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Efficient Spectrum Sensing Pattern Using Intelligent Matrix in Cognitive Radio Network

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Abstract
Cognitive radio (CR) can successfully deal with the growing demand and scarcity of the wireless spectrum. To exploit limited spectrum efficiently, CR technology allows unlicensed users to access licensed spectrum bands. Since licensed users have priorities to use the bands, the unlicensed users need to continuously monitor the licensed users' activities to avoid interference and collisions. How to obtain reliable results of the licensed users' activities is the main task for spectrum sensing. Based on the sensing results, the unlicensed users should adapt their transmit powers and access strategies to protect the licensed communications. One of the key effecting factors on the CR network throughput is the spectrum sensing sequence used by each secondary user. In this paper, secondary users' throughput maximization through finding an appropriate sensing matrix (SM) is investigated. The proposed intelligent learning and optimization cycle, based on neural networks, finds the optimal sensing sequence for each secondary user without any prior knowledge about the wireless environment. The structure of the proposed scheme is discussed in detail, and its efficiencies are verified through numerical results.

Keywords
Cognitive radio, Sequential spectrum sensing, Neural networks, Sensing sequence, Spectrum holes

I. Introduction

Cognitive radio network (CRN) concept has been developed to mitigate the lack of frequency resources for the ever-growing spectrum demand by allowing secondary users (SUs) to opportunistically share the spectrum with licensed primary users (PUs) [1]. To this end, sensing capability is exploited in the CRNs' nodes, which enables them to find some temporarily available transmission opportunities called white spaces also called Spectrum Holes (SH). The average throughput of the SUs is one of the most important performance metrics, which depends on the candidate primary channels for sensing and transmission.

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 [6]. 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. Based on the sensing results, SUs can obtain information about the channels that they can access. However, the channel conditions may change rapidly and the behavior of the PUs might change as well. To use the Spectrum bands effectively after they are found available, spectrum sharing and allocation techniques are important. As PUs have priorities to use the spectrum when SUs co-exist with them, the interference generated by the SU transmission needs to be below a tolerable threshold of the PU system. Thus, to manage the interference to the PU system and the mutual interference among SUs, power control schemes should be carefully designed.

In this paper, an intelligent spectrum sensing sequences setting is proposed, which does not need any prior information and presumptions about the wireless media as well as PUs' data traffics. More specifically, a multilayer feed forward (MFF) neural network [9] is exploited to replace the mathematical modeling by learning the actual impact of the design parameters, i.e., the various permutations of elements in the sensing sequences, on the CRN average throughput. Then, a Kennedy-Chua (KC) neural network [10] is used to optimally find the SS of each SU.

II. System Model

A fully synchronized time slotted secondary and primary networks with Ns SUs, equipped with narrowband sensing capability, and Np PUs, each having one channel, and are assumed. Each SU sequentially senses the channels based on its SS provided by the CRN coordinator, i.e., the SU senses the first channel assigned in its SS for a predetermined time duration (channel sensing time), and then changes its sensing circuitry, which takes a constant time τho, and senses the second channel if and only if the first channel is sensed to be busy. This procedure will continue until a transmission opportunity is found. Sensing matrix (SM) is defined as a matrix with the dimensions of Ns × Np, in which the i-th row contains the SS for the i-th SU [8].

Average SU throughput is maximized through finding the optimal SM elements, specifically, if r represents the average throughput of the SUs, the optimization problem can be formulated as [8]:

S*= arg max r
s 1,1,s 1,2,……..,S Ns ,Np

III. Local Spectrum Sensing

Spectrum sensing enables SUs to identify the SHs, which is a critical element in CR design. To protect the PU transmission, the Secondary User(SU) transmitter needs to perform spectrum sensing to detect whether there is a Primary User (PU) receiver in the coverage of the SU transmitter. Instead of detecting PU receiver directly, the SU transmitter can detect the presence or absence of PU signals easily. 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. It is worth noting that, in general, it is difficult for the SUs to differentiate the PU signals from other pre-existing SU transmitter signals. Therefore, we treat them all as one received signal, s (t). The received signal at the SU, x (t), can be expressed as [8].

$$x(t) = \begin{cases} n(t) & , H0 \\ s(t) + n(t) & , H1 \end{cases}$$

Where n (t) is the additive white Gaussian noise (AWGN). H0 and H1 denote the hypotheses of the absence and presence of the PU signals, respectively. The objective for spectrum sensing is to decide between H0 and H1 based on the observation x (t).

The detection performance is characterized by the probabilities of detection, Pd, and false-alarm, Pf. Pd is the probability that the decision is H1, while H1 is true; Pf denotes the probability that the decision is H1, while H0 is true. Based on Pd, the probability of miss detection Pm can be obtained by Pm = 1 - Pd.

IV. Learning and Optimization by Kennedy-Chua (KC) Neural Network

Artificial neural networks are powerful tools for learning complicated mappings and for optimizing [10] [11]. The KC neural network has NsNp output voltages corresponding to the NsNp elements of the adaptable parameter x. This network calculates the optimal sensing matrix based on the cost function learned by the MFF network. Now, if there exists a training process to adjust the weight and bias values of the MFF network appropriately, and if the learned mapping approximates the actual cost function closely, then the KC network output represents the optimal elements of sensing matrix.

The dynamic equation implemented by the KC neural network is [10],

$$Ci\frac{dxi}{dt} = -\frac{\partial\phi}{\partial xi} - Gixi$$

Where xi denotes the i-th element of x, Ci and Gi are the output capacitor and the parasitic conductance of the neuron i.

V. Local Spectrum Sensing Techniques

A. 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.

B. Energy Detector

Energy detector is the most common spectrum sensing method. The decision statistics of the energy detector are defined as the average energy of the observed samples

$$Y = \frac{1}{N}\sum_{t=1}^{N} |(x(t)|^2$$

The decision is made by comparing Y with a threshold g. If Y ≥ g, the SU makes a decision that the PU signal is present (H1); otherwise, it declares that the PU signal is absent (H0). Energy detection is a binary decision making process. Power spectral density is calculated using Fast Fourier Transform. The channels have high power levels are considered occupied channels, by primary user. The channels have low power levels are considered to be free channel. The energy detector is easy to implement and requires no prior information about the PU signal.

VI. Proposed System

The Proposed method use ISMS (Intelligent Sensing Matrix Setting) algorithm is to maximize the throughput. It utilizes minimum energy. The proposed neural network-based Sensing matrix setting scheme consists of a KC neural network cooperating with an MFF neural network in a feedback loop, a training process which calculates and updates the weight and bias values of the MFF network, and a throughput estimator (TE) entity. The throughput estimator estimates the SU average throughput. This Estimation can be performed by inspecting the packets and their acknowledgments at the secondary transmitter for a period of time equal to Tep (estimation period) [14].

Computational complexity of the proposed system is due to the back propagation algorithm. The complexity of the back propagation is O (N), where N is the number of weights and biases of the MFF network [9].

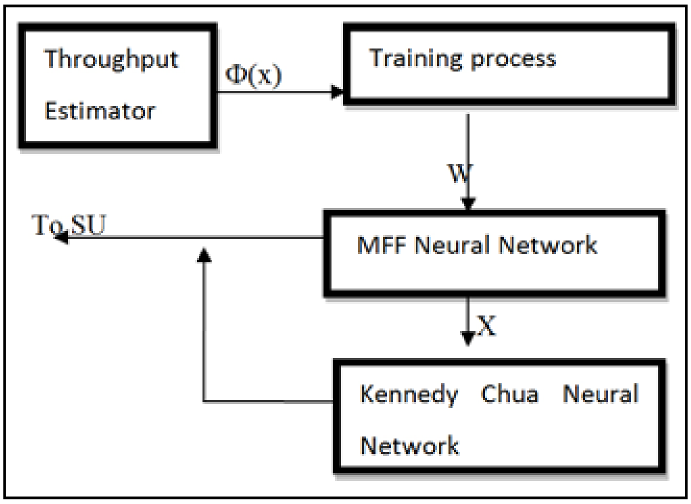

Fig. 1: Block diagram of the proposed ISMS

VII. Numerical Result

The proposed intelligent SM setting performance and compares the average normalized throughput of the SUs obtained through the proposed ISMS scheme with the results achieved by the analytical solutions, when a perfect channel sensing is exploited, i.e., false alarm and miss detection probabilities are set to zero. This comparison is performed for various channel sensing times.

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For each case, the result was obtained as the average of 100 time slots simulation. Results labeled optimal SM and SMS depict the average normalized throughput obtained by the analytical modeling and the sub optimal SMS algorithm presented and results labeled ISMS are those obtained through the neural network based sensing matrix. In the perfect sensing there is no error in the detection scheme. The proposed ISMS approach is at tradeoff between complexity of finding the optimal SM and the highest achievable throughput, and the low computational burden of the SMS scheme and its lower achievable throughput.

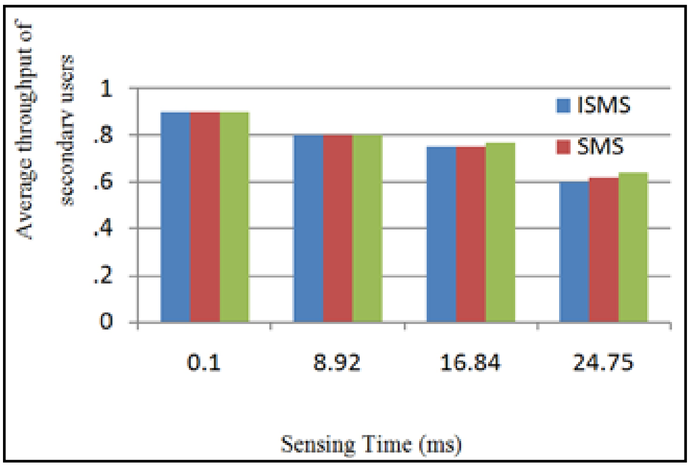

Fig. 2: The average secondary user's throughput versus sensing time for perfect sensing case.

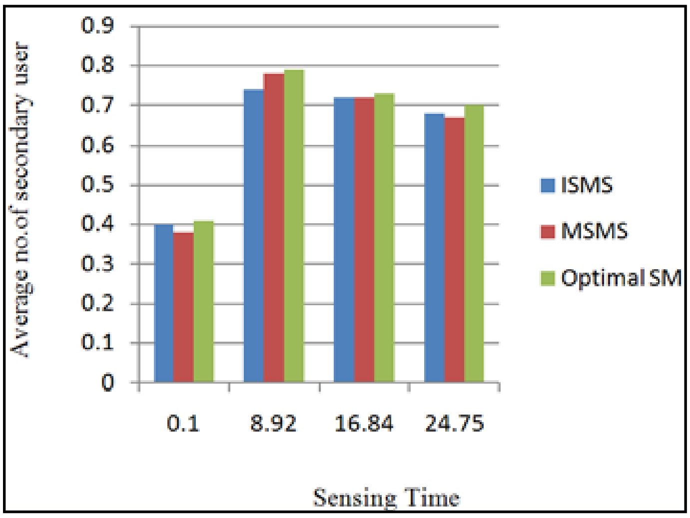

Fig.3. the average secondary user's throughput versus sensing time for imperfect sensing case.

VIII. Conclusion and Future Work

In this paper, a novel intelligent sensing matrix setting (ISMS) scheme has been proposed, which maximizes the Average secondary users' throughput based on a learning optimization cycle. The proposed ISMS method provides an average throughput close to the maximum one without any prior knowledge about the primary users' behavior as well as the wireless environment. Moreover, its computational complexity linearly increases with the number of secondary and primary users; this is much lower than computational burden imposed by finding the optimal sensing matrix. Finally, the effectiveness of the proposed method has been verified through numerical results. As a future work, we aim to extend the proposed system by modeling the impact of error and latency on the throughput estimator block.

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