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Spectrum Sensing in Cognitive Radio Network using Convolution Neural Network

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Abstract: *Cognitive Radio (CR) has received tremendous research attention over the past decade, both in the academia and industry, as it is envisioned as a promising solution to the problem of spectrum scarcity. A CR is a device that senses the spectrum for occupancy by licensed users (also called as primary users), and transmits its data only when the spectrum is sensed to be available. For the efficient utilization of the spectrum while also guaranteeing adequate protection to the licensed user from harmful interference, the CR should be able to sense the spectrum for primary occupancy quickly as well as accurately. In this paper we present the spectrum sensing performance with convolution neural network and enhance the existing model in terms of quality of services or measured performance parameters.*

Keywords: *Cognitive radio, Deep learning, Spectrum sensing, Convolution neural network, Classification, Machine learning*.

1. INTRODUCTION

Cooperative spectrum sensing is a powerful means of enhancing the spectrum awareness of cognitive radios in a fading environment by virtue of spatial diversity as opposed to stand-alone spectrum sensing. The duration of this collaborative endeavor is proportional to the sensing accuracy. However, an increase in sensing time causes a proportional loss in network throughput. Therefore, it is important to reduce spectrum sensing time given a spectrum sensing performance requirement, such as the probability of detection and/or false alarm, is satisfied. The tradeoff between sensing accuracy and throughput loss is referred to as sensing-throughput tradeoff. The spectrum sensing time is a function of the local sensing time as well as the manner spectrum sensing data is collected from participating SUs. Reporting or collection of sensing data also are critical to any practical implementation of CSS.

The details of sensing data reporting have been somehow overlooked in the literature, in spite of the thorough investigation of several CSS techniques in terms of performance analysis. Two sensing data collection methods have been identified in the literature: round-robin and random medium access. The first is to assign each participating SU an exclusive time slot to transmit its sensing data. This, however, requires continuous synchronization and management of allocated slots among SUs, especially when used in an ad-hoc setup where SUs continuously change their location like in a VANET. The other method is to use random medium access reporting, which is much simpler to implement. SUs are not allocated exclusive slots to report their sensing data, but use dialects of the celebrated Distributed Coordination Function (DCF) to coordinate access to a common control channel in a distributed manner. More specifically, when the reporting channel is detected idle, each terminal takes a random back off counter and transmits its report whenever this counter elapses. While it is waiting,

A terminal will pause its counter whenever it detects another transmission. Random medium access reporting, intuitively, has two major effects on the CSS process: the number of received reports is now a random variable due to the non negligible probability of collision, and the reporting times need to be carefully balanced to achieve successful reporting while not sacrificing throughput. Also, it is usually assumed that SUs use a dedicated channel to report their sensing results separate from the primary channel.

However, a dedicated reporting channel is not always available and SUs may have to report their sensing results to the FC over the primary channel they are detecting. Multiple efforts have been directed at balancing the sensing-throughput tradeoff. Some works focused on optimizing the local sensing time to achieve a minimum sensing accuracy. These, however, usually rely on the statistical characteristics of the PUs' signals, which might not be available to the SUs. Different SUs might also need different sensing times as perceived PUs' signals characteristics, even when available, vary across distant SUs in an ad-hoc network. This limits the usefulness of local sensing time optimization, as terminals will not report to the FC until they all finish sensing. Reporting time reduction also has been investigated in the literature.

A number of researchers have investigated sequential detection with round-robin reporting, where instead of using fixed sample size at each SU, SUs can terminate the sensing process early once enough evidence is received about the PU activity. The FC in a centralized CSS scheme also can apply sequential testing. More specifically, in a two-tier sequential sensing scheme, SUs gather samples for a given spectrum band then compare the accumulated decision metric to a pair of decision thresholds, and then reports to the FC once the decision metric passes either threshold. SUs reports can be soft or a hard local decision. The FC, itself, accumulates its own decision metric comparing it to a pair of thresholds as well, and then broadcasting its decision when either thresholds is passed and the CSS reporting process is terminated. Determining the optimal sequential spectrum sensing time has been the focus of most of these studies. These works, however, assume terminals transmit their reports to the FC at particular time slots specified by and coordinated with the FC. Such coordination is not always attainable. Furthermore, the agility of sequential sensing requires simultaneous sensing and reporting, and hence requires a dedicated Common Control Channel (CCC). While CR-VANETs, built over IEEE 802.11p PHY/MAC layers, have that, it still constitutes a burden over the WAVE/DSRC CCH that is originally intended for safety-related traffic. Moreover, using a CCC implies reporting can only start after all terminals have successfully made a decision or a maximum sensing time is reached, which would sacrifice the benefits of sequential detection.

2. COGNITIVE RADIO ARCHITECTURES

Cognitive Radio network architecture can be categorized into two groups, the primary network and the cognitive radio network [7]. The primary network is an existing infrastructure which has an exclusive right over a certain spectrum band, for example, the cellular networks and TV broadcast networks. The components of the primary networks are

• Primary User (licensed user): a user which has a license to operate in a licensed band. The PU operation should not be affected by the operations of CR users.

• Primary Base-Station (licensed base-station): a fixed infrastructure network component with spectrum license.

The CR network does not have license to operate in a licensed band and its spectrum access is allowed opportunistically. The components of the cognitive radio networks are:

• Cognitive Radio User (unlicensed user): a user who has no license over the spectrum. CR user can access the spectrum opportunistically only when PU is not present and CR user must vacate the channel immediately when the PU is detected.

Cognitive Radio Base-Station (unlicensed base-station): a fixed infrastructure component with CR capabilities, providing a single-hop connection to CR users. In cooperative spectrum sensing, the CR Base-Station also serves as a fusion center to gather the information from cooperative users and make the final spectrum sensing decision.

• Spectrum Broker (scheduling server): a central network entity that controls spectrum resource sharing among the CR users. Operate in determined spectrum band, it should keep track of the changes in the radio environment, as the radio environment can change over time and space. When the current spectrum band becomes unavailable, CR user needs to stop utilizing that channel immediately to avoid interference to the PU.

3. PROPOSED WORK

Machine learning is being widely used for classification problems. In this particular work, we have chosen Deep Neural Network to identify our signal. Deep Neural Network has high accuracy rate in contrast of other machine learning algorithms. One particular architecture for Deep Neural Network is Multi Layer Perception where all the layers are densely connected to each other. Neural network is a mapping function that maps input vector to an output vector. A neural network is consisted of different layers. Most basic layers are 1) input layer 2) hidden layer and 3) output layer. The building block of every layer is known as neurons. Warren McCulloch and Walter Pitts first proposed a simple model of the biological neuron. This model later became known as artificial neuron. As per the model, an output is activated by the neuron for some inputs. As mentioned earlier multi layer Perception (MLP) has three major layers. All the layers are connected to a bias neuron and densely connected to the next layer. Only the output layer is not fully connected to the previous layer. A figure of MLP is given below.

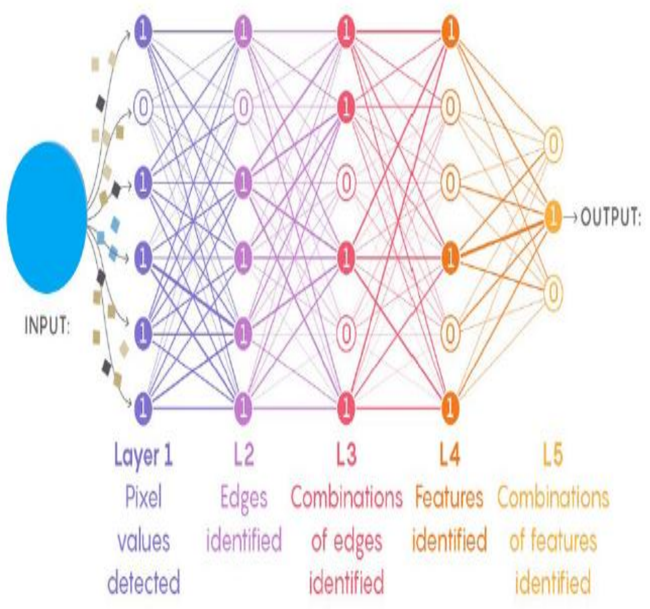

Figure 1: Multi-Layer Perception Neural Network with major layers (input, hidden and output) fully connected with each other.

One of the key challenges in Cognitive Radios (CR) is Spectrum Sensing (SS), which is the well-studied binary hypothesis testing problem of determining the presence or absence of a primary signal in a given frequency band of interest. In the future, CRs are envisioned to operate in various wireless environments, and in the presence of interference, changing noise statistics, etc,. Therefore, techniques used for SS need to be capable of handling various fading environments, primary signal models and different types of noise distributions. Energy Detection (ED) is a simple technique for SS, where the signal energy in the frequency of interest is measured over a sensing duration and compared to a threshold. However, in the presence of the background noise alone, it performs poorly in the low SNR regime under the NPU. In the presence of the non-Gaussian components, ED fails to satisfy the false-alarm probability constraint because of the underlying heavy tailed, non-Gaussian distribution with infinite variance.

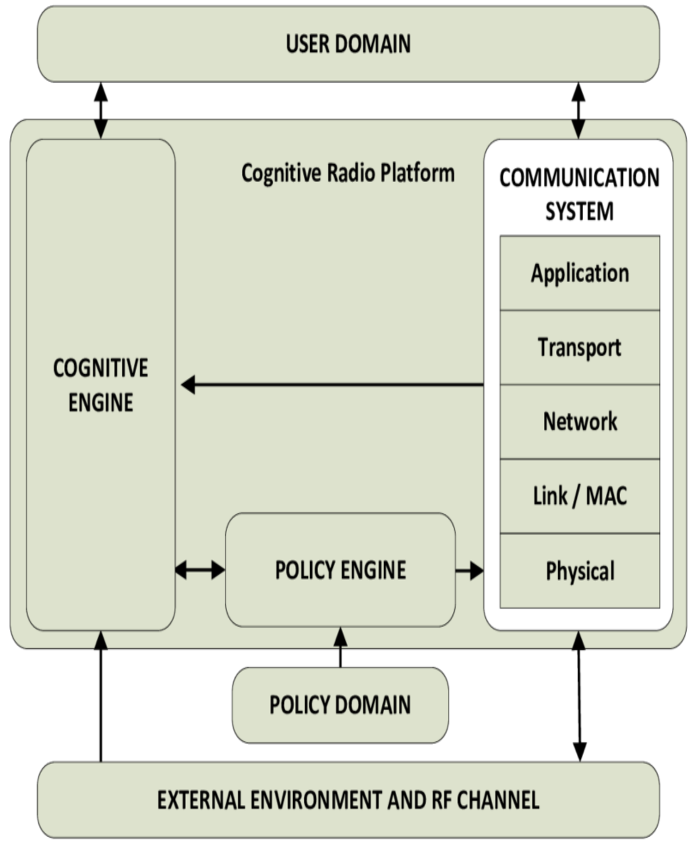

Figure 2: A proposed model for spectrum sensing.

4. EXPERIMENTAL WORK

The Simulation is an experimental process in that process proposed a simulated model for spectrum sensing and their efficiency using neural network and machine learning techniques, here we mention some standard parameters like 64 quadrature phase shift keying, 128 quadrature phase shift keying and, probability detection and, measured the performance evaluation with previous work and present work. For the performance evaluation of feature reduction classifier technique used MATLAB software package. MATLAB is a software package for high- performance numerical computation and visualization. It provides an interactive environment with hundreds of built in function for technical computation, graphics and animation.

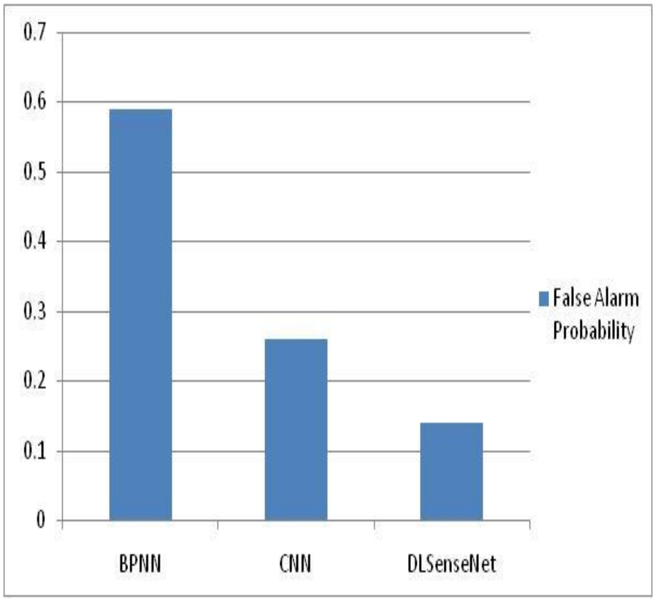

Figure 3: The above graph represents that other experimental result window for the 128 quadrature phase shift keying sample length with false alarm probability previous and proposed work.

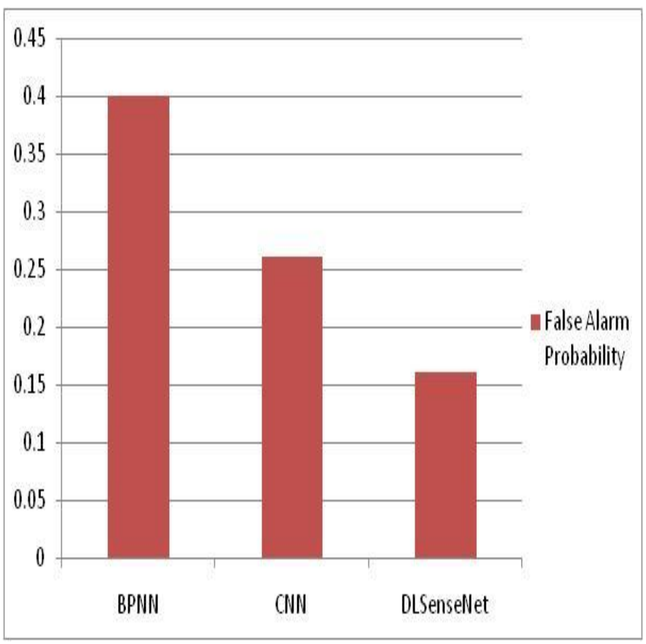

Figure 4: The above graph represents that other experimental result window for the 64 quadrature phase shift keying sample length with false alarm probability previous and proposed work.

5. CONCLUSION AND FUTURE SCOPE

Nowadays, there is an increased need for anywhere anytime connectivity, which is expected to increase significantly during the next few years. In order to meet the consequent high data traffic demands, dramatic expansion of network infrastructures as well as fast escalation of energy demands are expected. As a result, it becomes urgent for mobile operators not only to maintain sustainable capacity growth to meet these new demands, but also to limit their electric bill. In parallel, the fact that the spectrum resources are limited has led to another important problem, known as spectrum scarcity, which stresses the need for spectral efficient solutions. The aforementioned goals can be summarized into the joint maximization of energy and spectrum efficiency, which constitutes a fundamental design objective for next generation networks. To that end, exploiting cognition is expected to play a key role. In general, a cognitive network is able to sense its environment and dynamically adapt to it. In particular, cognitive networks, which could be alternatively characterized as context-aware or self-organizing networks (SONs), have the ability to perceive current network conditions, plan, decide, act based on those conditions, learn from the consequences of their actions, all while following end-to-end goals. This loop, the cognition loop, senses the environment, plans actions according to input from sensors and network policies, decides which scenario fits best its end-to-end purpose using a reasoning engine, and finally acts on the chosen scenario. The system learns from the past (situations, plans, decisions, actions) and uses this knowledge to improve the decisions in the future. In this work we present the spectrum sensing performance evaluation using the deep learning techniques, and our result shows that the better results than the previous work.

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