unused by the primary user. A critical component of cognitive radio is thus spectrum sensing. The secondary user should sense the spectrum efficiently, utilize the opportunities for transmission, and vacate the channel once primary user reoccupies it. In this paper, we propose approaches for cooperative spectrum sensing as per the IEEE 802.22 standard. This paper describes several simulation scenarios that can be used to evaluate spectrum sensing by single SU unit (local sensing) and multiple SUs in a cooperative setup. The detection accuracy and performance of the proposed algorithms are described using performance metrics called probability of detection and probability of false-alarm through extensive simulations using Matlab.

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Keywords: Cognitive radio; Cooperative sensing; Dynamic spectrum access; Machine learning; Spectrum sensing.

1. Introduction

The demand for radio spectrum has significantly increased due to recent growth in wireless services. The current wireless systems are regulated by fixed spectrum assignment policy where a given spectrum band is assigned to a licensed user on a long term basis and for larger geographic location. A recent investigation by FCC[1] has shown that most of such licensed spectrum remains unoccupied for large periods of time. In general, a large portion of the assigned spectrum is used by users sporadically with high variance in time. As a result, under the current fixed spectrum assignment policy, the utilisation of radio resource is quite inefficient. This limited availability and inefficiency of spectrum usage necessitates a new communication paradigm to exploit the existing wireless spectrum opportunistically.

Cognitive Radio (CR) addresses the issue of designing wireless communications systems which aims to enhance the utilization of the Radio Frequency (RF) spectrum[2]. It is built on a Software Defined Radio (SDR) with the convergence

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of two key technologies: Digital radio and computer software. It is viewed as an intelligent wireless communication system, which is aware of its environment and adapts to the statistical variations in the input stimuli. The cognitive radio is widely regarded as one of the most promising technologies for future wireless communication systems.

The definition of cognitive radio as adopted by FCC[1] is "A radio or system that senses its operational electromagnetic environment and can dynamically and autonomously adjust its radio operating parameters to modify system operation, such as maximize throughput, mitigate interference, facilitate interoperability, access secondary markets". As stated by Simon Haykin[3], the cognitive radio adapts its internal states to statistical variations in the incoming RF stimuli by making corresponding changes in certain operating parameters (e.g. transmit-power, carrier frequency and modulation strategy) in real-time, with two primary objectives in mind, i) Highly reliable communications whenever and wherever needed and ii) Efficient utilization of the radio spectrum. In addition to the fact that cognitive radio is generally implemented as a control process (presumably as part of a software defined radio) and imply some capability of autonomous operation, the following are some general capabilities found in CR[4]:

- **Observation** – the radio is capable of acquiring information about its operating environment.
- **Adaptability** – the radio is capable of changing its RF operating parameters.
- **Intelligence** – the radio is capable of applying information towards a purposeful goal.

To determine the presence or absence of primary user transmission, different spectrum sensing techniques using matched filter, cyclostationary detection, wavelet detection and energy detection have been proposed in the literature[5–8]. These sensing techniques can be helpful for each SU to make the decision locally in its hypothesis testing space. Compared with other detectors, the energy detection is well suited for local sensing[9] because it does not require any prior knowledge about PU signal properties. Also, it has low computational complexity. The performance metrics[10] of spectrum sensing is defined by using two parameters: Probability of Detection (P_d) and Probability of false-alarm (P_f). The performance limiting factors of the spectrum sensing can be due to noise uncertainty, channel fading and shadowing effect. To overcome these, the SUs have to make collaborative decision which is known as Cooperative Spectrum Sensing (CSS)[11,12]. CSS schemes such as hard combination, soft combination and CSS using machine learning schemes, Coalition game formation etc. have been proposed in the literature[13–15].

1.1 Present work

This paper discusses a framework of local sensing using energy detection and cooperative sensing based on machine learning to meet the functional requirement of IEEE 802.22 WRAN standard. The simulation results of the proposed spectrum sensing algorithm leads to formulation of effective coalition formation game for efficient strategic interaction among SU's. The main contributions of this paper are:

- The Simulation scenario of spectrum sensing algorithm has been formulated to meet the requirements of IEEE 802.22 WRAN standard.
- Local sensing phase is carried out using energy detection to scan the complete available channel set from 54 MHz–682 MHz with channel bandwidth of 7 MHz.
- The Cooperative Spectrum Sensing (CSS) phase is based on the Machine Learning technique. The reason for adopting learning algorithm in CSS is because of its ability to dynamically adapt and train at any time, able to "learn" features and attributes of the system which is often difficult to formulate analytically. The performance of our proposed algorithms is evaluated using detection probability and target false alarm rate.

1.2 Related work

The concept of cognitive radio was first proposed by Joseph Mitola III[16] in 2000. The fundamental activities of cognitive radio include (i) monitoring the available spectrum band in RF radio environment and capturing spectrum hole information (observe), (ii) Estimating the captured spectrum signal information by identifying functional relation between measurements and system configurations (orient), (iii) evaluating the outcome of orientation phase by gathering knowledge to be exploited in future with the aim of improving decision capability (learn), (iv) choosing appropriate spectrum band according to the spectrum characteristics and user information (decide), and

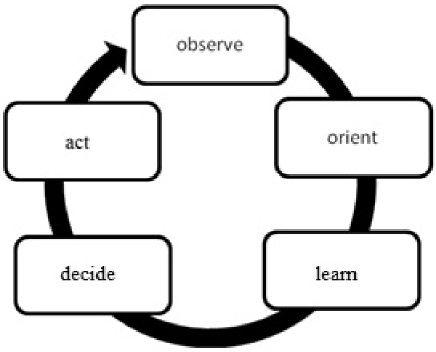

Fig. 1. Cognitive cycle[16].

(v) performing actions by effectively utilizing available bands (act). This set of activities, referred to as cognitive cycle[16], is represented in Fig. 1.

In 2004, the IEEE 802.22 working group[17] was formed to define the cognitive Wireless Regional Area Network (WRAN) PHY and MAC specifications. While IEEE started 802.22 with a special interest of defining procedures for cognitive operation in TV bands, after three years of preparation, FCC launched the TV band unlicensed service project in 2006 with cognitive radio technology. The IEEE 802.22 WRAN standard aims to provide fixed wireless access with a typical cell radius of 33km and maximum radius of 100km in rural and remote areas using Cognitive Radio (CR) technology in TV white spaces. It helps to provide broadband access to rural areas with low cost. In most of the existing work, the simulation scenario of CSS algorithm has been based on common theoretical assumptions rather than meeting the operational requirements of WRAN standard.

The reminder of this paper is organized as follows. In Section 2, background and system model are briefly explained which highlights local and cooperative sensing schemes with detailed description of algorithm. The simulation setup and results are discussed in Section 3. Finally, the paper is concluded in Section 4.

2. Background and System model

Our work deals with local sensing scheme using energy detection model and cooperative sensing technique using perceptron learning, which is briefly explained below.

2.1 Energy detection model

Energy detector[18] is the optimal way of local spectrum sensing which does not require any prior knowledge about primary signal. In order to measure the energy of the received signal, the output signal of band pass filter with bandwidth W is squared and integrated over the observation interval T. Finally the output of the integrator is compared with a threshold to detect whether the primary (licensed) user is present or not. The spectrum estimation can be computed in frequency domain by averaging bins of a Fast Fourier Transform (FFT) using Periodogram approach. The equation for a Periodogram[19] is given as,

$$s(\omega) = \frac{1}{N}\left|\sum_{n=1}^{N} x(t)e^{-j\omega t}\right|^2 \tag{1}$$

In this, the processing gain is proportional to FFT size N and the averaging time (t). Increase in the size of FFT improves the frequency resolution which is helpful in detecting narrow band signals. If we reduce the averaging time, the SNR improves by reducing the noise power. In the application of spectrum sensing, the Periodogram method is superior as it provides a better variance for the set of input data. Variance represents how far apart a particular set of data is spread out in amplitude. The block diagram of energy detection model is shown in Fig. 2.

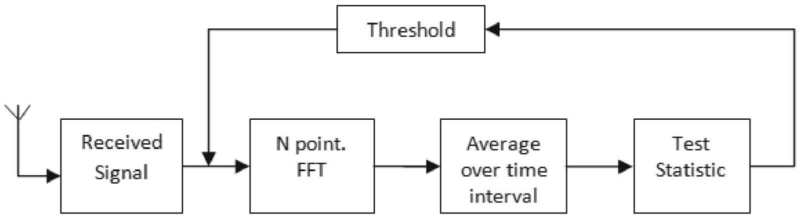

Fig. 2. Energy detector model.

Typically, the variance of the entire FFT data will be larger than the FFT of the data in the segments due to the larger data variations in the entire frame versus the variance of the segments. Because of this, a Periodogram will generally produce a smoother graph and will enable the system to detect and display signals in the presence of noise. The distribution of the total power over a specific range of frequencies is represented by power spectral density, which is the Fourier transform of the autocorrelation function. However, assuming white noise, the autocorrelation function reduces to an impulse.

The operation of energy detector is based on Binary Hypothesis testing problem which can be performed by each SU to decide presence/absence of PU. The statistical inference drawn from Binary hypothesis test[20] includes H_0 and H_1 to represent presence and absence of PU respectively. Based on this, the received signal of the i^{th} SU at sample index n is given by,

$$x_i(n) = \begin{cases} w_i(n), & H_0 \\ h_i(n)s(n) + w_i(n), & H_1 \end{cases} \tag{2}$$

where $w_i(n)$ is the Additive White-Gaussian Noise (AWGN), $s(n)$ is the primary user signal and $h_i(n)$ is the gain of the sensing channel between PU and SU. The decision metric[18] for the energy detector can be written as,

$$M_i = \sum_{n=0}^{N} |xi(n)|^2 \tag{3}$$

where N is the observation vector. The performance of energy detector can be evaluated by using two probabilities: Probability of detection P_d and Probability of false alarm P_f. The probability of detection is to decide the presence of primary user when it is truly present. In contrary, the P_f is to decide the presence of PU when it is actually not present. It can be formulated as,

$$\begin{aligned} P_d &= P_r(Mi > \lambda/H_1) \\ P_f &= P_r(Mi > \lambda/H_0) \end{aligned} \tag{4}$$

where λ is decision threshold which can be selected for finding the optimum balance between P_d and P_f. By setting a desired probability of false alarm and calculating the variance of a data set, the system sets a threshold to indicate signals above the noise level. Each SU processes its received energy and compares with a local threshold. The received signal strength of each SU varies based on its distance from Primary transmitter.

The description of local sensing algorithm is given in Algorithm 1 below. First, the primary user signal is added with noise according to the distance from the primary user. The noise added signal, 'signal_at_node' acts as input to different SU's. For each of the 10 secondary users, periodograms are calculated for signal_at_node, and based on which a Power Spectral Density (PSD) graph is obtained. The channel bandwidth is considered as 7 MHz in the frequency range of (54–698 MHz) which is scanned in steps of channel width giving around 92 channels whose decision can be either "occupied" or "available". The average energy values at each channel are compared to a threshold calculated based on a random probability of false alarm. If the energy value of the channel is greater than the threshold, the channel is specified as "occupied" otherwise it is "available".

```
Function Energy detection ( ) {
  Begin
    For user = 1 to No_of_Nodes
        Signal_at_node = Primary_User_Signal + AWGN;
              L= size(Primary_User_Signal);
              Threshold = qfuncinv(Pf(user) )/sqrt(L)+1;
        Periodogram_at_node=periodogram (Signal_at_node);
              Occupied[length(Periodogram_at_node)]=0;
              while  i < length(Periodogram_at_node) do
                  If Periodogram_at_node(i) > threshold
                     then
                     occupied(i)=1;
                  Endif
                     i=i+1;
              Endwhile
        Channel_width= 7 Mhz
        For every channel width in "Occupied"
  Begin
        Energy =0;
        Sum=0;
        For every frequency in the channel width
        Begin
              If occupied=1 at that frequency then
                 Begin
                    Sum=sum+1;
                    Energy= Energy+periodogram_at_node(freq);
                 End
              Endif
                If  sum>width/2
                  Channel_available=1;
                Else
                  Channel_available=0;
                Endif
        End   //End of users loop
  End      //End of Function
Function changeVelocities(velocityi,velocityj,x)
    Begin
        If(mod(x,4)==0)
      Begin
        Reverse the velocityi
      If (mod(x,2)==0)
        Reverse the velocity
      Endif
         Else If (mod(x,4)==1)
      Begin
           Reverse the velocityj
             If (mod(x,2)==1)
                 Reverse velocityi
             Endif
    End
  Function changeDistances(velocityi,velocityj,X,Y)
        X=X+velocityi;
        Y=Y+velocityj;
      If (X,Y)>(100,100)
        Begin
            (X,Y)=(X,Y)-2*(velocity,velocity);
        Endif
      If (X,Y)<(0,0)
        Begin
            (X,Y)=(X,Y)+2*(velocity,velocity);
        Endif
End }
```

Algorithm 1. Local sensing based on energy detection

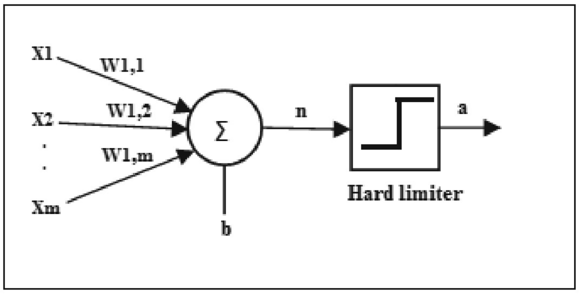

Fig. 3. Perceptron network.

The collection of energy vectors of each SU is represented using a matrix shown below. In this matrix, the row vectors and column vectors are considered as secondary users and number of channels respectively. Each secondary user has an array of values specifying the availability of each of the 92 channels. These are called local decisions.

$$Y_i(t) = \begin{array}{c c} & \begin{array}{cccc} Ch_1 & Ch_2 & \dots & Ch_N \end{array} \\ \begin{array}{c} SU_1 \\ SU_2 \\ \\ SU_N \end{array} & \begin{pmatrix} x_1(n) & x_1(n) & \dots & x_1(n) \\ x_2(n) & x_1(n) & \dots & x_2(n) \\ & & & \\ x_N(n) & x_N(n) & \dots & x_N(n) \end{pmatrix} \end{array}$$

Based on the local decisions of the N SU's, the fusion center will take a final decision as explained in the next sub-section.

2.2 Cooperative spectrum sensing model

All SUs report the estimated energy level (decision vectors) to the Fusion Centre (FC) through a reporting channel to make the final decision. We compute the final decision based on the soft combination of the local decisions (weighted average method). The weights corresponding to each secondary user is computed using the energy values as captured by every secondary user. For every channel, we calculate the mean energy value and the weight for each secondary user is the ratio of the corresponding energy value and the mean computed for the channel. This weight essentially captures how variant is the energy levels to the mean in that particular channel. For every channel, the mean value calculated is as follows,

$$\text{mean} = \sum_{N=1}^{10} x_i(n)/N \tag{5}$$

The weight of each secondary user is determined by using the mean value. The weight assigned to every secondary user is multiplied to the local decision value and the cumulative sum obtained from all the secondary users (N) is used to determine the final decision of the FC. This linear combination of the weights and the local decision vectors produce the Target Output. The model proposed further is evaluated by comparing its results to the target output of the weighted average method. In this paper, we propose CSS scheme based on perceptron networks. The schematic representation of perceptron networks[21] are shown in Fig. 3.

The FC collects local sensing results (decision vectors) of each SU and it acts as input to the perceptron network. The decision vector is denoted as,

$$Y = (X_1, X_2 \dots X_N) \tag{6}$$

The weight vectors (w) are determined by the method proposed earlier using the mean of the energy values. The bias value (b) is used for shifting the hyperplane away from the origin. The hardlimit function determines the network

```
Load energy (j, i) //Stores energy values of jth secondary  user for the ith band
Load local_decision(j,i)
While  i < no_of_bands //For computing the average energy for in this run corresponding to the ith energy channel
    While  j < no_of_nodes
        sum(i)= sum(i) + energy(j,i)
    Endwhile
        avrg(i) = sum (i) / no_of_nodes  // For computing weights for every user corresponding to this run(iteration)
    While j < no_of_nodes
        weight(j) = energy (j,i) / avrg(i)
        cumulative = cumulative + weight(j)* local_decision(j,i);
    Endwhile
    If  cumulative > 0
        Final_decision(i)=1
    Else
        Final_decision(i)=0
    Endif
    Write  final_decision  //prints the output for channel i
Endwhile
//Perceptron Code
Load InputVectors
InputVectors(i,j) ← Local decision by the ith secondary
user in the jth column
TrainingVectors ← First 50% vectors in the InputVectors Size i x (j/2)
TestingVectors ← Remaining 50% of the InputVectors
TargetOutput(j) ← Final Ouput of the FC  weighted Average of first 50% vectors
//perceptron initialization
net ← perceptron
net.configure(net,TrainingVectors,TargetOutput)
net.bias ← 0
net.weight ← Weight vector weight(j) for i th channel in initial run
Train the perceptron with input vectors
//Testing for continuous inputs
PerceptronOutput ← net(TrainingVectors)
```

Algorithm 2. Proposed cooperative spectrum sensing scheme

output which gives the final decision of FC about availability of primary channel. The input (n) to the hardlimit function is determined as,

$$n = \sum_{i=1}^{m} w_i \, x_i + b \tag{7}$$

Since the reporting channel is bi-directional, the FC sends its final decision to all SUs. The goal of the perceptron is to correctly classify the set of externally applied stimuli (energy vectors) into one of the two classes H_0 or H_1. The algorithm steps involved in the proposed CSS scheme is shown in Algorithm 2.

3. Simulation Setup and Results

The performance of the proposed cooperative sensing scheme has been analyzed with perceptron learning model using MATLAB. We consider a CR simulation scenario with one primary transmitter which operates in the frequency range of (54–698) MHz with channel bandwidth of 7 MHz. Multiple secondary users are randomly deployed in a grid topology of area 120×120 Sq.km, using one FC as shown in Fig. 4. The distance coordinates of each SU varies during each iteration. We have carried out 100 iterations. The value of SNR for each SU changes based on the distance from the primary transmitter.

The signal power estimation (power per unit frequency) has been carried out using Periodogram approach as explained in Section 2. The estimation of Power Spectral Density (PSD) for each SU varies based on the distance coordinates. Based on the signal estimation, each SU identifies the channel availability by scanning the complete set

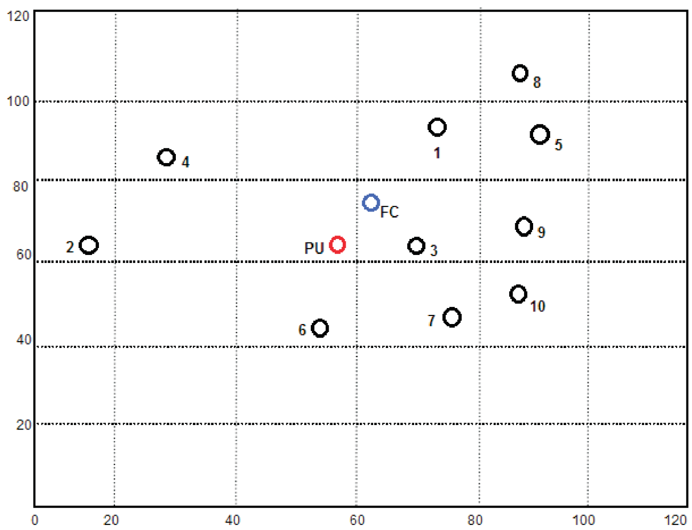

Fig. 4. Node placement.

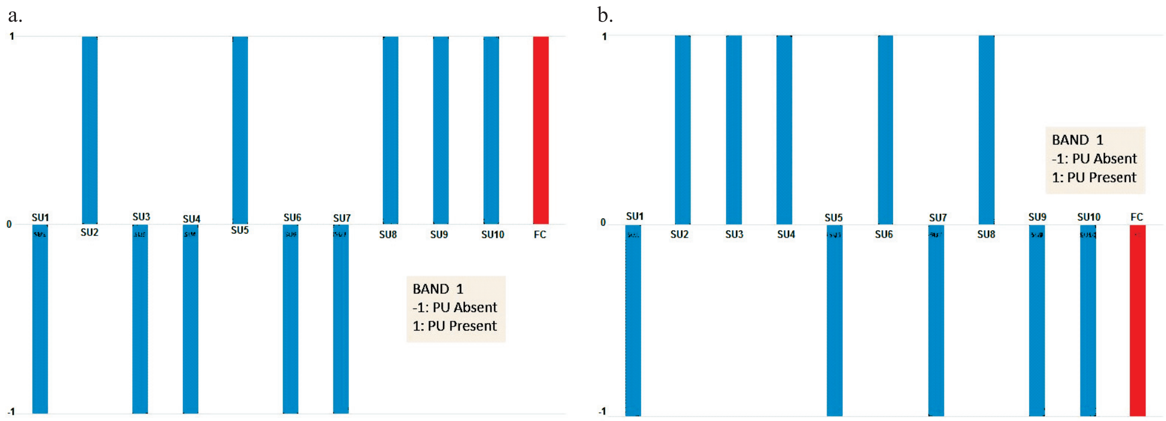

Fig. 5. Channel availability results of band 1 during (a) iteration 6; (b) iteration 83.

of primary frequency bands. The FC collects all the sensing information from each SU and makes the global decision. The channel availability results of each secondary user and FC for band 1 is shown in Fig. 5(a) and (b) during iteration 6 and 83. The blue bar represents status of primary user band in that region and the red bar represents the decision of FC. These band availability diagrams are based on the local decisions of the corresponding secondary user. Further, it is evident from these figures that the uncertainty of channel availability information may lead to interference to the primary user. Figure 6 depicts the channel availability results of FC. The white stem represents the availability of spectrum holes in particular channel. On comparison of Fig. 5 with Fig. 6, we can see that the FC provides a more accurate channel availability status. The local decisions of the secondary user for some channels are incorrect and the correct decision is communicated to secondary user by the FC.

Our proposed CSS scheme makes correct decisions by maintaining the target probability of error rate as 0.1. The FC decides the final availability of channel information using perceptron learning module with low error rate. The simulation result of FC is shown in Fig. 7. The perceptron module in FC uses 70% of local sensing energy vectors as training set to meet the desired target output.

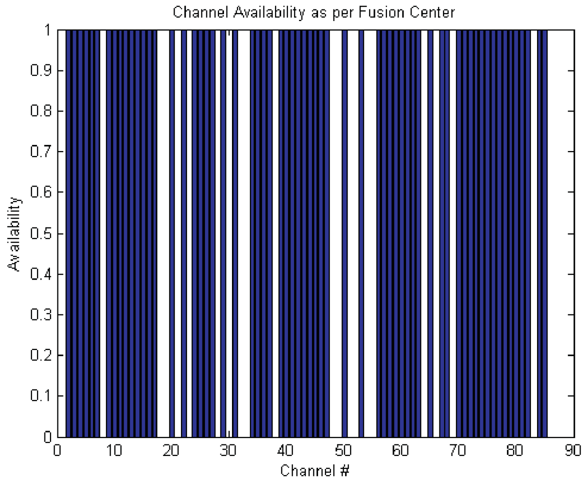

Fig. 6. Channel scanning results of FC.

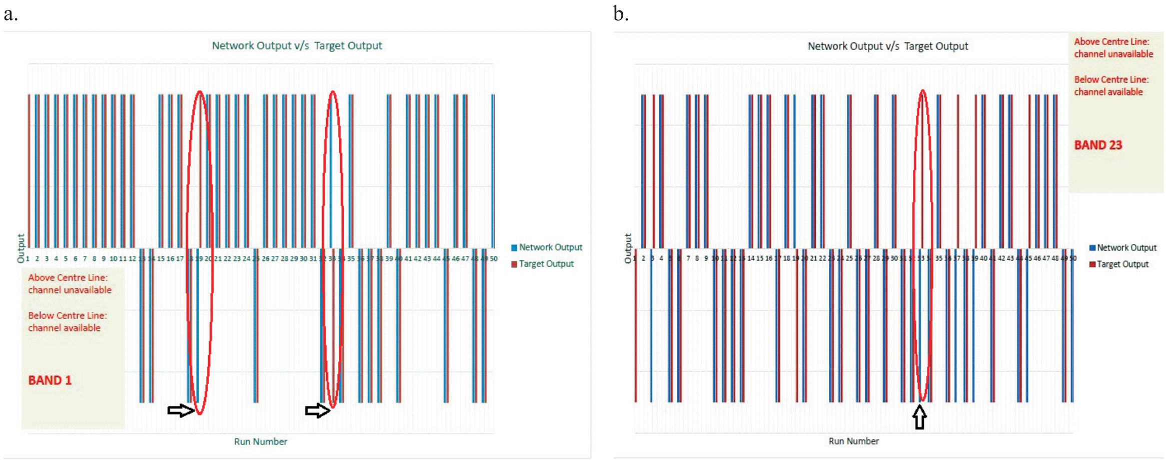

Fig. 7. (a), (b) Perceptron network output versus target output.

The output obtained from the perceptron model is called the network output. To determine the performance of perceptron learning on CSS scheme, we consider network output versus target output. The target output determines the probability of error rate. Figure 7 shows the comparison of the network output with the target output. The highlighted section (marked by arrow) shows the mismatch between the target output and network output and that is an error instance. As we can see for 50 iterations (different secondary user positions), we have less than 10% error rate. Here, we have depicted the performance for only Channel 1 and Channel 2. The network output of our proposed algorithm meets the target false-alarm rate of 0.1 for all the simulation conducted.

4. Conclusion

In this paper, we have developed a cooperative spectrum sensing algorithm using perceptron learning scheme for Cognitive radios. The simulation scenario has been formulated to meet the requirements of IEEE 802.22 WRAN standard. The proposed CSS scheme has the capability to learn from the radio environment to achieve cognitive tasks. Further, it is observed that the Perceptron learning module improves the decision capability of FC and significantly reduces the error rate to meet the target false-alarm rate. As future work, the proposed scheme can be extended to make effective strategic interaction among SU's using the approach called coalition game formulation.

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