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Soft Fusion Combining For Cooperative Spectrum Sensing Using Artificial Neural Network

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Abstract

Cognitive radio (CR) technology is an emerging technology that overcomes the scarcity and poor utilization of spectrum resources. Under the constraint of system energy, this paper puts forward a cooperative spectrum sensing algorithm to minimize the sensing overhead, considering the mutual relation between sensing duration and the number of cognitive users. This paper has introduce an neural network model that learns the channel data behavior when primary user transmit data not. Estimated energy value from different secondary sources is used to train the error back propagation neural network. Experiment was performed on different number of secondary user cases under AWGN channel. Results were compared with existing methods on different evaluation parameters and it was obtained that proposed model perform well.

Keywords: Cognitive radio, Spectrum sensing, Narrowband sensing, Wideband sensing, Compressive sensing.

I. INTRODUCTION

The cognitive radio is an emerging technology in wireless communication. It is still too early to tell what a cognitive radio seems to be for different wireless applications due to complexity in implementation of cognitive radio in practical. Cognitive radio is a type of wireless communication where a transceiver can intelligently distinguish the channels for communication which are being used and which are not being used, and move into unused channels while maintaining a strategic distance from occupied ones. This enhances the utilization of available radio-frequency spectra while interference is minimized to other users. This is an ideal model for wireless communication where transmission or reception parameters of system or node are changed for communication dodging interference with licensed or unlicensed clients [1].

As two types of Cognitive Radios are present first is full Cognitive Radio: Full Cognitive Radio (CR) considers all parameters. A wireless node or network can be conscious of every possible parameter observable. Second is spectrum Sensing Cognitive Radio, this detects channels in the radio frequency spectrum.• Fundamental requirement in cognitive radio network is spectrum sensing. To enhance the detection probability many signal detection techniques are used in spectrum sensing. [2]

So the principal step of spectrum sensing is that it decides the presence of primary user on a band. The cognitive radio has the capacity to impart the result of its detection with other cognitive radios in the wake of sensing the spectrum. The main objective of spectrum sensing is to discover the spectrum status and activity by periodically sensing the target frequency band.

In cooperative sensing, a fusion scheme refers to the process of combining locally sensed data of individual secondary users. Depending on which type of sensing data is transmitted to the fusion center or shared with neighboring users, CSS can employ data or decision fusion schemes. In soft decision schemes (data fusion), secondary users exchange their test statistics calculated from their local observations. On the other hand, in the hard decision schemes (decision fusion), secondary users only exchange their individual binary decisions. Soft Combining and Data Fusion Existing receiver diversity techniques such as equal gain combining (EGC) and maximal ratio combining (MRC) can be utilized for soft combining of local observations or test statistics [3, 4]. If the channel state information (CSI) between the primary users and the secondary users are perfectly known, the optimal combining strategy, which is MRC, can be used for achieving the highest output SNR. It was shown that the soft combining scheme yields better gain than the hard combining scheme. However, there is a significant different ence in the cooperation overhead between the hard and soft decision based detectors, which requires a wideband control channel for the soft decision cooperative approach. The soft information based signal detection method for the single-carrier case and multi-carrier case was investigated in [4].

Hard Combining and Decision Fusion In the hard combining scheme, the final decision is reached by taking into consideration the individual local decisions reported by each secondary user. When binary local decisions are reported to the fusion center, it is convenient to apply linear fusion rules to obtain the cooperative decision. The main advantage of the hard combining scheme is the reduction of communication overhead. Hard decision combining for CSS has been considered in several works [5]. The commonly used fusion rules are AND, OR, and majority voting rules which are special cases of the general K-out-of-M rule.

This work utilizes soft combining and fusion techniques for spectrum sensing. Rest of this paper was organizing into few section where proposed methodology explanation was done with literature survey of work done by researcher of this field. Experiment and results shows a comparison of proposed work with previous existing methods.

II. RELATED WORK

In [6], Bagwari et al. evaluated the performance of the cyclostationary based sensing method and adaptive spectrum sensing, and presented a reliable spectrum sensing scheme using dual detectors. To improve3 the spectrum detection performance and reduce the algorithm complexity under low signal-to-noise ratio (SNR).

In [7], Tandra et al. have proposed a robust statistic approach, and derived the minimum SNR threshold for robust detection under noise power uncertainty model. The impact of noise power estimation error on the decision threshold of energy detection is analyzed through theory and simulations.

In [8], Deepak et al. discussed the use of filter bank method with discrete-time Fourier transform in a dynamic scenario to minimize the error probability of spectrum sensing in presence of noise uncertainty.

In [9], the maximum likelihood estimation method is applied for estimating the noise variance, and the performance of the energy detection with estimated noise power is analyzed. As the noise power is known, energy detection can achieve robust capability at any low SNR by increasing the number of samplings. However, the actual noise power is usually uncertain, and most of researches on adaptive cooperative spectrum sensing do not consider the noise power uncertainty.

In [10] enhance the performance of energy detection scheme we go for adaptive threshold. Adaptive threshold is a function of fixed threshold and SNR of primary user signal received at CR. However the individual CR may not give valid results due to Multipath fading and Shadowing. Therefore we go for cooperative spectrum sensing. In cooperative spectrum sensing(CSS) , each individual CR will sense the spectrum using adaptive threshold and give its decision to Fusion Center(FC). At fusion center all the binary decisions are fused together and give final decision about the availability of the spectrum.

In [11] analyze performance of cooperative spectrum sensing under counting rules when exponential model is utilized to characterize the burst nature of primary user (PU) link. Our objective is to minimize the average error probability (AEP) so that the link utilization in the considered link achieves its maximum. We derive a closed-form expression of AEP as well as the probability of interference (PoI) by classifying cognitive transmission into six events. Then, we consider the minimization of AEP over counting rules under the constraint of interference.

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.

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 prmary 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.

$$\boldsymbol{r(t)} = \begin{cases} \boldsymbol{D(t) + W(t) + n(t)} \\ \boldsymbol{W(t) + n(t)} \end{cases}$$

2. 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.

IV. RELATED WORK

In [13] presented an approach using closest neighboring algorithm with cosine analogy to classify research papers and patents published in several fields and stored in different conferences and journals database. Experimented results proves that user get better outcomes by traversing research paper or patent in specific category. The primary advantage of presented technique is that search area become compact and waiting time for query's solution has reduced. They have calculated the threshold depending upon similarity of terms of query, patent and research paper. Threshold calculation was not numerical value based. Hence the presented technique categorize more precisely than existing approach.
In [14] examined that social media posts can analyze the personal intelligence. Primary base of human behavior is personality. Personality tests elaborate the individual's persona that influences the relations and priorities. User reveals their opinions on social media. The text classification was exploited to predict the character and nature on the basis of their comments. Indonesian and English language were used for this test. Naïve Bayes, SVM and K-Nearest Neighbor are executed methods for classification. Naïve Bayes performed better than other techniques. The research work uses My Personality dataset. In this dataset used to classify the personality based-on an online ques
In [15] traversed internet for huge data to gather knowledge. It consists of huge unstructured data like text, image and video. Challenging issue is organization of big data and gathers useful knowledge that could be used in bright computer system. Ontology covers the big area of topic. To construct ontology with specific domain, big dataset on web was used and arranging with particular domain before the completion of organization. Naïve Bayes classifier was implemented with Map reduce model to organize big dataset. Plant and animal domain articles from encyclopedia available online were used to experiment. Proposed technique yielded robust system with high accuracy to classify data into domain specified ontology. In this research work, datasets use plant and animal domain animal's article in online encyclopedia and Wikipedia as dataset.
In [16] presented a Bayesian classification technique for text categorization using class-specific characteristics. Unlike regular approaches of text categorization proposed method chose a particular feature subset in every class. Applying such class-dependent characteristics for classification, a Baggenstoss's PDF Projection Theorem was followed to recreate PDFs from class-specific PDFs and construct a Bayes classification rule. The importance of suggested approach is that feature selection criteria, like: MD (Maximum Discrimination), IG (Information Gain) is included easily. Evaluated the performance on several actual benchmark data set and compared with feature selection approaches. The experiments, they tested approach for texture classification on binary real time benchmarks : 20-Reuters and 20-Newgroups.
In [17] proposed a BI-LSTM (Bidirectional long short term memory) network to inscribe the short text classification with 2 settings. The short-text classification is required in applications of text mining, especially health care applications in short texts mean linguistic ambiguity bound semantic expression due to which traditional approaches fails to capture actual semantics of limited words. In health care domains, the text includes infrequent words, in which due to lack of training data embedding learning is not easy. DNN (Deep neural network) is potential to boost the performance as per their strength of representation capacity. Initially, a common attention mechanism was adopted to guide network training with domain knowledge in

dictionary. Secondly, direct cases when knowledge dictionary is unavailable. They presented a multi-task model to learn domain knowledge dictionary and performing text classification task in parallel. They applied suggested technique to existing healthcare system and exclusively available ATIS dataset to get better results.

In [18] surveyed the process of text classification and existing algorithms. Large amount of data is stored as e-documents. Text mining is a technique of extracting data from these documents. Classifying text documents in specific number of pre-defined classes is Text classification. Its application consists of email routing, spam filtering, language identification, sentiment analysis, etc.

In [19] introduced a fuzzy logic based technique to solve text classification. Data inserted in proposed model are extracted from twitter's message. Social media offers plenty of data to study human behavior. Hurricane Sandy 2012 was used to extract information and classifying text. It's beneficial to analyze the relation between human influenced events and social media. Several fuzzy rules are designed and de-fuzzification methods were combined to get desired results. Suggested technique was compared to popular search method as per rate and quantity correctness. Results show that proposed technique is suitable for classification of twitter messages. The experimental uses the twitter review using social media.

In [20] proposed a technique which uses the connection between lexical things and labels before finishing Latent Dirichlet Allocation (LDA) theme display. They modified parameters of SVM (Support Vector Machine) to locate optimized values by K-crease cross approval. It's an awesome test that comprehending high-measurement and content scarcity issues in short content arrangement. Also, utilizing piece SVM as classifier, we effectively arrange named short Chinese content reports. Contrasting and other two regular techniques k-Nearest Neighbor and Decision Tree of short content arrangement, the exploratory outcomes demonstrate that our strategy outflanks them on order exactness, accuracy, review and F-measure.

V. CONCLUSIONS

Text Classification using analytical approach project proposed a design of the application that can effectively classify text files into appropriate folder depending upon the theme of the file, using the training data to model the classifier. So this paper has summarized current methodologies that have been basically created. Here it was obtained that people develop high social networking sites than create various document set. It was obtained that most of work use clustering techniques for segregating content from other class of contents. In future it is desired to develop the highly accurate algorithm which not only detects the spam but spammer profile as well.

$$E(t) = |r(t)|^2$$

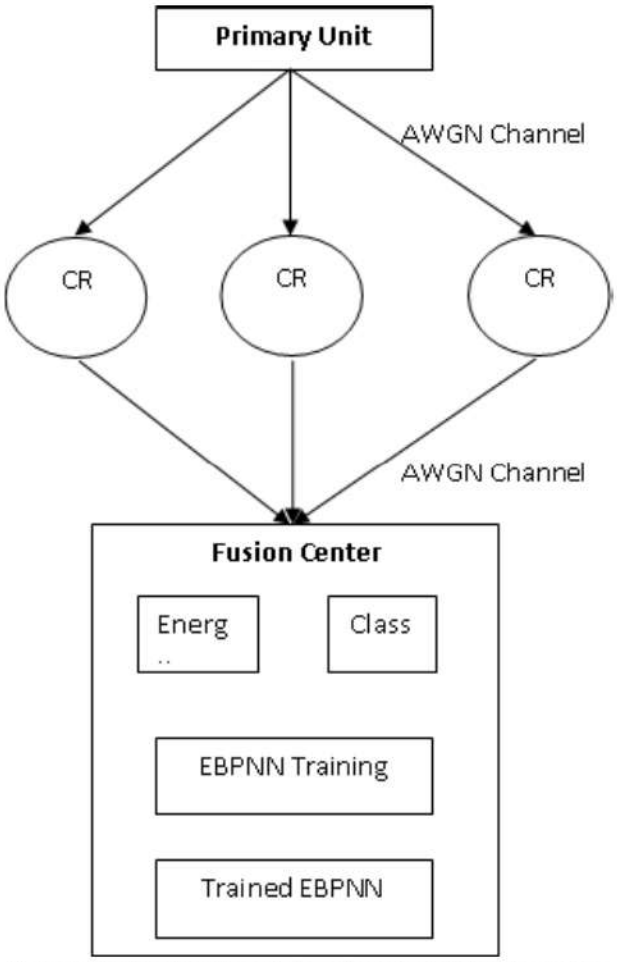

Figure 1: Training module of cooperative spectrum sensing.

1. 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:

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

where, $X_j = \sum x_i \,.\, w_{ij} - \theta_j$, $1 \le i \le n$; 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 with obtained is consider 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.

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

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

$$Eq.(6)$$

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.

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

$$= \left((1/(1+\mathrm{e}^{-\mathrm{x}}) \times (1-(1/(1+\mathrm{e}^{-\mathrm{x}}))\right)$$

$$--Eq.(7)$$

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

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

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:

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

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.

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

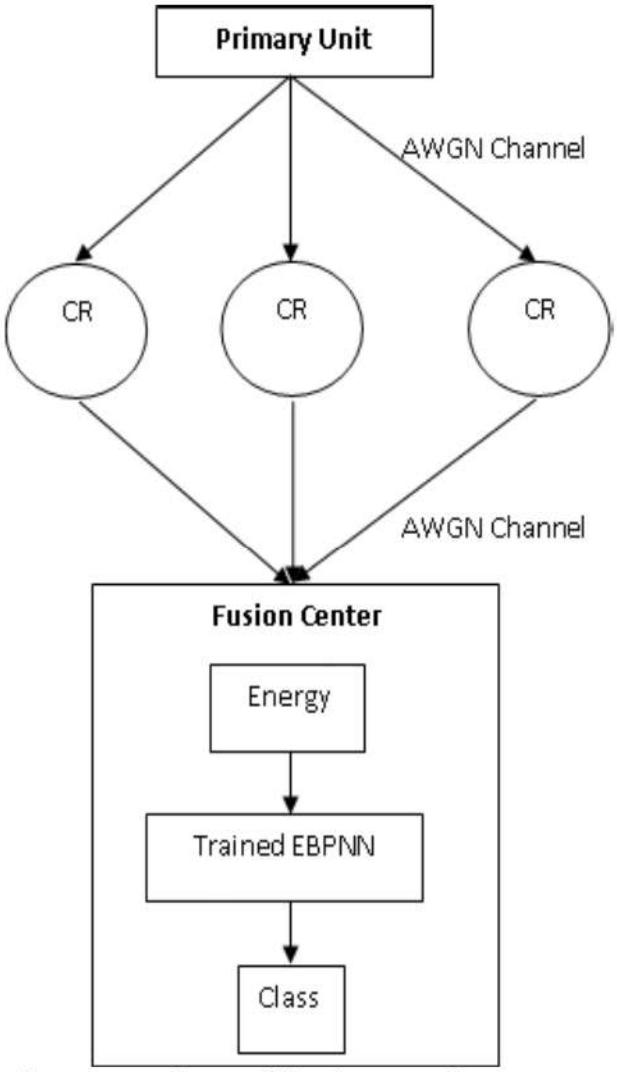

Figure 2: Testing module of cooperative spectrum sensing.

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

ek(n) = dk(n) – yk(n)

The ebpnn weight updation was done by above matix of ∂W_i

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.

Experiment and Result

Whole work was implementing on MATLAB software. It is utilize on account of its rich library which has numerous inbuilt function that can be specifically use 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 evaluate the performance of the spectrum sensing techniques, a number of metrics have been proposed, including the probability of detection, Pd, the probability of false alarm, Pfd, and the probability of miss detection, Pmd. Pd is the probability that the SU declares the presence of the PU signal when the spectrum is occupied [3]. The probability of detection is expressed as:

Pd = Prob (H0/H1)

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 probability that the SU declares the presence of the PU signal when the spectrum is actually free (idle). It is expressed as:

Pfd = Prob (H1/H0)

The lower the Pfd, the more the spectrum access the SUs will obtain.

The probability of miss detection, Pmd, is the probability that the SU declares the absence of a PU signal when the spectrum is occupied.

Pmd = Prob (H0/H1)

Result

Results were compared with existing method in [12]. This section shows comparative analysis on above evaluation parameters.

Average Value comparison values

Table 1: Average Value comparison values

	Previous Work	Proposed Work
Probability of Detection	0.9417	0.99
Probability of Missed Detection	0.0583	0.01
Probability of False Detection	0.33	0.14

Above table 1 shows that proposed work has improved the average evaluation parameters values as compared to previous method used in [12]. Here use of neural network has increase the accuracy of the work. As proper training in different noise condition increase the accurate detection rate.

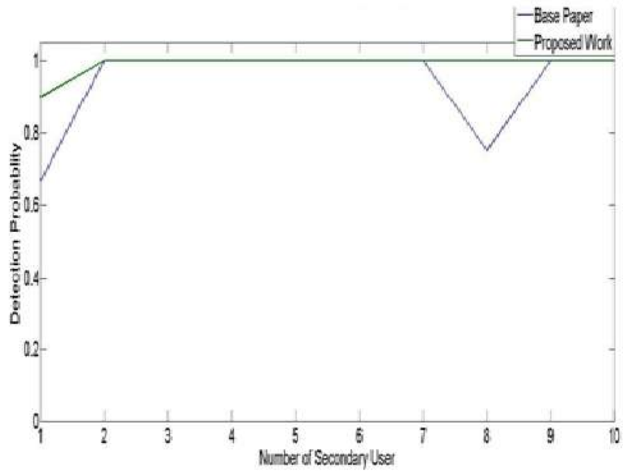

Figure 3: Comparison of probability of detection with different number of secondary user.

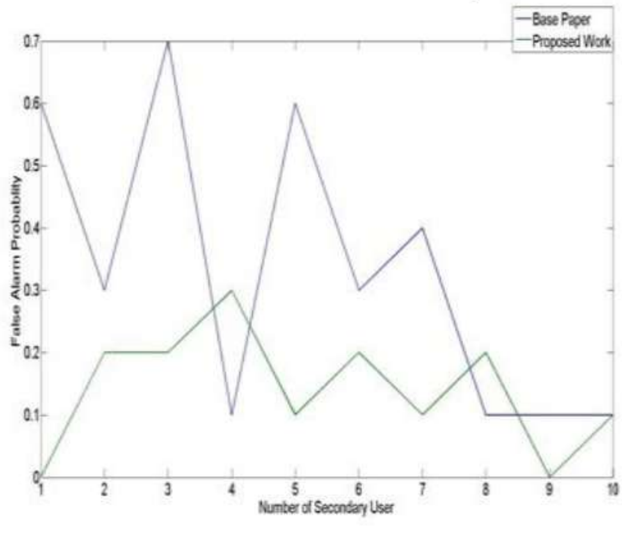

Figure 4: Comparison of probability of false alarm with different number of secondary user.

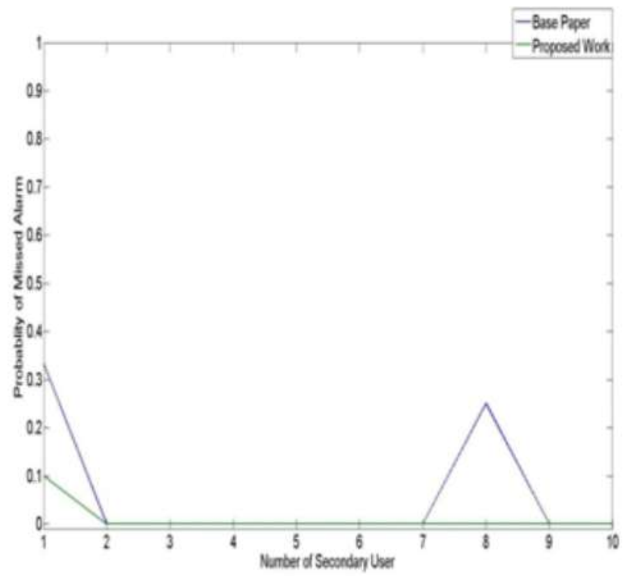

Figure 5: Comparison of probability of detection with different number of secondary user.

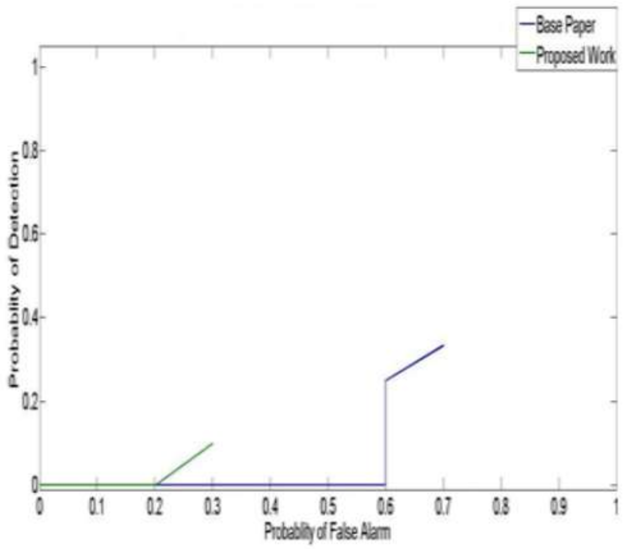

Figure 6: Comparison of probability of detection with different number of secondary user.

Above fig. 3, 4, 5 and 6 shows that proposed work has improved the average evaluation parameters values as compared to previous method used in [12]. Here use of neural network has increase the accuracy of the work. As proper training in different noise condition increase the accurate detection rate.

VI. CONCLUSION

Spectrum requirement increases day by day hence researcher is continuously working for increasing the utilization methods. This work has utilized the neural network model for detecting the spectrum utilization. For training neural network sensed energy value from the secondary values were passed with different number of users. Here this training improved the detection accuracy under awgn channel. Experiment was performed on different number of secondary users and results values were compared with existing methods. It was showed the probability of detection was increased by 0.95%, while probability of false alarm was decreased by 2.35 times.

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