

Performance Analysis of Spectrum Sensing in Cognitive Radio Network using Classification Techniques

Dr. Rizwana Parveen

Assistant Professor

Department of Computer Science, NRI Group of Institutions, Bhopal, (M.P.), India

Abstract: Cognitive radio networks (CRNs), an assemble of smart schemes intended for permitting secondary users (SUs) to opportunistically access spectral bands vacant by primary user (PU), has been deliberated as a solution to improve spectrum utilization. Cooperative spectrum sensing (CSS) is a vital technology of CRN systems used to enhance the PU detection performance by exploiting SUs' spatial diversity, however CSS leads to spectrum sensing data falsification (SSDF), a new security threat in CR system. The SSDF by malicious users can lead to a decrease in CSS performance. In this paper we proposed the r spectrum sensing model using the deep neural network classification and gives better result than the existing techniques.

Keywords: Cognitive Radio Network, Classification Techniques, Neural Network, Support Vector Machines, Deep Neural Network.

1. INTRODUCTION

The Internet of Things (IoT) has emerged as a significant network application, interconnecting billions of devices worldwide, enabling continuous data collection and sharing to enhance services and value. However, the growth of IoT networks faces several challenges: the demand for higher bandwidth to accommodate a multitude of hybrid communication devices, security issues associated with diverse devices and networks, elevated implementation costs, inadequate spectrum availability, and increased energy consumption compared to traditional systems. To address spectrum shortages stemming from the proliferation of wireless devices, Cognitive Radio (CR) technology has been developed, which allows Secondary Users (SUs) to utilize the licensed spectrum of Primary Users (PUs). In a Cognitive Radio based IoT (CR-IoT) network, CR-IoT users access idle licensed frequency bandwidths when licensed users are absent. These users detect unoccupied licensed channels suitable for data transmission and vacate the spectrum once a PU resumes communication to prevent conflicts.

The effective detection of unoccupied licensed spectrum is crucial in Cognitive Radio Networks (CRNs) to avoid issues between PUs and SUs. Various licensed spectrum detection

techniques exist, which can be categorized into non-coherent spectrum sensing, coherent spectrum sensing, Non-Cooperative Spectrum Sensing (NCSS), and Cooperative Spectrum Sensing (CSS). Non-coherent spectrum sensing does not require prior knowledge of the PU's signal, while coherent sensing mandates this knowledge for accurate detection. In NCSS, CR-IoT users operate without exchanging information with each other, leading to potential performance degradation due to issues like hidden terminal effects and multi-path fading. In contrast, CSS involves cooperation among CR-IoT users to enhance spectrum detection by sharing information with a Fusion Center (FC), which consolidates detection results to make a global decision on the presence of the PU signal.

Several spectrum sensing methodologies have been explored under different conditions, such as matched filter methods, cyclostationary feature methods, entropy-based methods, eigenvalue-based methods, and Energy Detection (ED) methods. Both matched filter and cyclostationary methods are straightforward but require prior knowledge of the PU signals, including carrier frequency and modulation characteristics. On the other hand, the ED method stands out as a simple approach for assessing the received signal energy of PU signals without needing pre-existing knowledge,

making it widely utilized in CRNs. Nonetheless, ED is vulnerable to noise fluctuations and relies on a clear understanding of noise signal power at the receiver, which can diminish detection performance in environments characterized by noise uncertainty and low Signal to Noise Ratios (SNR).

2. SMART GRID COGNITIVE RADIO

Conventional power grids represent extensive interconnected systems responsible for the distribution of electricity from producers to consumers. These grids operate predominantly by allowing electric power to flow solely from generating stations to end-users, while information and monitoring processes are confined to the localized distribution networks that manage electricity within urban settings. However, these traditional grids encounter several contemporary challenges, including increased energy requirements, deteriorating infrastructure, the advent of renewable energy sources, and ongoing issues regarding reliability and security. In response to these pressing issues, the Smart Grid (SG) paradigm has been developed, leveraging a range of advanced enabling information technologies. These technologies encompass embedded sensing, broadband wireless communication, pervasive computing, adaptive control, and intelligent management systems. The implementation of SG technologies is anticipated to yield marked enhancements in several key areas: efficiency, effectiveness, sustainability, reliability, security, and overall stability of the electrical grid.

3. Spectrum Sensing Techniques

Due to the rapid growth in the field of communication, there is an increasing demand for higher data rates. Static frequency assignment cannot fulfill the requirements of higher data rates. In CR communication, spectrum sensing is performed before an SU starts using the spectrum. By spectrum sensing, the white holes are determined and these holes are used efficiently. There are certain methods for sensing the unused spectrum. Spectrum sensing techniques (Cooperative detection, Transmitter detection and Interference-based detection) are shown in below figure.

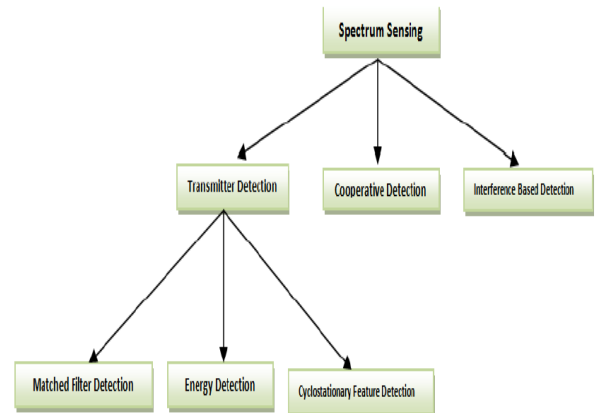


Figure 1: Different Spectrum Sensing Techniques.

4. PROPOSED WORK

The rapid development of wireless communication technology has led to more and more wireless network services. The radio spectrum, as the most valuable resource in wireless networks, cannot meet the requirements of wireless services at present and in the future. The existing fixed spectrum allocation method makes the spectrum utilization low and seriously uneven. According to the investigation, the average spectrum utilization is less than 5% at any time or place. Dynamic spectrum access (DSA) is considered to be the main technical solution to the contradiction between supply and demand. As the basis of DSA, cognitive radio (CR) technology has become one of the most cutting-edge research topics in the field of wireless networking. Note that the proposed schemes here balance sensing performance and sensing complexity. Although the considered CNN networks are classical, they are easy to implement due to their high popularity. Both the data acquisition and the network structure have low complexity. However, the sensing performance is at a high level according to the results of the simulation experiments. In summary, the proposed schemes in this paper are necessary and useful for the possible performance improvement of SS.

System Model

Sensing Scenario

As shown in below figure, each SU directly transmits the local sensing information to the FC, and the FC makes the final decision and then sends it to each SU for the centralized CSS. The details of centralized CSS are as follows:

1. The energy vector of each sensing node is obtained by the sampling and signal processing.

4. The final decision result at FC is sent to each local sensing node.

A line graph with 'Previous Work' and 'Present Work' on the x-axis and a numerical scale from 0 to 2.0 on the y-axis. A red line with diamond markers connects the points (Previous Work, 1.8) and (Present Work, 0.5). The y-axis has horizontal grid lines every 0.2 units. The x-axis has vertical grid lines for each category.

Work Type	Accuracy Drop
Previous Work	1.8
Present Work	0.5

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93:  s1 = 0;
94:  for i = 1:power(10,ceil(1/10));
95:      for kx = 1:6
96:          t = 1/(1+2i/kx);
97:
98:          X = sin((t*pi^2));
99:          x = (x > 0);
100:          x = x^2+1;
101:          noise = randn(1,length(t));
102:          Q0 = (t/2000000)^.25;
103:          a = exp(1/2*norm(t));
104:          Xk = a.*Q0*(2*pi*(t^2));
105:          y = a.*Xk;
106:
107:          ps = norm(abs(y).^2);
108:          YV = y/abs(y);
109:          z1 = (b-exp(1/2*exp(t).*exp(1/2*exp(t)*YVd1)));
110:          z1 = (b-exp(1/2*exp(t).*exp(1/2*exp(t)*YVd2)));
111:          z1 = (b-exp(1/2*exp(t).*exp(1/2*exp(t)*YVd3)));
112:          sum1 = sum(abs(YV).^2);
113:          if sum1>1
114:              s1 = s1+1;
115:          end
116:          if sum1>2
117:              aYVd1=1;
118:          end

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5. CONCLUSION

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vector machines. We have demonstrated that the use of Channel Boosted input can improve the performance of a DNN.

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