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Comparative Evaluation of Spectrum Sensing Techniques for Cognitive Radio

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ABSTRACT
Radio transmission involves the use of part of the electromagnetic spectrum, which is a natural scarce resource. Although use of spectrum is regulated by government agencies such as Federal Communications Commission (FCC) in the United States, scarcity of the same is a trending issue. Cognitive radio provides solution to the spectrum scarcity problem. The biggest question related to spectrum sensing is in developing sensing techniques which are able to detect very weak primary user signals while being adequately swift and low cost to implement.

Keywords - *Cognitive Radio; spectrum analysis; Neural network, Energy detection technique, Cyclostationary detection*

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I. INTRODUCTION

The available electromagnetic radio spectrum is in scarcity and is getting utilized day to day. It has been established that the allocated spectrum is underutilized because of its static allocation which is the standard approach of spectrum management and is very inflexible to operate in a certain frequency band. And most of the useful radio spectrum already allocated, it is difficult to find vacant bands to either deploy new services or to enhance existing ones. To combat this issue, we need to develop a means for enhanced utilization of the spectrum generating opportunities and i.e. Dynamic spectrum access. It gives spectrum access to unlicensed user which is called secondary user while licensed user, i.e. primary user is not accessing with respective frequency band.

Main functions of cognitive radio are [6]: spectrum sensing, spectrum management, spectrum mobility and spectrum sharing. Spectrum sensing detects the unused spectrum and shares it eliminating harmful interference with other licensed users thus increasing efficiency of the transmission. Spectrum Management is basically selecting the best available and unoccupied spectrum to fulfill communication requirements. Spectrum Mobility is defined as the process when a cognitive radio user interchanges its frequency of operation. Spectrum sharing decides which secondary user can use the spectrum hole at some specific time.

The necessity for higher data rates is increasing as a result of the transition from voice-only communications to multimedia type applications. Due to the constraints of the natural frequency spectrum, it is evident that the current static frequency allocation schemes cannot accommodate the requirements of an increasing number of higher data rate devices. Thus, there is a demand of innovative techniques that can offer new ways of exploiting the available spectrum. Cognitive radio is such a solution to the spectral congestion problem in transmission

The cognitive radio is built on a software-defined radio and is defined as an intelligent wireless communication system that is aware of its environment and uses the methodology of understanding by building to learn from the environment and adapt to statistical variations in the input stimuli [12]. Spectrum sensing for CR is an extremely well researched topic. [4] The biggest concern related to spectrum sensing is in developing sensing techniques which are able to detect extremely weak primary user signals while being accurate with high speed. [17]

II. SPECTRUM SENSING

Spectrum sensing is the ability to measure, sense and be aware of the parameters related to the radio channel characteristics, availability of the spectrum and transmit power, interference and noise, radios operating environment, user requirements and applications, available networks (infrastructures) and nodes, local policies and other operating restrictions. It is done across amplitude, frequency, time, geographical space, code and phase.

The literature on spectrum sensing focuses on primary transmitter detection based on the measurements of secondary users, since detecting the primary users that are collecting data is in general very difficult. There are three different techniques for sensing spectrum namely Energy detection, Cyclostationary detection & matched filter. [9]

Artificial Neural Network model does not require a priori knowledge of signal therefore it offers different options for modelling channel status predictor. Thus secondary users can access the licensed spectrum without interference to the primary user. Secondary user may want to conserve sensing energy by avoiding busy portions of the spectrum during sensing. Channel sensing plays important role as secondary users may predict the status of channel based on the sensing history & sense only if channel is predicted to be idle so ultimately it saves sensing energy & also uses spectrum efficiently.

In transmitter detection we have to find the primary transmitters that are transmitting at any given time whereas in receiver detection, we have to design techniques which we have some information about primary receiver.

III. SPECTRUM SENSING TECHNIQUES

IV. THE FIRST PARAGRAPH UNDER EACH HEADING OR SUBHEADING SHOULD BE FLUSH LEFT, AND SUBSEQUENT PARAGRAPHS SHOULD HAVE A FIVE-SPACE INDENTATION. A COLON IS INSERTED BEFORE AN EQUATION IS PRESENTED, BUT THERE IS NO PUNCTUATION FOLLOWING THE EQUATION. ALL EQUATIONS ARE NUMBERED AND REFERRED TO IN THE TEXT SOLELY BY A NUMBER ENCLOSED IN A ROUND BRACKET (I.E., (3) READS AS "EQUATION 3"). ENSURE THAT ANY MISCELLANEOUS NUMBERING SYSTEM YOU USE IN YOUR PAPER CANNOT BE CONFUSED WITH A REFERENCE [4] OR AN EQUATION (3) DESIGNATION.

V. FIGURES AND TABLES

Energy Detection Technique

Energy detection is a non-coherent detection spectrum sensing technique in which no prior knowledge of data is required.

As shown in figure 2, the input filter selects the center frequency & bandwidth of interest. Filter is followed by squaring device to measure the received energy then the integrator determines the observation interval. Finally the output of integrator is compared with threshold to decide whether primary user is present or not.

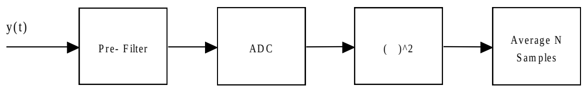


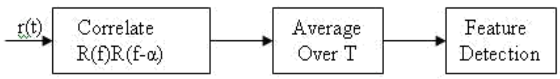
Fig. 2 Energy detection block diagram

Ho: y(n) = w (n) ; signal is absent

H1: y(n) = w(n)+s(n); signal is present

Cyclostationary Spectrum Sensing

Cyclostationary feature detection is a method for detecting primary user transmissions by exploiting the cyclostationary features of the received signals.



A signal is said to be cyclostationary, if its autocorrelation is a periodic function of time t with some period. A zero-mean continuous signal is called cyclostationary if its time varying autocorrelation function defined as;

$$R_{xx}(t,\tau) = E[\, x(t)\, x^*(t,\tau)]$$

is periodic in time t for each lag parameter and it can be represented as a Fourier series

$$R_{xx}(t,\tau) = \sum_{\alpha} R_{xx}^{\alpha}(\tau)\, exp^{j2\pi\alpha t}$$

Where the sum is taken over integer multiples of fundamental cyclic frequency for which cyclic autocorrelation function (CAF) is defined as:-

$$R_{xx}(t,\tau) = lim_{x\to\infty} \int_{-\frac{T}{2}}^{\frac{T}{2}} R_{xx}(t,\tau)\, exp^{-j2\pi\alpha t}\, dt$$

The Fourier transform of is called the cyclic spectrum (CS) which is defined as:

$$S_{xx}^{\alpha} = \int_{-\infty}^{\infty} R_{xx}^{\alpha}(\tau) exp^{-j2\pi\alpha t} d\tau$$

The detection of the presence and absence of signal is performed based on scanning the cyclic frequencies of its cyclic spectrum or its cyclic autocorrelation function. The decision is made on the basis of autocorrelation function, i.e. at a given cyclic frequency if the cyclic spectrum or its cyclic autocorrelation function is below the threshold level, the signal is absent otherwise signal is present

NEURAL NETWORK FOR SPECTRUM SENSING

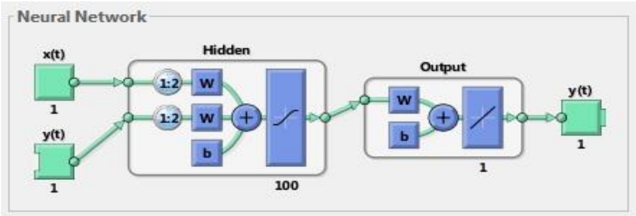


Fig. 4 the Structure of the Neural Network

As shown in the block diagram, input signal is power spectral density of signals has been taken as input features. As statistical variations are more then it will take more time to train neural network along with that there may have chances to miss signal with low SNR characteristic. Considering these signals are taken as input feature to train the neural network.

Seventy percent of our data was used for network training & this training was done till mean square error (MSE) is used as performance function was minimum. Fifteen percent of total data was used to validate the network & stop training before the network is over fitting.

The neural network has been selected is Levenberg- Marquardt method which is feed forward how in figure 2. Here, Random signal has been generated using matlab under the circumstances of parameters, Rs1 =10, fc1 =50 Hz, fs =500Hz, SNR= -30dB. This signal has been converted into Quadrature amplitude modulation (QAM) & energy calculated. Binary phase shift modulation (BPSK) is applied on process signal & Fast fourier transform (FFT) values calculated for giving training network

$$s(t) = x(t) + w(t) = A + \sqrt{2}\cos(2\pi ft + \theta)\cos(2\pi f_o t + \theta_o) + w(t)$$

A] Energy value –

$$E = \frac{1}{2\pi}\int_{-\infty}^{+\infty} |F(w)|^2 dw$$

Where, $|F(w)|^2$ represents the spectrum distribution

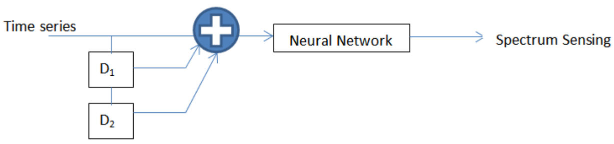


Figure 5. Focused Time Delay Neural Network

Net Type	FTDNN
Training Data Set Size	3650
No. of Hidden Neurons	100
Delay Element	2
Training Function	Train lm
Epochs	1000
Learning Rate	0.001

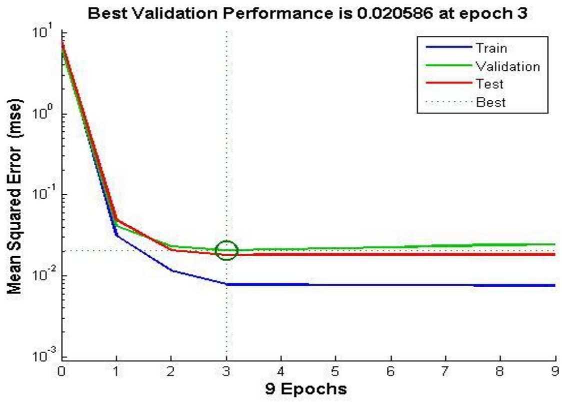


Fig. 6 Performance of network in terms of MSE

From figure 6, it has been observed that validation and test curves are very similar. Dashed line indicates here the best targeted value. If test curve had increased significantly before the validation curve increased then it is possible that some over fitting might have occurred. The performance matrices (Mean Square Error) MSE is less than 10^-1 in 9^{th} epoch as shown in figure 6.

VI. SIMULATION RESULTS

Energy Detection Technique

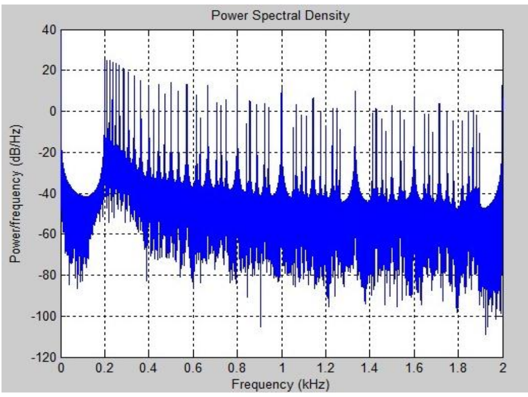


Fig. 7 Energy detector output for 30dB SNR for BPSK when primary user is present at 200Hz

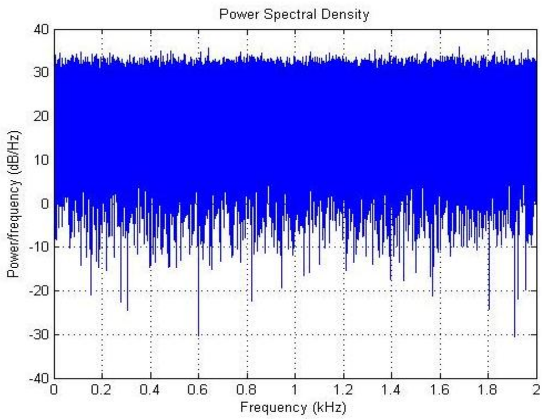


Fig. 8 Energy detector output for -30dB SNR for BPSK when primary user is present at 200Hz

Flow chart for the energy Detector implementation is shown in Fig. 4 shows the output of energy detector when there is a primary user present at 200 Hz using BPSK with very good SNR. It's very clear in the figure that there is peak at 200 Hz. So energy detector compared this peak with threshold value, in this case its greater then threshold. Hence, energy detector shows that primary user is present at 200 Hz.

Flow chart for the energy detector implementation is shown in Figure 8 shows the output of energy detector when there is a primary user present at 200 Hz using BPSK with low SNR. It's very clear in the figure that only noise signal is shows across the graph. Hence, energy detector shows that primary user is not identified.

Cyclostationary Detection Technique

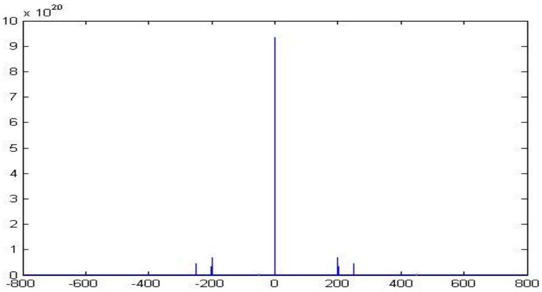


Fig. 9 Cyclostationary detector output for-30dB SNR for BPSK when primary user is present at 200Hz

Fig. 7 shows the output of cyclostationary feature detection when there is a primary user at200 Hz using BPSK is present with very poor SNR. It's very clear in the figure that it's very difficult to detect second peak at 400. So we have to compare second peak with threshold value. Hence, cyclostationary feature detection compared value of each peak with threshold; in this case no peak is greater than threshold. Hence, cyclostationary feature detection said that primary user is not present.

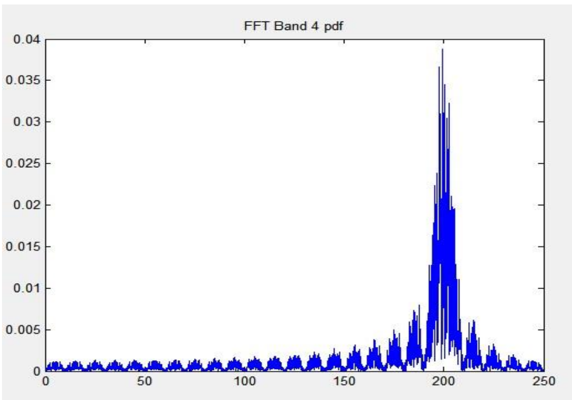


Fig. 10 Performance of Neural network output for
-30dB SNR for BPSK when primary user is present at 200Hz (Detection of busy channel)

Flow chart for the energy Detector implementation is shown in Figure 10 shows the output of neural network when there is a primary user present at 200 Hz using BPSK with poor SNR. It's very clear in the figure that there is peak at 200 Hz. So, trained neural network gives output in terms of 1 and 0. So, here detection of busy channel has been found by neural network.

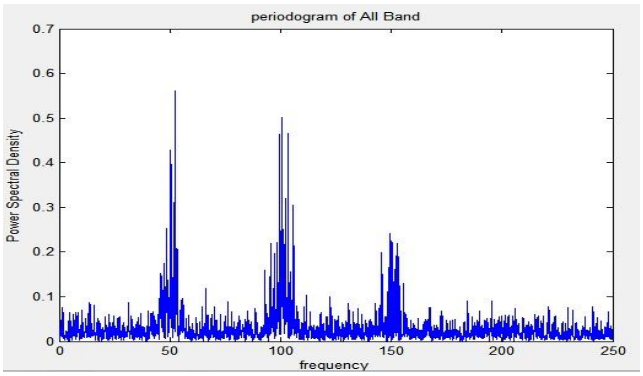


Fig. 11 Performance of Neural network output for
-30dB SNR for BPSK when primary user is absent at 200Hz (Detection of free channel)

Flow chart for the energy Detector implementation is shown in Figure 11 shows the output of neural network when there is a primary user absent at 200 Hz using BPSK with poor SNR. It's very clear in the figure that there is no peak at 200 Hz. So, trained neural network gives output in terms of 1 and 0. So, here detection of free channel has been found by neural network.

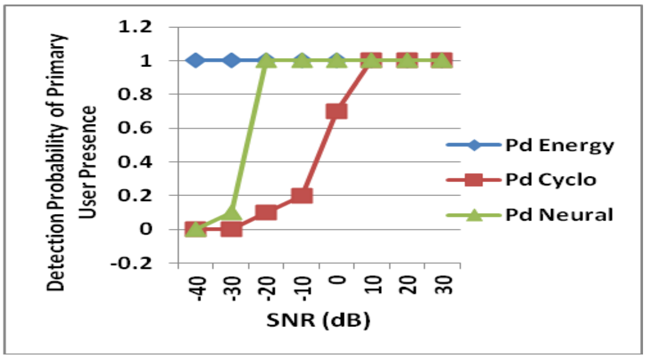


Fig. 12 Comparison of spectrum sensing technique when primary user is present

As shown in figure 12, Energy detector is still better under noisy condition compared with cysclostationary detector. Artificial neural network technique exhibited effective detection like energy detector. But drawback of energy detector is its inability to differentiate between noise and primary user. So, energy detector is susceptible technique and neural network is most useful other that two.

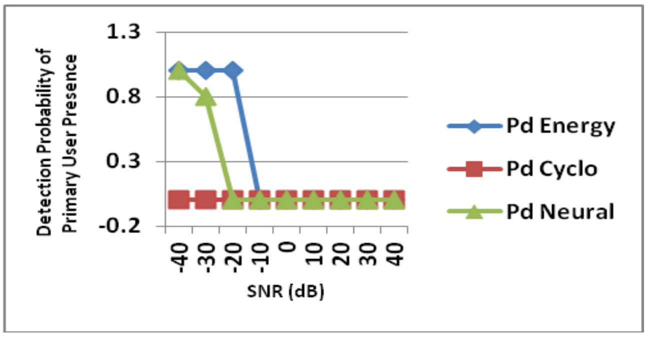


Fig. 12 Comparison of spectrum sensing technique when primary user is absent

Figure 12, shows that when there is no primary user present even then energy detector detects primary user at low SNR which makes energy detector unreliable technique under low SNR value. Hence, cyclostationary and neural network are the best technique for feature detection.

VII. CONCLUSION

This research was aims towards the detection and classification of primary users. As the demand of radio spectrum increases in last few years and licensed bands are used inefficiently, improvement in the existing spectrum utilization policy is expected. Dynamic spectrum access is to resolve the spectrum shortage by allowing unlicensed users to dynamically use the spectrum holes across the licensed spectrum on no interfering basis. First all the transmitter detection techniques are compared on the basis of three parameters: Sensing time, Detection sensitivity and Ease of implementation. By comparing these techniques it is indicates that Neural Network based detection gives best results but take long computation time for training but gives results in short time for testing compared to energy detection & cyclostationary detection technique.

This paper introduces and evaluates learning schemes based on artificial neural networks and can be used for discovering the performance. It was observed that for every detection technique & Cyclostationary detection technique has an SNR threshold value below which it fails to operate robustly. Using Artificial Neural Network based detection will help when noise present in the signal whereas the energy detection will fail as the noise in the signal exceeds the threshold. Thus performance of Artificial Neural Network based detection technique was better than energy detection technique & Cyclostationary detection technique when noise in the signal exceeds the threshold.

REFERENCES

[1] Amir Ghasemi, Elvino S. Sousa: "Spectrum Sensing in Cognitive Radio Networks: Requirements, Challenmges and Design Trade- Offs, IEEE Communication Magzine April 2008. page(s): 32-39

[2] L. Berlemann, S. Mangold, B.H.Walke, Policy-based reasoning for spectrum sharing in cognitive radio networks, in: Proc. IEEE DySPAN 2005, November 2005, pp. 1–10.

[3] I.F. Akyildiz, Y. Altunbasak, F. Fekri, R. Sivakumar, "AdaptNet: adaptive protocol suite for next generation wireless internet", IEEE Communications Magazine 42

[4] J.A. Stine, Spectrum management: the killer application of ad hoc and mesh networking, in: Proc. IEEE DySPAN 2005, November 2005, pp. 184–193.

[5] I.F. Akyildiz, X. Wang, W. Wang, Wireless mesh networks: a survey, Computer Networks Journal 47 (4) (2005) 445–487. A. Ghasemi and E. S. Sousa, "Collaborative Spectrum Sensing for Opportunistic Access in Fading Environment", in Proc. IEEE DySPAN, pp. 131-136, Nov. 2005.

[6] F. F. Digham, M. S Alouini and M.K Simon, "On the energy detection of unknown signals over fading channels", in Proc. IEEE International Conference on Communication (ICC003), pp. 3575-3579, May 2003.

[7] I.F Akyildiz,W Lee, M.C Vuran, S Mohanty, "Next Generation/ Dynamic spectrum access/cognitive radio wireless networks: A survey Computer Networks" 50(2006) 2127-2159, May 2006.

[8] B Saklar, "Digital Communications: Fundamentals and Applications" (2nd Edition) (Prentice Hall Communications Engineering and Emerging Technologies Series).

[9] D. Cabric, S. M. Mishra, and R. W. Brodersen, "Implementation Issues in Spectrum Sensing for Cognitive Radios",in Proc. 38thAsilomar Conference on Signals, Systems and Computers, pp. 772776, Nov. 2004.

[10] A. Sahai, N. Hoven and R. Tandra, "Some Fundamental Limits in Cognitive Radio", in Proc. Allerton Conf. on Comm., Control and Computing 2004.