Secondary User Cognitive Radio Spectrum Sensing Using Error Back Propagation Neural Network

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Abstract**—** The primary issue in the society is the need for efficient utilization of spectrum in wireless environment. The growing era of mobile environment needs a dynamic spectrum access (DSA) scheme that uses the spectrum in an opportunistic way. The goal of DSA is to utilize the spectrum holes by an unlicensed user without causing interference to the licensed user. This paper has proposed a neural network based cognitive radio network spectrum sensing. Input for training of Error Back Propagation Neural Network is sensed energy value by secondary users and class of channel (either occupied or free). Here soft fusion center received secondary user sensed energy value data in case of testing of neural network. Experiment is done on different number of secondary users and results were compared with existing methods on the basis of different evaluation parameters. It proposed work values are better as compared to previous approaches.

Index Terms— Cognitive Radio, Spectrum Sensing, Narrowband Sensing, Wideband Sensing, Compressive Sensing

I. INTRODUCTION

Wireless system and information traffic have developed exponentially over the last few decades, which end result in an extreme demand for the radio spectrum resources [1].

The current radio spectrum distribution policy comprises of allotting the channels to particular users with licenses for precise wireless technologies and services. Those licensed users have right of entry to that spectrum segments to spread/accept their data, whereas others are prohibited even when those spectrum portions are vacant [2]. Owed spectrum portions are not used all the time by their holders, called primary users (PUs), which forms spectrum holes. A spectrum hole, also called white space, is a frequency band assigned to a PU, but it is not being utilized at a specific time and at a specific location.

Consequently, the radio spectrum is incompetently broken [3]. Therefore, the shortage and incompetence of the spectrum administration need an urgent interference to improve the radio spectrum access and attain high network performance. A enhanced method to conquer the spectrum shortage issue is enthusiastically controlling it by sharing vacant channels with unlicensed users, called secondary users (SUs), without interfering with the PUs signals.

The Opportunistic Spectrum Access (OSA), also called Dynamic Spectrum Access (DSA), has been projected to attend the spectrum allotment issue. In contrast to the FSA, DSA permits the spectrum to be shared between licensed and non-licensed users, in which the spectrum is separated into various bandwidths allocated to one or more dedicated users [4]. In order to advance the use of the OSA, several solutions have been proposed, including cognitive radio [5]. According to Mitola [6], cognitive radio is an intellectual radio frequency transmitter/recipient intended to identify the existing channels and regulate its transmission parameters enabling more communications and recovering radio operating behaviour [6].

A cognitive radio system can monitor and discover from its atmosphere, get used to the environmental circumstances, and make choices in order to economically use the radio spectrum. If the secondary users are not able to group enough information about the PU signal, the most favourable detector is an energy detector, also called as a radiometer. Energy recognition is a non coherent detection technique that is used to sense the licensed User signal. If the noise power is known, then energy detector is good choice It is a simple method in which prior knowledge of primary or licensed user signal is not required, it is one of the admired and simplest sensing technique of no cooperative sensing in cognitive radio networks. It is ordinary means for recognising of unknown signals.

Cooperative sensing permits SUs to cooperate and combine their spectrum sensing hard work in order to arrive to the further correct ending about spectrum accessibility. This move towards of spectrum sensing emerges as a resolution to a chief disadvantage of non-cooperative sensing, that is the result of the secreted node problem on the sensing outcome. Cooperative sensing method is categorised in subsequent practices: 1) Decentralized Uncoordinated Techniques: In uncoordinated techniques Cognitive Radio will separately identify the channel and will leave the channel when it discovers a primary user without notifying the other users.

So Cognitive Radio users will experience terrible channel understanding sense the channel inaccurately thus causing intervention at the primary receiver. So these are not beneficial when compared to coordinated techniques. 2) Centralized Coordinated Techniques: Here in this technique we have Cognitive Radio controller. When one Cognitive Radio senses the existence of main user then it intimates the Cognitive Radio controller about it. Then that controller notifies all the Cognitive radio users by transmit means.

This is additionally more categorized into two methods as partially cooperative in which network nodes cooperate only in sensing the channel. The other method is completely cooperative in which nodes cooperate in relaying each other's data in addition to cooperatively sensing the channel.

II. Related Work

Zhang and Xie [6] proposed a neural network that performs decision making in cognitive radio engine. It utilises Genetic Algorithm (GA) for the resolution making support. Various changeable and unchangeable information are processed such as signal rate, bandwidth and encryption detail. LM algorithm is used to train the model and the accuracy of the decision is measured using Mean Square Error (MSE).

Zhu et al. [7] designed an Adaptive Resonance Theory (ART2) Neural network that combines Wireless Mesh Network (WMN) structure with wireless personal area network system. WMN constitutes cluster and various channels, which collects the sensed information and pass it to the cluster head. The data fusion in channel sensing is handled by ART2.

Katidiotis et al [9] proposed an Artificial Neural Network based learning scheme for discovering the data rate that can be achieved by a specific configuration in a cognitive radio network. In this work the anticipated performance, which is achievable transmission data rate is predicted for a given configuration input and taken into account the recent information sensed.

Cai et al. [10] presented an Incremental Self Organizing Map with HNN model for signal classification. In ISOM-HNN model the weight of the neuron is increased automatically when the number of inputs grows dynamically and unknown signals are detected without depending on the input dimensionality. This model enhances the capacity.

In [11], we studied the cross-layer pattern for crowding, disagreement and power control in multi-hop type cognitive radio ad-hoc network. A model is designed between the energy efficiency and maximum utilization of network that is two cross layer algorithms is designed which includes efficient power-controlled MAC set of rules for cognitive radio ad-hoc network. First algorithm permits cognitive sources and cognitive link to align their transmission capabilities based on law of diminishing returns. Second algorithm controls the persistence probability and transmits power so that it can compensate the offered load. At last these algorithms are then verified and compared with original MAC schemes.

In [12], proposed the two strategies: well-organized power control by employing directional transmission to take full advantage of the secondary channel rate and energy control by employing directional transmission to exploit the energy efficiency of secondary user. These schemes are projected to develop the reprocess spectrum by secondary user with no affecting the attainable main rate. This will boost the possibility of synchronized transmission with the lesser cost.

Jens P. Elsner et al [13] have demonstrates that linear compression with time-shifted casual preintegration is equivalent to compressed sensing with Toeplitz-structured random matrices. It preserves the autocorrelation properties that help in efficient compressed signal detection and joint compressed spectrum estimation in CR terminals.

III. Proposed Methodology

In this step proposed work explanation was done, here training of error back propagation neural network was done by passing the spectrum data obtain from the secondary spectrum sensing user. Here whole work was detailed into bock diagram shown in Fig. 1.

Develop Signal

Signal generate by the primary unit is of 100 bit where each digital information is transform into analog signal. So carrier signal was involved where BPSK modulation was applied. This formation of signal is done at primary user side, in case data is not present at primary signal than channel has carrier waveform only. So if channel is utilized by primary user than channel has data, carrier waveform and noise while in case if primary user has no data than channel has carrier waveform and noise.

So let D(t) is data packet, W(t) is carrier waveform, while n(t) is noise in the channel than r will be wave in transmitting channel.

$$\boldsymbol{r(t)} = \begin{cases} \boldsymbol{D(t) + W(t) + n(t)} \\ \boldsymbol{W(t) + n(t)} \end{cases} \text{\_ \_ \_ \_ \_ \_ Eq. (1)}$$

Estimate Energy in CR

Each cognitive radio or secondary user sense the channel continuously to send o=its data but decision of sending data is depend on fusion center who get collective information from CR units. Here secondary unit estimate energy of the signal from the channel by Eq. 2.

$$E(t) = |r(t)|^2 \text{\_ \_ \_ \_ \_ \_ Eq. (2)}$$

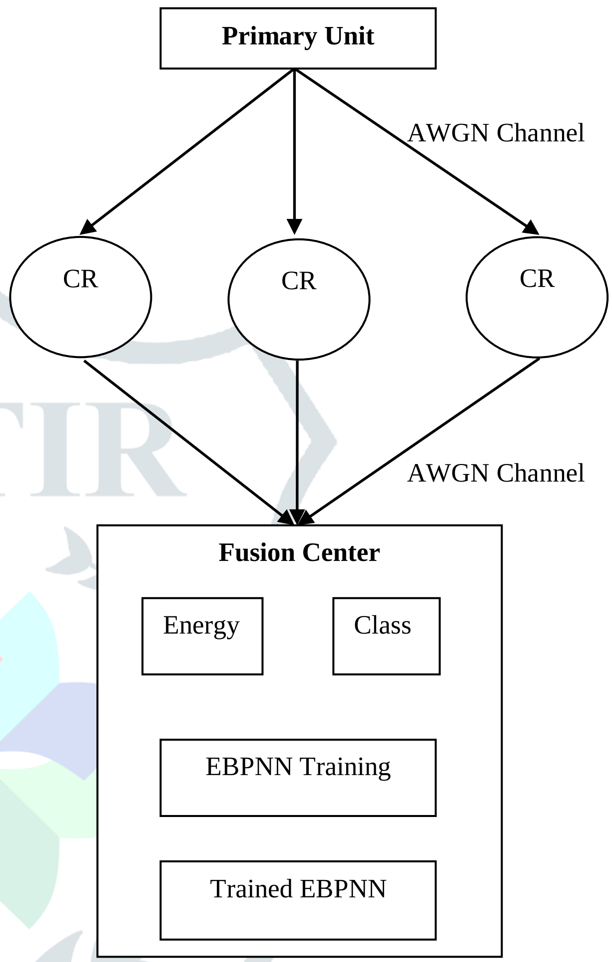

Fig. 1 Training Module of Cooperative Spectrum Sensing.

Fusion Center

Once energy estimate by the secondary user than fusion center collect information from all units and during training it is know in prior that channel has data or not. So training vector is estimated energy while testing vector is in form of 0 or 1 where 0 means no data present in channel and 1 means channel has data.

Training of Error Back Propagation Neural Network (EBPNN):

- Let us assume a three layer neural network.
- Now consider i as the input layer of the network. While j is consider as the hidden layer of the

network. Finally k is consider as the output layer of the network.

- If w_{ij} represents a weight of the between nodes of different consecutive layers.
- So the output of the neural network is depend on the below equation sigmoidal function shown in Equation 5:

$$Y_j = \frac{1}{1+e^{-x_j}} \_\_\_\_\_\_ \text{Eq. (5)}$$

where, $X_j = \sum x_i \cdot w_{ij} - \theta_j$, $1 \le i \le n$; n is the number of inputs to node j, and θ_j is threshold for node j. Where each value obtained from the previous weight matrix multiplication is passed through the sigmoidal function 5. Therefore small variation in the output value was done by this function.

Difference between the expected value and the obtained one is considered as the error. This error need to be correct by adjusting the weight values of each layer. So here forward movement of the neural network is over and error back propagation starts by Equation 6.

$$\frac{\partial E_i}{\partial O_i} = \frac{\partial(-1 * ((y_i * \log(O_i) + (1 - y_i) * \log(1 - O_i))}{\partial O_i}$$

$$\frac{\partial E_i}{\partial O_i} = (-1 * ((y_i * \log(O_i) + (1 - y_i) * \log(1 - O_i)\_ \text{ Eq. (6)}$$

In similar fashion other values can be calculate to find other set of derivatives for sigmoid of equation 7. Here as per output derivative value may vary.

$$\frac{\partial O_i}{\partial H_i} = \frac{\partial(\frac{1}{1+e^{-x}})}{\partial x}$$

$$= \left((1/(1+e^{-x}) \times (1 - (1/(1+e^{-x}))\right)\_\_\_ \text{ Eq. (7)}$$

For each input to neuron let us calculate the derivative with respect to each weight. Now let us look at the final derivative

$$\sum_{i=1:n} \frac{\partial H_i}{\partial W_{i(j,k)}} = \frac{\partial(h_{i(ouput)} * W_{i(j,k)})}{\partial W_{i(j,k)}} \_\_\_\_\_\_ \text{Eq. (8)}$$

Now by using chain rule final derivates were calculate for the same. Here multiplication of output obtained from equation 6, 7 and 8 was done in following way:

$$\frac{\partial E_i}{\partial W_i} = \frac{\partial E_i}{\partial O_i} * \frac{\partial O_i}{\partial H_i} * \frac{\partial H_i}{\partial W_i} \_\_\_\_\_\_ \text{Eq. (9)}$$

So overall ∂W_i can be obtained by getting value of weight from above equation, here all set of weight which need to be update are change by below matrix values.

$$\partial W_i = \begin{bmatrix} \frac{\partial E_1}{\partial W_{1,1}} & \frac{\partial E_2}{\partial W_{1,2}} & \frac{\partial E_3}{\partial W_{1,3}} \\ \frac{\partial E_1}{\partial W_{2,1}} & \frac{\partial E_2}{\partial W_{2,2}} & \frac{\partial E_3}{\partial W_{2,3}} \\ \frac{\partial E_1}{\partial W_{3,1}} & \frac{\partial E_2}{\partial W_{3,2}} & \frac{\partial E_3}{\partial W_{3,3}} \end{bmatrix}$$

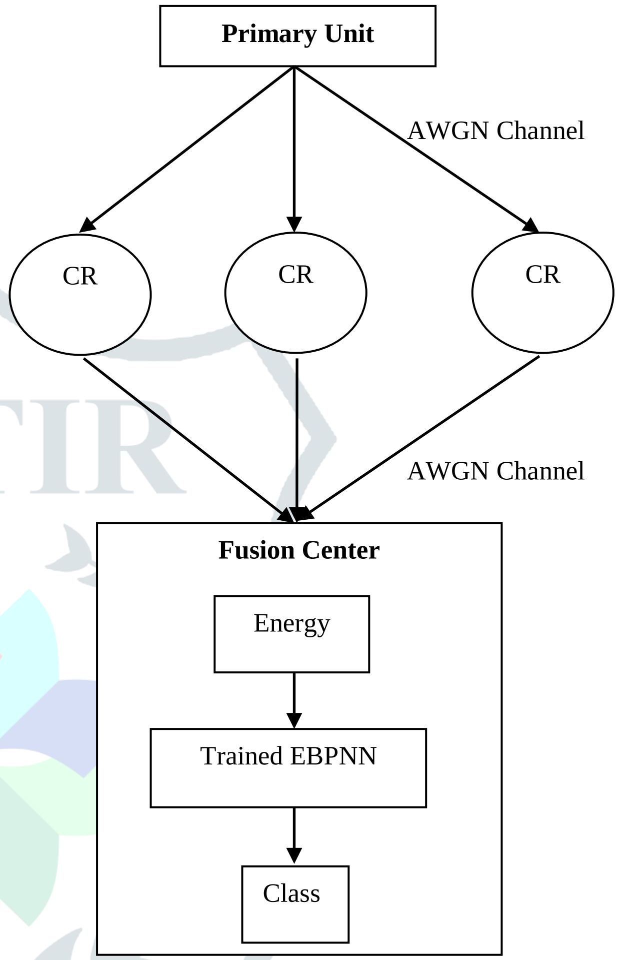

Fig. 2 Testing Module of Cooperative Spectrum Sensing.

- So error corresponds to the input data was estimate by differencing desired output obtain from output layer.

$$e_k(n) = d_k(n) - y_k(n)$$

- The EBPNN weight updation was done by above matix of ∂W_i

$$w_{ij} = w_{ij} + \Delta w_{ij}$$

So end of above iteration steps over when error obtained from the output layer get nearer to zero or some constant such as 0.001.

Testing of EBPNN

Testing of trained neural network obtained from fig. 2 steps. Here energy estimate by the secondary units as per the sensing of received signal were collect at fusion center. Now fusion center pass received energy values as input testing vector to the trained neural network. Hence majority output of neural as per different energy value is final decision of fusion center.

IV. Experiment and Result

Whole work is implemented in MATLAB. It is utilized on account of its rich library which has numerous inbuilt function that are specifically used in this work. This section of paper show experimental setup and results. The tests were performed on an 2.27 GHz Intel Core i3 machine, equipped with 4 GB of RAM, and running under Windows 7 Professional.

Evaluation Parameters: To appraise the presentation of the spectrum sensing methods, a number of metrics have been planned, together with the probability of detection, Pd, the probability of false alarm, Pfd, and the probability of miss detection, Pmd [21]. Pd is the possibility that the SU announce the occurrence of the PU signal when the spectrum is engaged [3]. The probability of detection is expressed as:

$$P_d = \text{Prob}\ (H_0/H_1) \_\_\_\_\_\_ \text{Eq. (10)}$$

where H0 and H1 denote respectively the absence and the presence of the PU signal. The higher the Pd, the better the PU protection is.

The probability of false alarm, Pfd, is the possibility that the SU announces the occurrence of the PU signal when the spectrum is truly free (idle). It is expressed as:

$$P_{fd} = \text{Prob}\ (H_1/H_0) \_\_\_\_\_\_ \text{Eq. (11)}$$

The lower the P_{fd}, the more the spectrum access the SUs will obtain.

The possibility of miss recognition, Pmd, is the probability that the SU announces the deficiency of a PU signal when the spectrum is engaged.

$$P_{md} = \text{Prob}\ (H_0/H_1) \_\_\_\_\_\_ \text{Eq. (12)}$$

Results

Results were compared with existing method in [15]. This section shows comparative analysis of above evaluated parameters.

Table: Average Value comparison values

Average Value comparison values			
	Previous Work	Majority	Proposed Work
Probability of Detection	0.5876	0.5301	0.6645
Probability of Missed Detection	0.4124	0.5582	0.4698
Probability of False Detection	0.5646	0.4699	0.3355

Above Table 1 shows that the proposed work has improved values of evaluation parameters as compared to previous methods used in [15]. Here, use of neural network has increase the accuracy of the work. As proper training in different noise conditions increases the accurate detection rate.

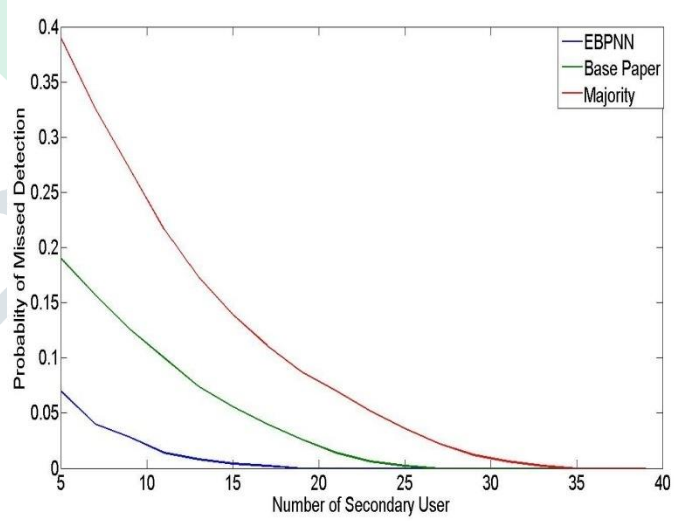

Fig. 3 Comparison of Probability of Missed detection vs Number of Secondary User.

From above Fig. 3 it was obtained that with increase in number of secondary user probability of missed detection was reduce. Here use of EBPNN for spectrum sensing decrease the missed detection probability. In previous approach [15] hard fusion and soft fusion center approach increase the missed detection value with increase in number of secondary users.

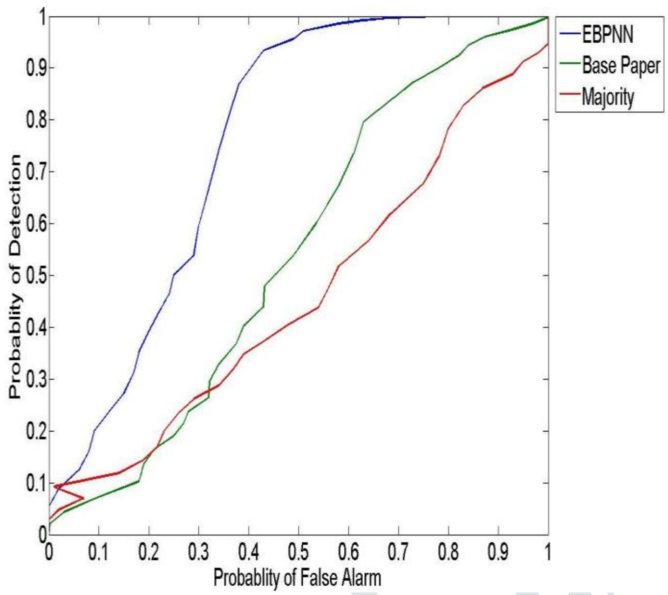

Fig. 4 Comparison of Probability of Detection vs Probability of False Alarm.

From above Fig. 4 it was obtained that with increase in probability of detection false alarm probability value was also increased. Here use of EBPNN for spectrum sensing decrease the missed detection probability. In previous approach [15] hard fusion and soft fusion center approach increase the false alarm probability.

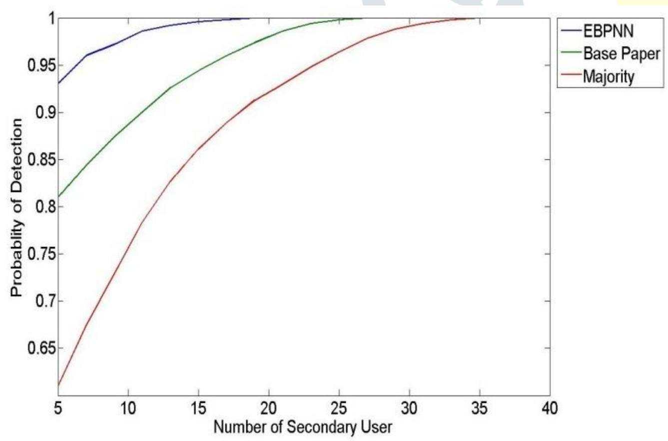

Fig. 5 Comparison of Probability of Detection vs Number of Secondary user.

From above Fig. 5 it was obtained that with increase in number of secondary user probability of detection was increased. Here use of EBPNN for spectrum sensing decrease the missed detection probability. In previous approach [15] hard fusion and soft fusion center approach reduce the detection probability value with increase in number of secondary users.

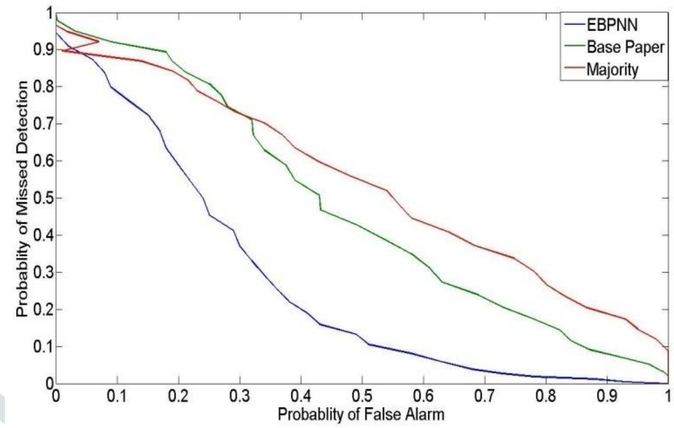

Fig. 6 Comparison of Probability of Missed Detection vs Number of Secondary User.

From above Fig. 6 it was obtained that with decrease in probability of detection false alarm probability value was increased. Here use of EBPNN for spectrum sensing decrease the missed detection probability. In previous approach [15] hard fusion and soft fusion center approach increase the false alarm probability value.

V. Conclusion

Spectrum is a extremely important supply in wireless Communication Systems and it has been a most important research theme from last numerous decades. Cognitive radio is a gifted knowledge which allows spectrum sensing for opportunistic spectrum usage by providing a means for the usage of white spaces. In this paper centralized fusion of secondary sensed data user was done for the decision of spectrum sensing. At fusion center trained neural network error back propagation was used where set of sensed energy values from secondary user was passed in EBPNN. Use of trained neural network gives effective decision of spectrum occupied by primary user or not. Experiment is done with different number of secondary users in same region of primary user. Results shows that proposed work has improved the detection probability by 11.57% percent and reduce the false alarm by 68.28%.

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