AN EFFICIENT ACCESS OF SPECTRUM IN COGNITIVE RADIO USING MACHINE LEARNING

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ABSTRACT

Communication technologies are evolving drastically in recent years. However, the scarcity of spectrum began to appear with the accelerating usage of various communication technologies, as well as the preservation of traditional channel access methods. Cognitive Radio (CR) is an innovative solution for spectrum scarcity. Spectrum sensing is a key task of the CR life-cycle that gains significance as spectrum holes can be detected during this task. Cognitive Radio organization is displayed by utilizing MATLAB programming so both essential and optional clients can detect the range and offer the range successfully by utilizing the methodology of delaying time assessor which gives ways of behaving and movement framework. Candidates are made to share the spectrum and hereafter to share the range and in the future transmission postponement and throughput are analyzed when underlay and entwine range sharing were being used. In this project, a deep learning based spectrum access scheme is proposed to adaptively allocate multimedia data over multiple idle spectrum holes. Taking into consideration the rigorous delay and throughput performance requirements of multimedia applications. The simulation results show that the proposed scheme can quickly converge to a stable state in terms of throughput, power efficiency, and collision probability.

1. INTRODUCTION

Due to the rapid growth of wireless communications, more and more spectrum resources are needed. Within the current spectrum framework, most of the spectrum bands are exclusively allocated to specific licensed services. However, a lot of licensed bands, such as those for TV broadcasting, are underutilized, resulting in spectrum wastage. This has promoted Federal Communications Commission (FCC) to open the licensed bands to unlicensed users through the use of cognitive radio (CR) technology. The IEEE 802.22 working group has been formed to develop the air interference for opportunistic secondary access to TV bands.

In practice, the unlicensed users, also called secondary users (SUs), need to continuously monitor the activities of the licensed users, also called primary users (PUs), to find the spectrum holes (SHs), which is defined as the spectrum bands that can be used by the SUs without interfering with the PUs. This procedure is called spectrum sensing. There are two types of SHs, namely temporal and spatial SHs, respectively. A temporal SH appears when there is no PU transmission during a certain time period and the SUs can use the spectrum for transmission. A spatial SH appears when the PU transmission is within an area and the SUs can use the spectrum outside that area.

To determine the presence or absence of the PU transmission, different spectrum sensing techniques have been used, such as matched filtering detection, energy detection, and feature detection. However, the performance of spectrum sensing is limited by noise uncertainty, multipath fading, and shadowing, which are the fundamental characteristics of wireless channels. To address this problem, cooperative spectrum sensing (CSS) has been proposed by allowing the collaboration of SUs to make decisions.

LOCAL SPECTRUM SENSING

Spectrum sensing enables SUs to identify the SHs, which is a critical element in CR design. Figure 1 shows the principle of spectrum sensing. In the figure, the PU transmitter is sending data to the PU receiver in a licensed spectrum band while a pair of SUs intends to access the spectrum. To protect the PU transmission, the SU transmitter needs to perform spectrum sensing to detect whether there is a PU receiver in the coverage of the SU transmitter.

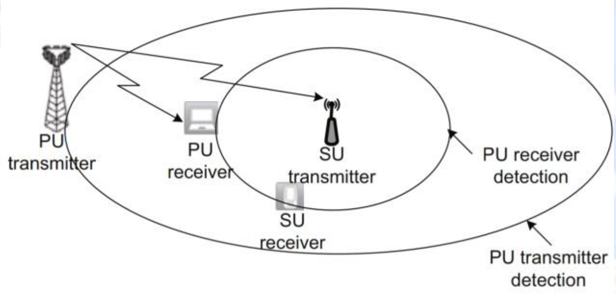

Fig. 1 Spectrum Sensing Concept

Instead of detecting PU receiver directly, the SU transmitter can detect the presence or absence of PU signals easily. However, as shown in Figure 1.1, the radius of PU transmitter and PU receiver detections are different, which lead to some shortcomings and challenges. It may happen that the PU receiver is outside the PU transmitter detection radius, where the SH may be missed. Since the PU receiver detection is difficult, most study focuses on PU transmitter detection.

To identify the SHs and protect PU transmission, different local spectrum sensing techniques have been proposed for individual SUs by applying the hypothesis testing criteria discussed above.

SENSING SCHEDULING

When and how to sense the channel are also crucial for spectrum sensing. Usually, short quiet periods are arranged inside frames to perform a coarse intra-frame sensing as a pre-stage for fine inter-frame sensing. Accordingly, intra-frame sensing is performed when the SU system is quiet and its performance depends on the sample size in the quiet periods. The frame structure for CR network is shown in Figure 2. Based on this structure, there are sensing-transmission tradeoff problems. Under the constraint of PU system protection, the optimal sensing times to maximize the throughput and to minimize outage probability of the SU system have been studied, respectively.

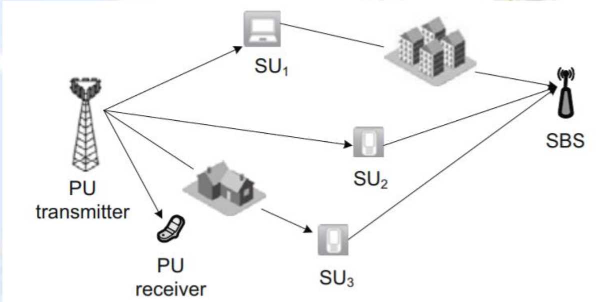

Fig. 1.3 Cooperative Spectrum Sensing Model

The performance of spectrum sensing is limited by noise uncertainty, multipath fading, and shadowing, which are the fundamental characteristics of wireless channels. If the PU signal experiences deep fading or blocked by obstacles, the power of the received PU signal at the SU may be too weak to be detected, such as the case for SU3 as shown in Figure 1.3. If the SU transmitter cannot detect the presence of the PU transmitter while the PU receiver is within the transmission range of the SU, the transmission of the PU will be interfered. To address this problem, CSS has been proposed. With the collaboration of several SUs for spectrum sensing, the detection performance will be improved by taking advantage of independent fading channels and multiuser diversity. Based on the decision fusion criteria, CSS can be realized in either a centralized or a distributed manner.

In this proposed system, radio spectrum is sensed for voids detection and secondary user assignment. Cognitive users are participating the white band either by transmitting alongside with primary users or waiting until the hole is getting vacant. During the period of transmission, the behaviors of primary users are studied for determining the spectrum occupancy status. So that both primary and secondary users can sense the spectrum and share the spectrum effectively by employing the approach of waiting time estimator which provides behaviors and activity matrixes. Two techniques are used to share the spectrums which are Feed Forward Neural Network.

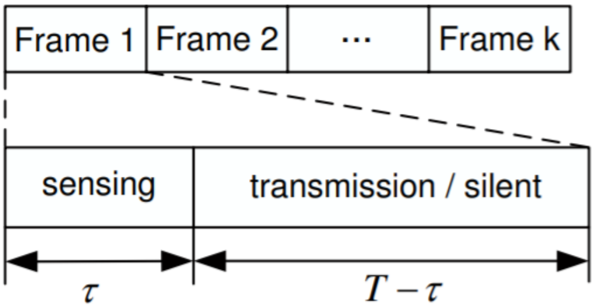

Fig. 2 Frame Structure for Periodic Spectrum Sensing

2. RELATED WORKS

MATCHED FILTERING DETECTOR

If the SUs know information about the PU signal, the optimal detection method is matched filtering, which correlates the known primary signal with the received signal to detect the presence of the PU signal and thus maximize the signal-to-noise ratio (SNR). The matched filtering detector requires short sensing time to achieve good detection performance. However, it needs knowledge of the transmit signal by PU that may not be known at the SUs. Thus, the matched filtering technique is not applicable when transmit signals by the PUS are unknown to the SUs.

ENERGY DETECTOR

Energy detector is the most common spectrum sensing method. The energy detector is easy to implement and requires no prior information about the PU signal. However, the uncertainty of noise power imposes fundamental limitations on the performance of the energy detector. Below an SNR threshold, a reliable detection cannot be achieved by increasing the sensing duration. This SNR threshold for the detector is called SNR wall. With the help of the PU signal information, the SNR wall can be mitigated, but it cannot be eliminated. Moreover, the energy detector cannot distinguish the PU signal from the noise and other interference signals, which may lead to a high false-alarm probability.

EXISTING METHODOLOGY

In cognitive radio, since spectrum sensing is essential part of cognitive network; this existing system involved a comparative approach of three sensing techniques: cyclostationary, Energy detection and matching filter. The performance of every one ranked base on time, technique complexity and whither information need to be acquired about primary user's behaviors prior to perform the spectrum operations.

Spectrum sharing algorithm based on existing to solve spectrum sharing which can be viewed as a binary hypothesis-testing problem. Their model was Firstly, the feature of the presence of the primary user signal and the presence of only the noise signal are extracted, and then, the extracted features should be pre-processed, which are used as the training input of the existing model.

Finally, the test input is fed into the trained model, which is aiming to detect the presence of the primary user. Their results show that a reasonable model is built and the proposed algorithm has higher detection probability than cyclo-stationary feature detection (CFD) about less performance.

Depending on spectrum bands that the SUs use, the schemes can be divided into two types, namely open spectrum sharing and licensed spectrum sharing. In the open spectrum sharing system, all the users have the equal right to access the channels. The spectrum sharing among SUs for the unlicensed bands belongs to this type. The licensed spectrum sharing can also be called hierarchical spectrum access model. In such systems, the licensed PUs has higher priorities than the unlicensed SUs. Usually, there are no conflicts among PUs since they all have their own licensed bands. For the SUs, they need to adjust their parameters, such as transmit power and transmission strategy, to avoid the interruption to the PUs. According to the access strategies of the SUs, the hierarchical spectrum access model can be further divided into spectrum underlay and spectrum overlay.

In the spectrum underlay system, the SUs are allowed to transmit while the PUs are transmitting. The interference generated from the SUs need to be constrained to protect the PUs. The power control problem is one of the key issues in the systems. In the spectrum overlay systems, the SUs can only transmit when PUs are not or the SUs create interference-free transmission to the PUs by using some advanced techniques. Spectrum overlay is also called opportunistic spectrum access (OSA).

Another classification depends on whether there exists a central node to manage spectrum allocation and access procedure [6]. The whole procedure may be controlled by a central node. Due to the cost of the central node and information feedback, the centralized approaches may be impractical in some cases. In this case, the SUs may make their own decisions based on the observations of the local spectrum dynamics. This is called distributed spectrum sharing. Of course, several SUs in a system may cooperate with each other, which is called cooperative spectrum sharing

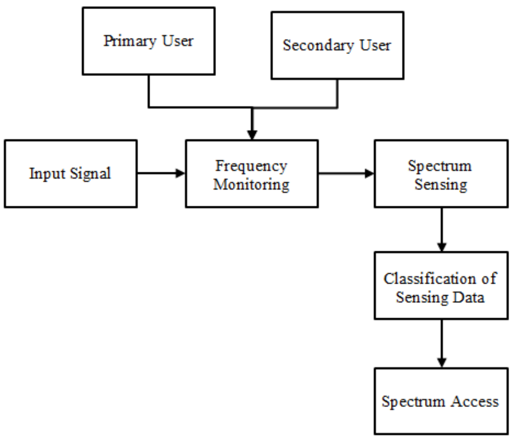

Fig. 3 Common Block Diagram of Spectrum Sensing and Access

3. PROPOSED METHODOLOGY

In cognitive radio systems, the detection performance of the energy detector depends on the high accuracy selection of the threshold expression. When developing spectrum sensing models, it is aimed that the noise and primary user signals are fully distinguished. Developed models are generally evaluated based on parameters such as accuracy and correct positive rate. However, the actual performance can be analyzed by using backwardly artificially generated estimates in the measurements. In this section, a new threshold expression model based on online learning algorithm is presented to improve spectrum sensing and sharing performance in cognitive radio networks.

FEED FORWARD NEURAL NETWORK

Feed Forward Neural Network is applied on the technologies of radio spectrum utilization and shown great performance as compared with the classical spectrum sharing approaches. However, FFNN is used in this project to optimize the time delay (to minimize the queuing time) and to enhance the throughput. Neural network is performed the said process in which made the spectrum utilization much efficient by learning the behaviors of primary users and secondary users and hence by allocating the radio spectrum to those users who are willing to login without (lesser than expected) congestion. In first stage of processing, data of users activity is provided to the Feed Forward Neural Network classifier in which taking this data and trying to analyze it during the training phase.

Feed forward neural network is training used LM (LEVENBERG-MARQUARDT) algorithm which is integrated in MATLAB toolbox, however, as it mentioned before, LM algorithm is working to update the weights and biases coefficients of neural network until reaching the best possible training performance (lesser error rate).

FEED FORWARD NEURAL NETWORK

FFNN is a powerful technique based on the neural structure of the brain for binary classification. It has a natural propensity for storing experiential knowledge and makes it available for use, which means that knowledge is acquired by the network through a learning process and it can be used to store the knowledge.

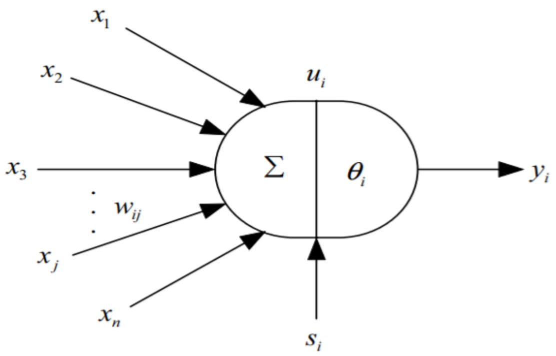

Fig. 4 Structure of Neuron

The block diagram of neuron is shown in Fig. 4.1. The parameter ui denotes the internal state of neural i, θi is the threshold, xi represents the input signal, wij is the value connected with neuron xj , and si indicates the external input signal.

The fundamental nature of spectrum sensing is a defined binary hypothesis testing problem that depends on the threshold expression. Tis relationship is illustrated in Fig. 4.3. Tis shows the expected distribution of a difference between two groups under H0 [true negative (TN)] and H1 [true positive (TP)]. It is clear that if we increase the type I error rate [false positive (FP) or false alarm], we reduce the type II error rate [false negative (FN) or missed detection], and vice versa. Changes in the accuracy of H0 and H1 hypotheses cause changes in the total error probability.

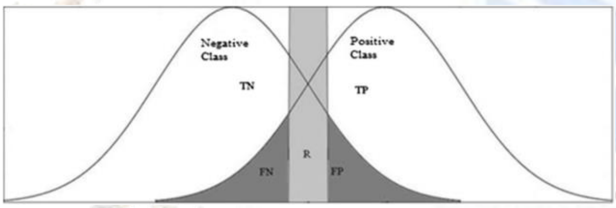

Fig. 5 Statistical Distribution Curves Related to Classes

Therefore, there is a very delicate balance between the possibility of miss detection and the possibility of false detection. To maintain and analyze the balance between these two, two classes are created by classifying the negative and positive data as shown in Fig. 4.3.

SENSINGPERFORMANCE PARAMETER

The sensing process consists of two stages and is controlled by signals from the upper layers to sense a specific bandwidth B, as shown in Figure 4.4. In the first stage, the received signal x(t) is filtered to the bandwidth of interest B to reject band noise and adjacent signals. It is then amplified using a low noise amplifier and is down converted to an intermediate frequency. In the second stage, the received signal is sampled and quantized using an A/D converter. Next, a square-law device and an integrator with sensing interval T measure the received signal energy. Finally, the output of the integrator, represented by the test statistic Y, is compared to a predetermined threshold λ to determine the existence (H1) or absence (H0) of a PU.

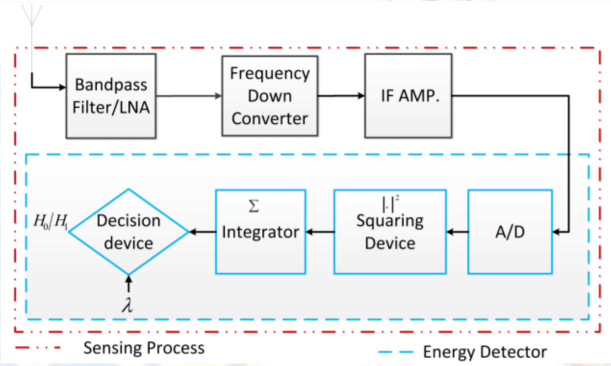

Fig. 6 Schematic of sensing abstraction including an energy detector

Gaussian noise (AWGN) with zero mean and variance σ2. h is the channel coefficient which is assumed to be constant during the period of observation, i.e., for N samples, H0 is the hypothesis test when noise only is present and H1 is the hypothesis test when both noise and signal are present. We also assume that the noise samples are independent and identically distributed, and they are independent of the signal samples.

Then, the distribution of the decision variable Y will be central chi-square χ2 N under H0 and noncentral chisquare χ˜ 2 N with N degrees of freedom under H1. Notice that to reduce the overuse of notations, we distinguish between central and noncentral chi-square by the symbol (∼).

Evaluating test Y by the decision device, which is shown in Figure 4.4, may result in two types of errors. We define the notation P(Hi, Hj) to distinguish between these errors.

- When the decision device decides H1 but H0 is true, denoted as P(H1; H0), this is called the probability of a false alarm (Pfa).
- When the device decides P(H0, H1), this represents the probability of misdetection (Pmd).
- The complementary to Pmd is the probability of detection (Pd = 1 − Pmd = P(H1; H1)).

The performance of the energy detector can be characterized by the probability of detection in a low SNR regime. An alternative performance metric is the ROC curves which are generated by plotting Pmd vs Pfa.

$$P_d = P(H_1; H_1) = P(y > \lambda; H_1)$$

$$= \int_{\lambda}^{\infty} f_Y(y)dy, \qquad H_1$$

$$P_{fa} = P(H_1; H_0) = P(y > \lambda; H_0)$$

$$= \int_{\lambda}^{\infty} f_Y(y)dy, \qquad H_0$$

SHARINGPERFORMANCE PARAMETERS

Throughput:

It is the ratio of the total number of bits transmitted (Btx) to the time required for this transmission, i.e. the difference of data transmission end time and start time (tstart).

$$\text{Throughput} = (B_{tx})/(t_{end} - t_{start}) \text{ bps}$$

Average Delay:

It is average transmission delay of packets transmitted from source to destination. D is computed as the ratio of the sum of individual delay of each received data packet to the total number of data packets received.

D= no.of received packed/total time

4. RESULTS & DISCUSSION

Spectrum sensing and sharing performance can be characterized by using the receiver operating characteristic (ROC) curve in cognitive radio networks. ROC curves are generated by plotting either detection probability versus false alarm probability or missed detection probability versus false alarm probability.

Detection probability and false alarm probability depend on the threshold, number of samples, fading parameters, number of diversity branches, and average SNR. The sensing performance of the proposed algorithm has been analyzed on different fading channels using energy-based detection and matched filter detection techniques.

SIMULATION RESULTS

Practical model is established to meet the methodology requirements and verity the assumption that made earlier in regards to cognitive radio. Simulation began by defining of working frequency (bandwidth) followed by licensed user band allotment.

According to the connection of probability detection initialized signal shown below. Without loss of generality, we assume the energy detection implementation shows the input periodogram when there is a primary user at 600 MHz with good SNR. It’s very clear in the figure that there is peak at 20dB.

So energy detector with peak value, in this case its greater than 20dB. Hence, energy detector shows that primary user is present at 200 MHz. Figure shows the input signal of energy detector when there is a primary user present at 200 MHz with 20dB/Hz. It’s very clear in the figure that with noise signal is shows across the graph equal to 0.5dB.

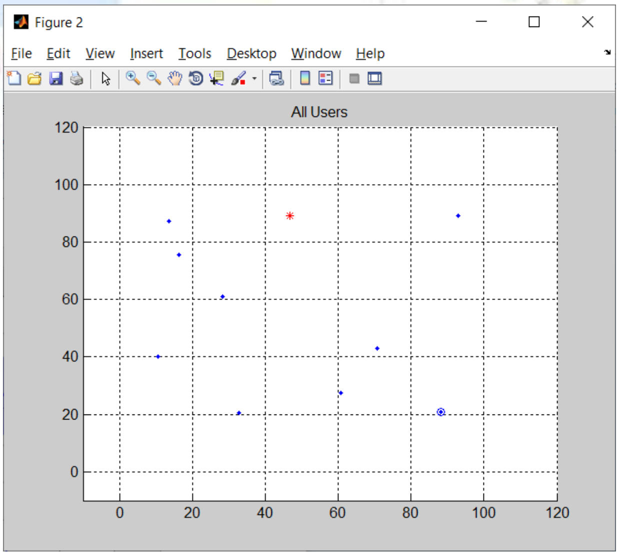

Fig. 7 No. of PU and SU Nodes

Here the figure explains the PU (Red Node) SU (1-10 Blue Node) as a source and destination pair of multi-user CRN, as consists of one primary source and destination pair (S_1-D_1), (N1) secondary source and destination pairs (Si-Di). All users are equipped with a single antenna. Besides, we assume that all secondary pairs share one channel of bandwidth of 1400MHz sampling frequency fs that is licensed to the primary pair. Normally, the PU has a higher priority to access the spectrum, and SUs have opportunistic access to the spectrum without affecting primary transmissions.

The successful transmission from source PU to destination SU embodies that both successful sensing and sharing are achieved; where the received signal at SU can be decoded with an arbitrarily small error if H0 is less than the capacity of H1; A pair (PU-SU) is active if SU to PU.

Detection probability and false alarm probability depend upon the limits, number of tests, blurring boundaries, number of variety branches, and normal SNR. The detecting execution of the proposed calculation has been investigated on various blurring channels utilizing energy-based identification and coordinated with channel matched filter detection discovery procedures.

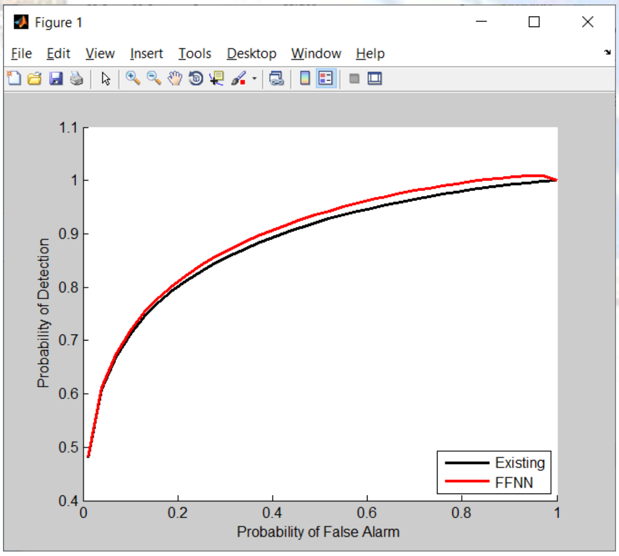

Fig. 8 ROC Comparison Pd vs. Pfa

Simulation results are provided to compare our existing with a conventional (FFNN) Feed Forward (calculated from Pfa=0.1). Because the performance of energy-based technique mainly depends on SNR (5 dB) considered. FFNN: Pd=0.3383; and proposed existing: Pd=0.5050. Spectrum sensing detection execution is subject to SNR. As the SNR expands, the probability of detection is improved

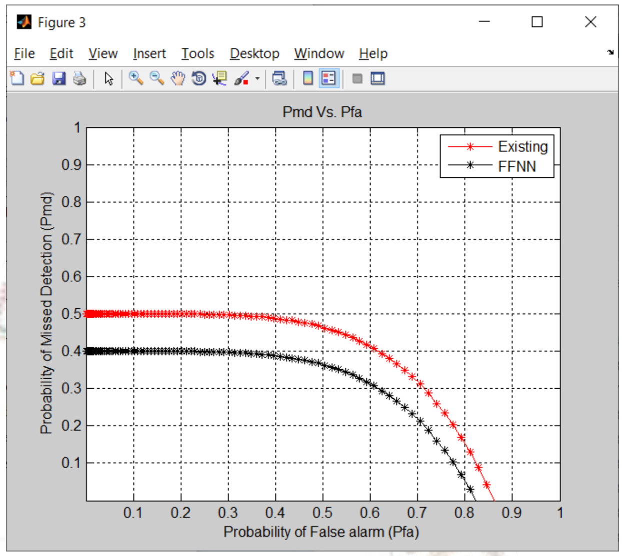

Fig. 9 ROC Comparison Pmd vs. Pfa of 5dB

Since the exhibition of energy-based method essentially depends with respect to SNR thought of. Figure shows the ROC bend for the Pmd versus Pfa. As can be seen, the presentation of the proposed calculation for various SNR situations is higher than those of existing FFNN calculation: limit (5 dB): Pmd =0.5371; and EXISTING (5 dB): Pd=0.4509; edge when the charts are analyzed, it is seen that the missing time recognition execution of intellectual radio increments with the proposed strategy. Plus, missing detection probability is less in AWGN blurring channel when contrasted with the current and other blurring channels.

With presence of AWGN channel, signal with different clients is sent for known time. Recurrence tweak is utilized to send signs of different frequencies over band restricted channel. This model is made and analyzed with assistance of MATLAB. Framework comprises of four practical devices to perform psychological radio errands as radio model, essential client's model, intellectual client's model and radio administration model.

In here, transmission capacity is partitioned similarly among the essential clients so that after supposition that is yielded: (PU-BW= complete BW/all out PUs).

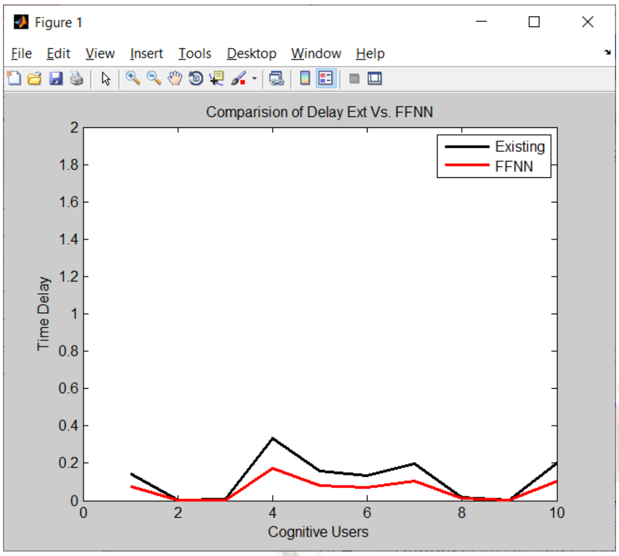

Fig. 10. Spectrum sharing – comparison of energy detector vs. FFNN of time delay

In order to justify the performance of the two different techniques (Feed Forward Neural Network and Back Propagation Neural Network), two performance metrics are used namely: time delay and model throughput. The time delay is the measure of the time required by the secondary user to get the position in the white band, the results of our experiments are shown in fig. and table for time delay, and The throughput is the actual number of users participating the band with respect to total available secondary candidates is bigger, the results of our experiments are shown in fig. and Table II for Throughput comparison.

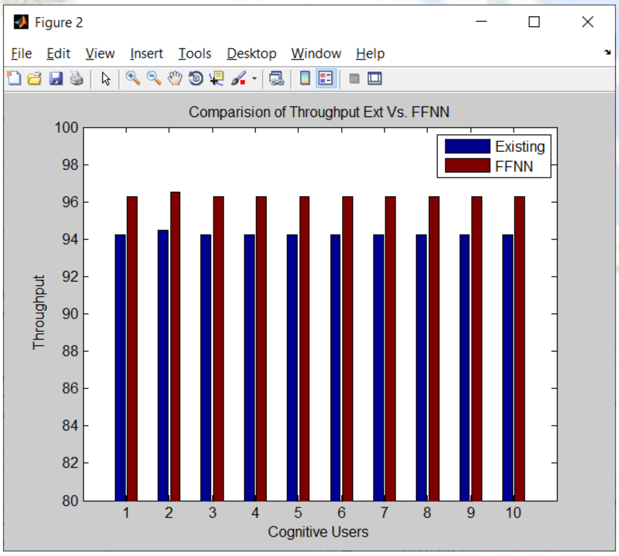

Fig. 11 Comparison of ffnn and exsiting of throughput

Fig. plots the throughput of primary and secondary users, respectively, with bands, taking both FFNN and EXISTING spectrum sharing scheme.

The throughput of PUs employing the sharing scheme as both user and throughput efficiency are increasing functions are larger.

The both output show the transmission delay and maximizes the energy efficiency throughput for primary users; The number of interfering users has a slight effect on the throughput and the energy efficiency of the primary pair due to the secondary control; The proposed scheme is beneficial for the throughput and the delay of the primary pair, and can be employed to compensate for the interference caused by secondary users.

5. CONCLUSION AND FUTURE SCOPE

In this project, a joint detection method for spectrum sensing and sharing based on the ANN with FFNN has been proposed. The approach could achieve better detection performance under low SNR compared with FF spectrum sensing technologies. Through combing the advantages of existing approach would reduce the computational complexity and boost the ability of anti-inference. The outcomes of this study shown that neural network is outperformed in both time delay minimization and throughput enhancement.

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