Soft Fusion Combining For Cooperative Spectrum Sensing Using Convolutional 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 introduced a convolutional neural network model that learns the channel data behavior when primary user transmit data or not. Estimated energy value from different secondary sources are used to train the convolutional neural network. Experiment was performed on different number of secondary user cases under AWGN, Rayleigh, Rician 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.**

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 [7].

Two types of Cognitive Radios (CR) are present: 1. Full Cognitive Radio: Full Cognitive Radio considers all parameters. A wireless node or network can be conscious of every possible parameter observable. 2. 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 [12].

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 [2], [3]. 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 difference 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 [3].

To mitigate the impact of the channel estimation error on the detection performance several diversity combining techniques have been proposed. The non-coherent combining schemes, which do not need the CSI are investigated in [11]. In this category, there are two techniques, Square Law Combiner (SLC) and Square Law Selection (SLS), which produces the decision statistic using the outputs of the square-law devices available in each of the diversity branch.

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 [4]. 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 square law combining and fusion techniques for spectrum sensing. Rest of this paper was organized into few sections where proposed methodology is explained with literature survey of work done by researchers of the field. Experiment and results show a comparison of proposed work with previous existing methods.

RELATED WORK

In [1], B. Priyanka et. al. enhances 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 [2], F. Salahdine, N. Kaabouch, and H. El Ghazi have proposed a method in order to reduce the scanning time as the convention scanning requires a great deal of processing time. The proposed method was based on compressive sensing which is faster than the convention spectrum scanning.

In [3], H. Reyes, S. Subramaniam, N. Kaabouch, and W. Chenhave have described a method for spectrum sensing based on autocorrelation of the received sample and was compare to the energy detection spectrum sensing technique. Performance of the Euclidean distance method is better than energy detection technique.
In [4], Hemlata Patil, Dr A.J.Patil, Dr S. G. Bhirud have presented a detailed survey on multichannel spectrum sensing techniques and evaluation methods. In the practical scenario of cognitive radio network, secondary users deal with multiple channels instead of single channel. The open research challenges have also been discussed related to the multichannel cooperative sensing.

In [5], M. Ranjeeth, Dr S.Anuradha, have carried out the performance evaluation of soft data fusion scheme called Square Law Combining (SLC) in several fading channels such as A WGN, Rayleigh, Rician, Nakagami channel. The Cooperative Spectrum Sensing (CSS) based on soft data fusion outperforms hard decision fusion at the cost of increased bandwidth. Performance of a CR based spectrum sensing improves with increase in fading parameters of fading channels with reduction in severity of fading.

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 improve the spectrum detection performance and reduce the algorithm complexity under low signal-to-noise ratio (SNR).

In [7], N. Kaabouch and W.-C. Hu have examined the emerging technologies which are being used to overcome the radio spectrum scarcity. An ever-growing demand for the greater data rates for wireless transmission tends to an increase in demand for spectrum channels. New insights on radio spectrum access and management issues have been discussed.

In [8], Qian Wang et. al. analyzes 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.

In [9], Mariani A et. al. 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], 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 [11], Sanjeewa P. Herath, Nandana Rajatheva and Chintha tellambura, the exact average detection probability over the nakagami fading channel is derived by using an alternative series representation of the Marcum q function.

In [12], T. Yucek and H. Arslam presented a survey of spectrum sensing methodologies for cognitive radio. While solving some of the traditional problems, the new interpretation of spectrum space creates new opportunities and challenges for spectrum sensing.

In [13], 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.

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 block diagram shown in Fig.1.

Develop Signal

Signal generate by the primary unit is of 100 bits where each digital information is transformed into analog signal. So, carrier signal was involved where BPSK modulation was applied. This formation of signal is done at primary user (PU) 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.

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

Estimate Energy in CR

Each cognitive radio or secondary user (SU) 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.1.

Convolution: ConvNets derive their name from the "convolution" operator. The primary purpose of Convolution in case of a ConvNet is to extract features from the input image. Convolution preserves the spatial relationship between pixels by learning image features using small squares of input data. We will not go into the mathematical details of Convolution here, but will try to understand how it works over images.

Max-pooling: Pooling (also called as subsampling or down-sampling) reduces the dimensionality of each feature map but retains the most important information. Spatial Pooling can be of different types: Max, Average, Sum etc.

In case of Max Pooling, define a spatial filter kxk window and take the largest element from the rectified feature map within that window. In practice, Max Pooling has been shown to work better. Here shifting was done as per stride value s and padding will be done as per p value.

ReLu: ReLU is an element wise operation (applied per pixel) and replaces all negative pixel values in the feature map by zero. The purpose of ReLU is to introduce non-linearity in our ConvNet, since most of the real-world data we would want our ConvNet to learn would be non-linear (Convolution is a linear operation – element wise matrix multiplication and addition, so we account for non-linearity by introducing a non-linear function like ReLU).

Steps of MCNN: Here whole model is divided into ten layers where first nine are various combination of convolution, ReLu and Max-pooling steps in each step fix set of strides, padding and window size Fig. 1 represent all working steps. Out of the last ninth layer of MCNN was pass in the final or tenth layer which adjust the weight value as per SoftMax function.

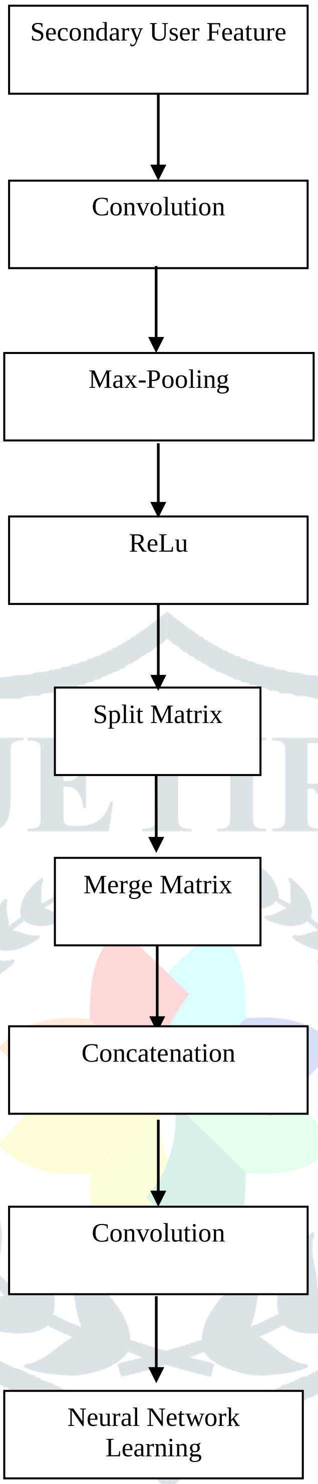

Fig. 1. Block Diagram of the Proposed Work.

Fully Connected Layer

The Fully Connected layer is a traditional Multi-Layer Perceptron that uses a SoftMax activation function in the output layer (other classifiers like SVM can also be used, but will stick to SoftMax in this post). The term "Fully Connected" implies that every neuron in the previous layer is connected to every neuron on the next layer. The output from the convolutional and pooling layers represent high-level features of the input image. The purpose of the Fully Connected layer is to use these features for classifying the input image into various classes based on the training dataset.

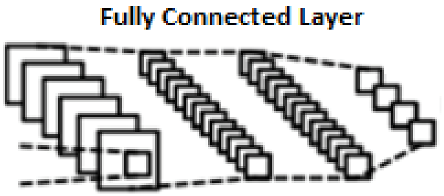

Fig. 2. Fully Connected Layer of Modified Convolutional Network.

Testing of CNN

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

The work is implemented in MATLAB software. It is utilized on account of its rich library which has numerous inbuilt function that can be specifically used in this work. This section of paper shows experimental setup and results. The tests were performed on 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, P_d, the probability of false alarm, P_{fd}, and the probability of miss detection, P_{md}. P_d is the probability that the SU declares the presence of the PU signal when the spectrum is occupied [2]. The probability of detection is expressed as:

$$P_d = \text{Prob}\ (H_0/H_1) \qquad \text{(Eq.2)}$$

Where, H_0 and H_1 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, P_{fd}, is the probability that the SU declares the presence of the PU signal when the spectrum is actually free (idle). It is expressed as:

$$P_{fd} = \text{Prob}\ (H_1/H_0) \qquad \text{(Eq.3)}$$

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

The probability of miss detection, P_{md}, is the probability that the SU declares the absence of a PU signal when the spectrum is occupied.

$$P_{md} = \text{Prob}\ (H_0/H_1) \qquad \text{(Eq.4)}$$

Result

Results were compared with existing method in [5]. This section shows comparative analysis on above evaluation parameters.

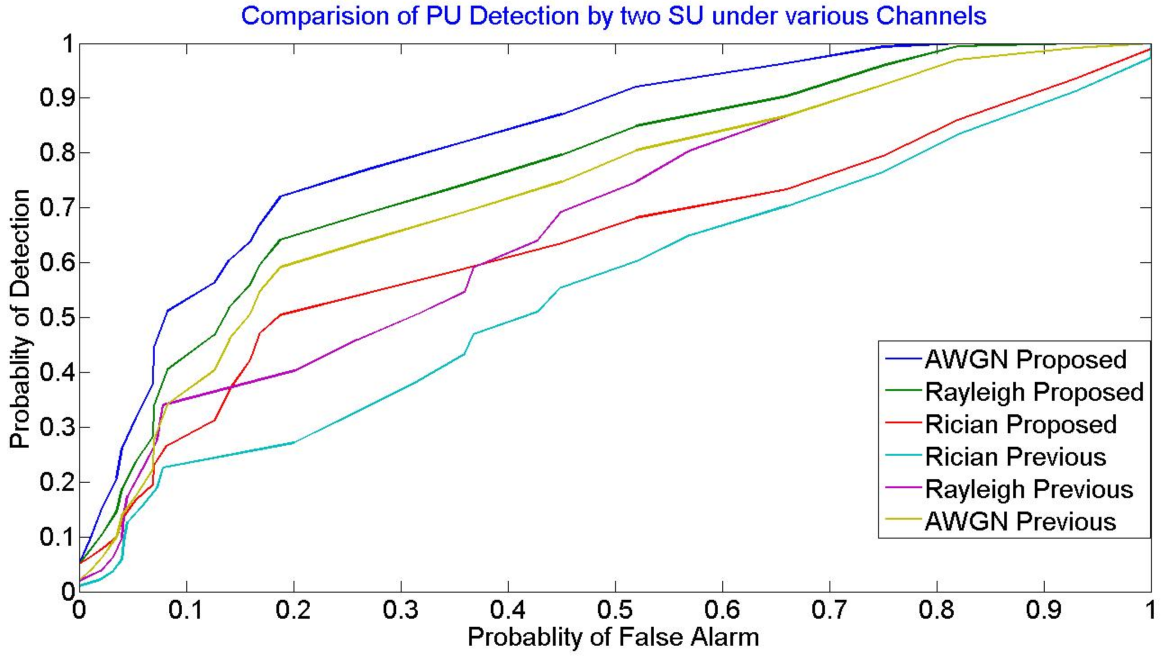

Fig. 3. Comparison of Two Secondary User Probability of Detection with Probability of False Alarm.

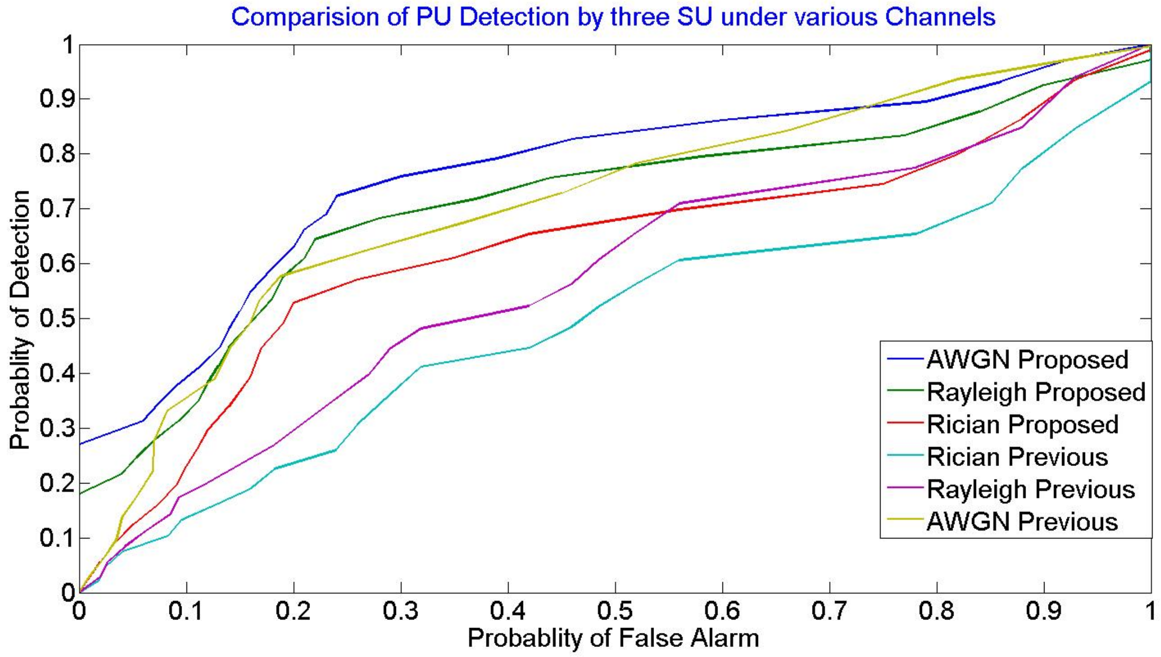

Fig. 4. Comparison of Three Secondary User Probability of Detection with Probability of False Alarm.

Above Fig. 3 and 4 shows that proposed work has increased the probability of detection by secondary user under various channel AWGN, Rayleigh, Rician where neural network leaning plays an important role. Proposed values are compared to previous method used in [5]. Neural network use for the detection of data in channel has reduced the missed alarm. Convolution model enhance the efficiency of the work by involving soft fusion and SoftMax function as well.

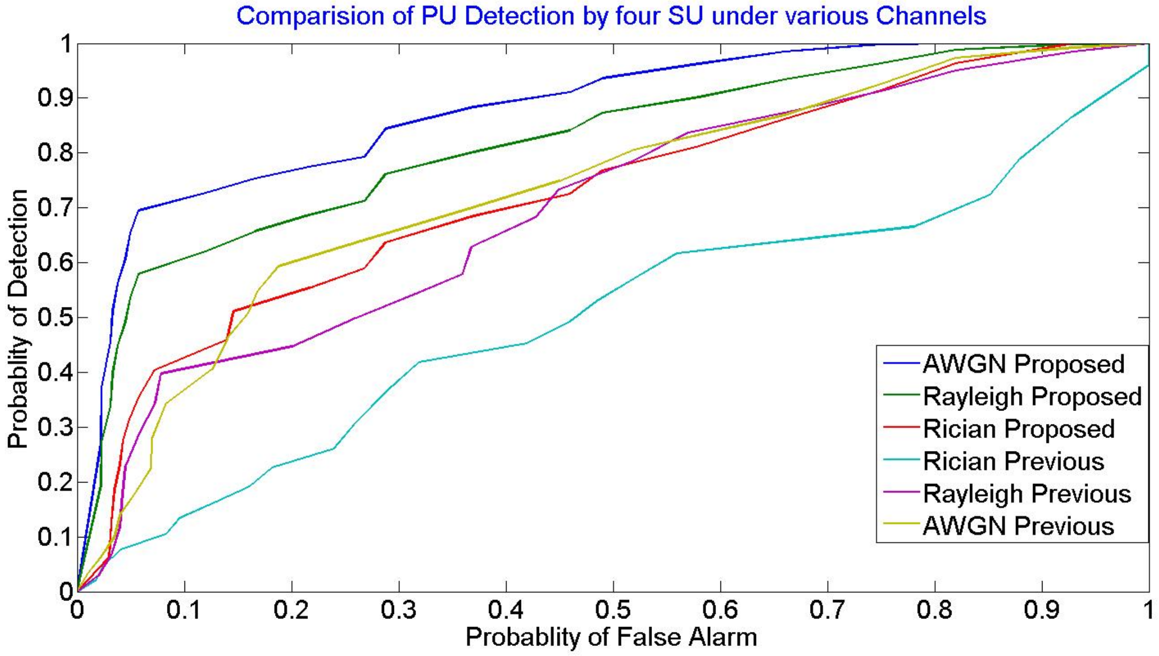

Fig. 5. Comparison of Four Secondary User Probability of Detection with Probability of False Alarm.

Above Fig. 3, 4 and 5 shows that proposed work has improved the probability of detection under various channel AWGN, Rayleigh, Rician evaluation parameters probability of detection is high. Proposed values as compared to previous method used in [5]. Here use of convolution neural network has increase the accuracy of the work. As proper training in different noise condition increase the accurate detection rate.

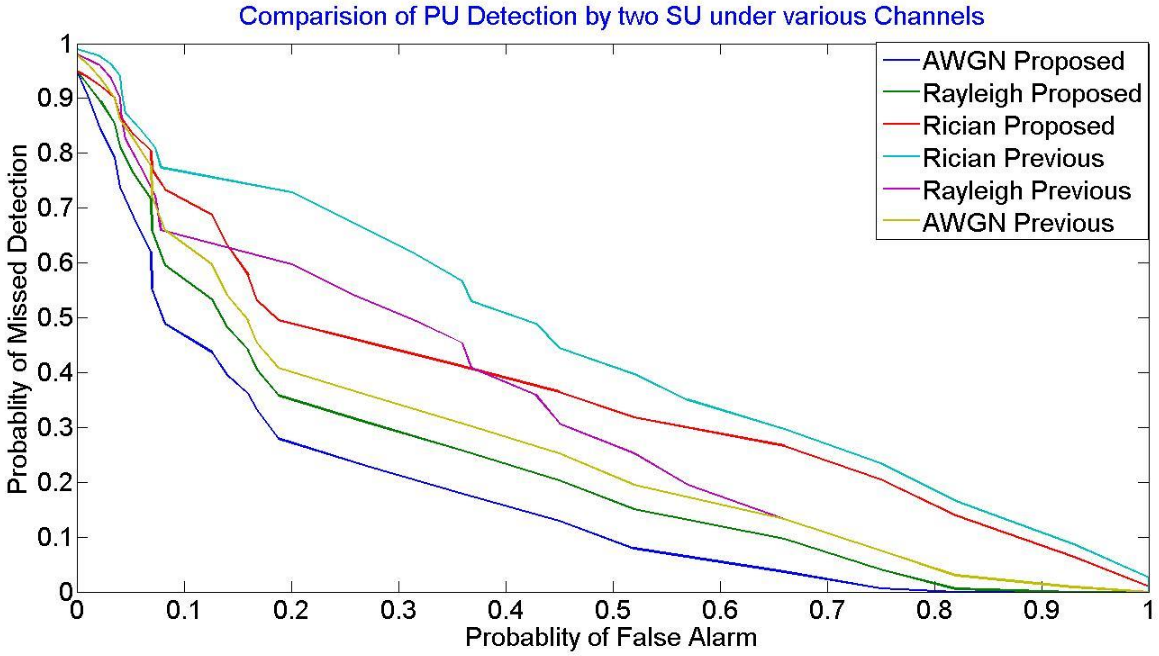

Fig. 6. Comparison of Two Secondary User Probability of Missed Detection with Probability of False Alarm.

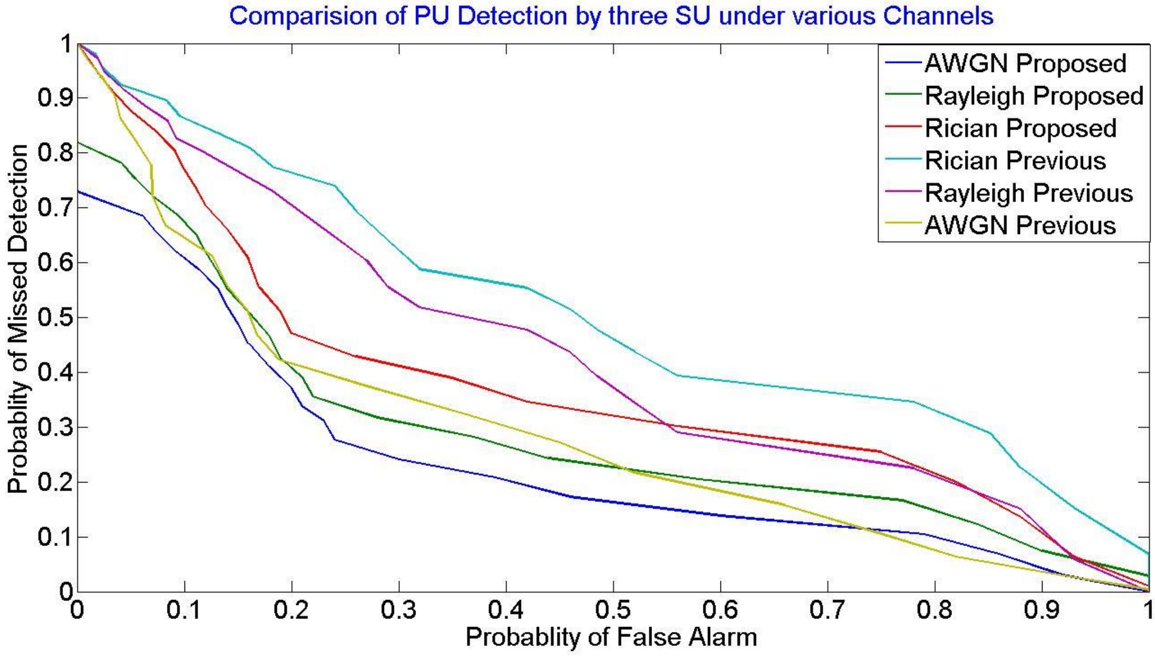

Fig.7. Comparison of Three Secondary User Probability of Missed Detection with Probability of False Alarm.

Above Fig. 6 and 7 shows that proposed work has decreased the missed detection by secondary user under various channel AWGN, Rayleigh, Rician. Proposed values are compared to previous method used in [5]. Neural network use for the detection of data in channel has reduced the missed alarm. Convolution model enhance the efficiency of the work by involving soft fusion and SoftMax function as well.

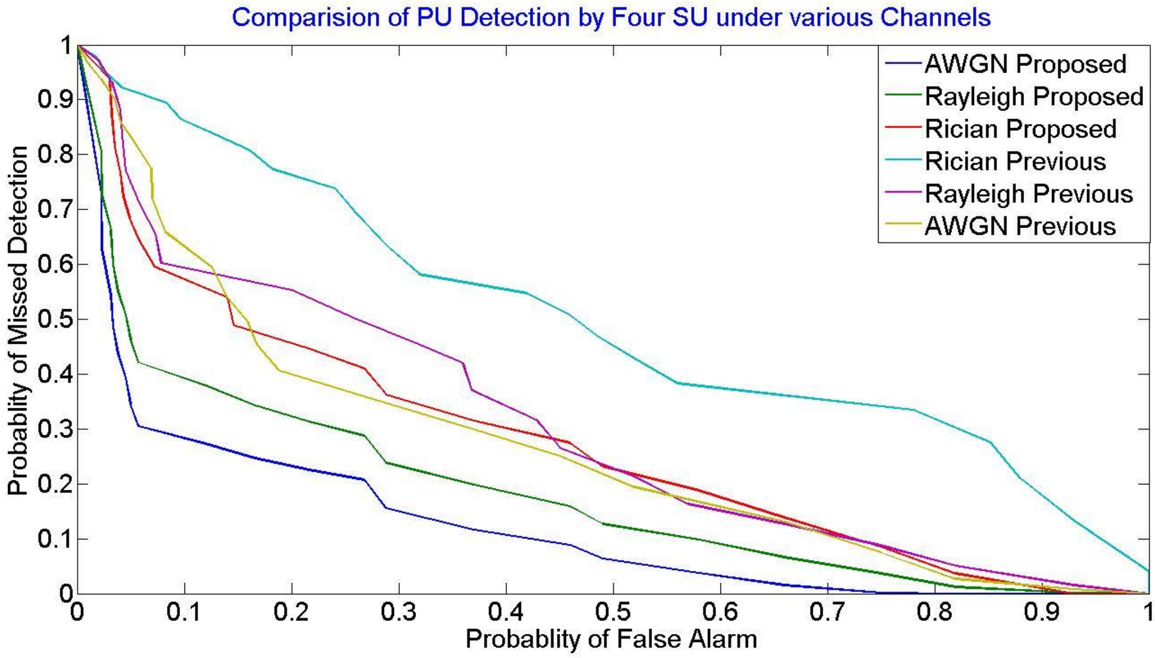

Fig. 8. Comparison of Four Secondary User Probability of Missed Detection with Probability of False Alarm.

Above Fig. 8 shows that proposed work has improved the probability of detection under various channel AWGN, Rayleigh, Rician evaluation parameters probability of missed detection is low. Proposed values are compared to previous method used in [5]. Here use of convolution neural network has increase the accuracy of the work. As proper training in different noise condition increase the accurate detection rate.

CONCLUSION

Spectrum requirement increases day by day hence researchers are 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 obtained that proposed model accuracy of channel detection increase by 24.37% under AWGN channel while 18.03% was improved under Rayleigh channel as compared to previous approach. In future, researcher can adopt other leaning model for increasing these result efficiencies.

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