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Spectrum Holes Sensing Policy For Cognitive Radio Network Using Reinforcement-Learning

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Abstract

Cognitive radio is a promising technology that allows Secondary (unlicensed) Users (SU) to access and share the frequency band originally allocated to Primary (licensed) Users (PU). Secondary nodes are cognitive radio and primary users have license to use spectrum. The secondary nodes utilize the spectrum whenever it is free or not occupied by primary user. Whether the spectrum is occupied or not is found by sensing techniques, like energy detection or cyclostationary etc. Energy consumption for spectrum sensing depends on techniques used in secondary nodes. If Secondary node follows periodic or random policy, energy consumption would be high or spectrum holes missing high respectively. And so the secondary user needs optimized spectrum sensing policy to detect spectrum holes. The main problem is, if the player does not have prior knowledge about the reward distributions of the different machines, it is obviously impossible to derive optimal action selection policies. The proposed sensing policy users use the Reinforcement Learning Algorithm (RL) in artificial intelligent techniques to learn behavior of primary users to predict when the spectrum is occupied and not. It provides energy sensing policy and also low probability of miss spectrum holes detection. The proposed system to improves the throughput of the secondary user and improves the energy efficiency while controlling the miss detection probability.

Keywords

Cognitive radio, Spectrum Holes, Spectrum sensing, Energy detection, cyclostationary, Reinforcement Learning

I. Introduction

Today Wireless systems are characterized by wasteful static spectrum allocations, fixed radio functions, and limited coordination. Some systems in unlicensed frequency bands have achieved great spectrum efficiency, but are faced with increasing interference that limits network capacity and scalability [10]. Cognitive radio systems offer the opportunity to use dynamic spectrum management techniques to help prevent interference, adapt to immediate local spectrum availability by creating time and location dependent in "virtual unlicensed bands:, i.e. bands that are shared with primary users. Unique to cognitive radio operation is the requirement that the radio is able to sense the environment over huge swaths of spectrum and adapt to it since the radio does not have primary rights to any pre-assigned frequencies.

The Electromagnetic Radio Spectrum, a natural resource, is currently licensed by regulatory bodies for various applications. Presently there is a severe shortage of the spectrum for new applications and systems. However various studies ([9], [10]) have concludes that at any time and place, very little of the licensed spectrum is actually utilized. The unutilized part of the spectrum results in 'Spectrum holes' or 'White Spaces'. Therefore, recently it has been proposed to allow utilization of the unused spectrum at a time to other users who do not hold the license. This will be possible by the Cognitive Radio technology. In cognitive radio terminology Primary user refer to a user who is allocated the rights to use the spectrum. Secondary user refer to the users who try to use the frequency bands allocated to primary user when the primary user is not using it.

Spectrum Sensing an essential component of the Cognitive Radio technology involves, 1) identifying spectrum holes and 2) When an identified spectrum hole is being used by the secondary users, to quickly detect the onset of primary transmission.

In practice Spectrum Sensing becomes a challenging task because the channel from the primary transmitter to the secondary user can be bad because of Shadowing and time varying multipath Fading. As a result, detecting the primary user based on the observation of a single secondary user may not be enough, especially under low SNR conditions. Hence to alleviate this problem, Spectrum Sensing [10] is envisaged, whereby the spatial diversity inherent in radio environment is leveraged by allowing multiple secondary users to cooperate. This reduces the average time to detect the primary user. It turn lowers the interference to the primary user (when it switches ON), while increasing the spectrum usage of the secondary's (when the primary switches OFF).

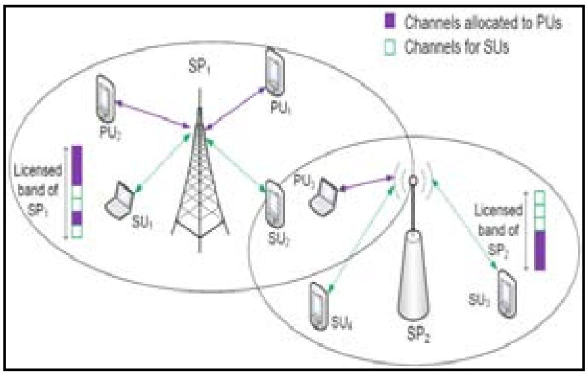

Figure 1: Cognitive Network showing Primary and Secondary users

II. System Model

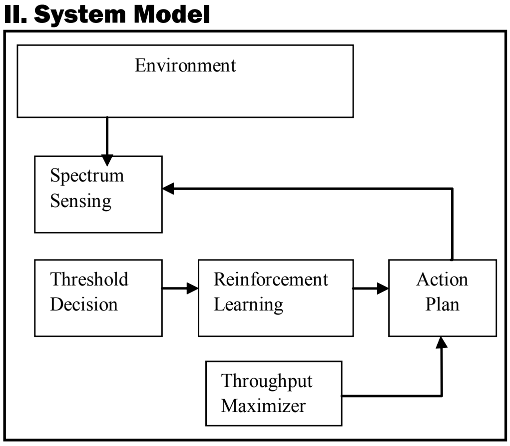

Figure 2: System Design

A. Environment

Environment in Cognitive radio system are channels that is assigned to primary user who acquired the license for their signal transmission. The channel utilization by primary users is not fair. The result of under utilization of the channel throughput decreased and frequency bands, channels are scarce resources, cognitive radio known as the secondary user communication developed to access the channel opportunistically.

B. Spectrum Sensing

Cognitive radio called secondary user, which have ability to tune different channel, sense the channel environment whether it is occupied or free. The sensing process carried out by energy detector technique. The cognitive radio tuned to a channel carrier frequency (channel bandwidth central frequency) and read samples from the channel in curtain duration. Those samples passed to energy detector block where the samples power measured.

Those samples given to energy detector measures power spectral density using Fast Fourier Transform (FFT) algorithm. The channel bandwidth frequency separated and made rest of things to zeros in the power exist in the sensed channel bandwidth. To achieve the goal of CR, it is a fundamental requirement that the cognitive user performs spectrum sensing to detect the presence of PU signal. The spectrum sensing is often considered as a detection issue where the CUs have to scan a vast range of frequencies to observe available spectrum 'white space' or 'holes' that are temporarily and spatially out of service. The goal of spectrum sensing is to decide between the following two hypotheses [4]:

H_0: Primary user is absent

H_1: Primary user is present

In order to avoid harmful interference to the primary system, the sensing time should be carefully chosen. If the sensing time too long, a PU may enter the band at which a CU is operating in and causes interference. There are three aspects of PU detection that need to be verified and quantified in order to define metrics for CR systems.

(a). The time until detection of the PU.

(b). The time needed to clear the spectrum once a PU has been detected.

(c). The reliability of PU detection; the probability of missed detection, PMD and the probability of false alarm, PFA.

In general, CU sensitivity should outperform PU receiver by a large margin in order to prevent what is essentially a hidden terminal problem. This margin is required because CU does not have a direct measurement of a channel between primary user receiver and transmitter. It must based on their decision and its local channel measurement to a primary user transmitter. This type of detection is referred to as local spectrum sensing (LSS) and the worst case hidden terminal problem would occur when the CU is shadowed, in severe multipath fading, or inside buildings with high penetration loss.

LSS detector can be a matched filter, an energy detector, or a cyclostationary feature detector [10]. In this section the advantages and disadvantages of each technique will be discussed. Table 1 summarizes the strengths and weaknesses of each spectrum sensing techniques mentioned above[8].

Table 1 Advantages and Disadvantages of Spectrum Sensing Techniques

Spectrum Sensing Technique	Advantages	Disadvantages
ED	Does not need prior information Low computational cost	Cannot work in low SNR Cannot distinguish users sharing the same channel
MF	Optimal detection performance Low computational cost	Requires synchronization and a prior knowledge of the PU
CFD	Robust in low SNR Robust to interference	Requires partial information of PU High computational cost

C. Energy Detector

Energy detection uses the energy spectra of the received signal in order to identify the frequency locations of the transmitted signal. Energy detection approach relies only on the energy present in the channel. Since the energy of a signal is defined as Integral of $|f(t)|$, no phase information is required [10]. The underlying assumption is that with the presence of a signal in the channel. Therefore, energy detection involves the application of a threshold in the frequency domain, which is used to decide whether a transmission is present a specific frequency. Any portion of the frequency band where the energy exceeds the threshold is considered to be occupied by a transmission.

The noise is assumed to be additive, white and Gaussian (AWGN) with zero mean and variance w. In the absence of coherent detection, the signal samples can also be modeled as Gaussian random process with variance x. Note that over-sampling would correlated noise samples. Now proceed with the construction of a simple energy detector that analyzes the signal in the workspace and determines whether or not a signal is present based on a threshold. As a result, the following steps that are also illustrated in Figure 2 will assist in producing the frequency representation of the intercepted signal.

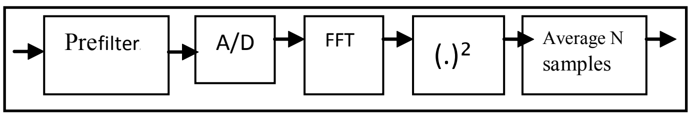

Figure 3: Frequency representation of the Intercepted signal.

In this architecture, two degrees of freedom to improve the signal detection. The frequency resolution of the FFT increases with the number of points K (equivalent to changing the analog pre-filter), which effectively increasing the number of averages N also improves the estimate of the signal energy. In practice, it is common to choose a fixed FFT size to meet the desired resolution with a moderate complexity and low latency. Then the number of spectral averages becomes the parameter used to meet the detector performance goal. We consider this approach

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in our experiments.
1. Pre-filtering of intercepted signal extracts frequency band of interest.
2. Analog-to-digital conversion (ADC) converts filtered intercepted signal into discrete time samples.
3. FFT provides the frequency representation of the signal.
4. Square-law device yields the square of the magnitude of the frequency response from the FFT output.
5. Average N samples of the square of the FFT magnitude.

III. Modules Description

A. Reinforcement Learning Algorithm

Reinforcement learning algorithm known as Q-Learning whereby the agent goes through a phase of learning before it can converge on an optimal solution for channel allocation. In this learning phase, the node makes decisions on what channels to select pseudo-randomly, the outcome of taking these actions will weigh strongly on what decisions are made later on. Once a node has finished learning, it can then make decision on what it has learned. It optimize bandwidth usage for itself and any other nodes that may be accessing the same channel. The proposed machine learning based spectrum sensing policy for cognitive radio that:[1]

- Provides high throughput for the SUs,
- Reduces missed detections,
- Is energy efficient,
- Is adaptive to non-stationary PU behavior and channel conditions.

1. Q-LEARNING ALGORITHM

Q- Learning algorithm works by learning an action-value function that gives an expected utility of taking an action in a particular state. The goal of repeating this process is for the agent to find an optimal policy for each state x in a recursive manner [12].
Sense environment and state s
For each iteration
Choose a from s using certain policy
Take action a, observe output, r, S_{t+1}
Update Q value for state-action pair (eqn.1)
$S=S_{t+1}$ (1)
Loop

2. E-GREEDY & E-DECREASING STRATEGY

Q-Learning allowed a period of random exploration before following the target policy of the agent. The policy used in selecting which action to take is dependent on the type of policy used. Only selecting the best action 1-E of the time and another action is chosen randomly selected for the remainder of the time, E. The value of E is in the range 0 < E < 1. The higher the value, the more random exploration will occur. A similar strategy known as E-decreasing strategy used in this experiment -Decreases over each iteration.

B. Energy Threshold Selection and Hypothesis Testing

It is well known that under the common detection performance criteria (most notably, the Neyman-Pearson criteria) likelihood ratio yields the optimal hypothesis testing solution and performance is measured by a resulting pair of detection and false alarm probabilities (P_d,P_{fa}). Each pair is associated with the particular threshold γ that tests the detection statistic:

T > γ decide signal present
T < γ decide signal absent

$$P_{fa} = Q\left(\frac{\gamma - N\sigma_w^2}{\sqrt{2N\sigma_w^4}}\right)$$

$$P_d = Q\left(\frac{\gamma - N(\sigma_w^2+\sigma_x^2)}{\sqrt{2N(\sigma_w^2+\sigma_x^2)^2}}\right)$$

IV. Experimental Results

In this simulation, the primary user's channel traffic is modified with markov chain model. When the primary user transmits signal through their channel licensed to them, the channel state is considered as occupied. Sometimes, when the channel is not used by its primary, the state is considered ad free or white space. The channel occupancy and free are realized with two state models as shown.

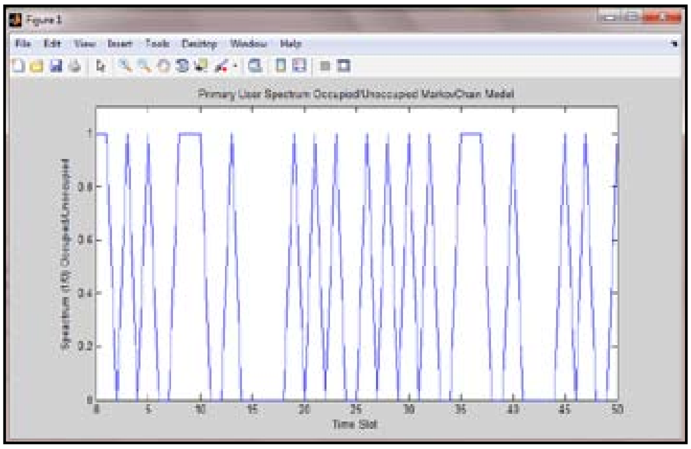

Fig. 4: Primary Channel User Activity

Probability of detection (Pd) and Probability of False alarm (Pf) are two important parameter to measure the performance induced from the SU on the PU is proportional to the probability of miss detection (1-Pd). The throughput of the SU is proportional to 1-Pf. Proposed sensing policy provides excellent performance in terms of throughput, detection probability and energy efficiency. In the primary channel detection rate is shown in figure 5 with respect to the signal to noise power and detection success ratio

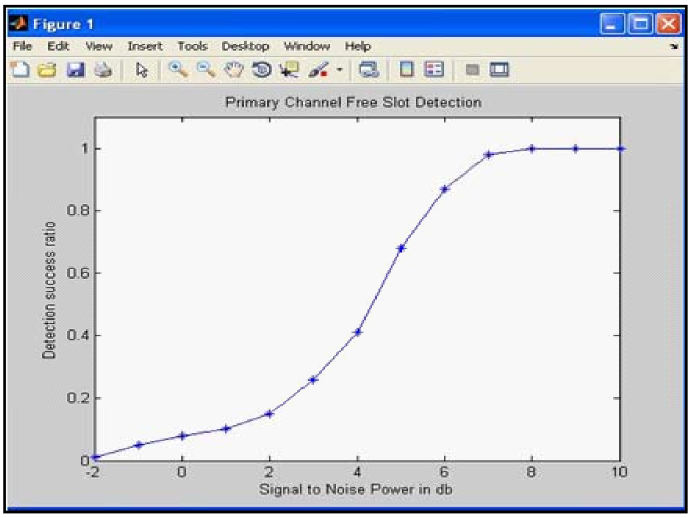

Figure 5: Primary channel free slot detection graph.

V. Conclusion

The energy detector (ED) arises as a suboptimal choice for non-coherent detection using an estimated threshold. If the ED requires no knowledge on the channel signals but a small error in estimating the hypothesis's threshold may result in an unreliable detection of Pus. The number of samples required to optimally detect the incoming signal is O(1/SNR²). This simulation results shows that proposed sensing policy provides excellent performance in terms of throughput, detection probability and energy efficiency.

VI. Future Enhancement

In the future enhancement of Reinforcement Learning(RL) is an adaptive method for a decision-making agent learning to choose optimal actions and maximize received rewards by interacting with its environment. RL based spectrum sensing policy for cognitive radio that provides high throughput for SUs and it reduces miss detection, energy efficiency, adaptive to non-stationary PU behavior.

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