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DETERMINING OPTIMAL SENSING TIME FOR MULTI-RADIO MULTI-CHANNEL COGNITIVE RADIOS

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Abstract—Fast and efficient spectrum sensing is vital for multi-radio multi-channel cognitive radio (CR) networks where unlicensed secondary users (SUs) have to sense and opportunistically transmit on multiple spectrum bands without causing any harmful interference to the licensed primary users (PUs) of those spectrum bands. Accordingly, this paper presents a smart, practical and efficient wideband spectrum sensing scheme based on an optimal sensing stop policy that aims to optimize SU throughput while adhering to the PU interference constraints. Unlike existing work, this scheme is smart because in determining the best time for the multi-transmitter SU to stop sensing and start data transmission based on the channels that have been sensed idle, this scheme explicitly takes into consideration the number of transmitters on the SU; so-called N-transmitters constrained SU. Further, we formulate and solve the optimal sensing stopping problem. The numerical and simulation results presented verify the efficiency of the proposed sensing scheme.

1. INTRODUCTION

To improve radio spectrum utilization and maximize the use of licensed bands, cognitive radio (CR) technology is being actively developed. The overriding principle behind CR networks is for unlicensed secondary users (SUs) to continuously sense licensed bands, dynamically identify unused bands, and then opportunistically operate in the underutilized "white spaces" without causing any

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harmful interference to the licensed primary users (PUs) of those radio bands [1–8], and references therein. Given the strict no-harmful interference to PU constraint, effective spectrum sensing by SUs is vital. What is more, PU signal characteristics are usually unknown to the SU and so coherent (matched filter and cyclostationary feature) detection of PU activity on licensed bands is less desirable. Consequently, to sense licensed bands and correctly detect if there is PU activity on them or not, energy detection has been tipped as the most feasible solution for CR networks [1–8], and references therein. Energy detection is the simplest and least complex of the three detection methods, which are some of the major reasons why it was also adopted in those works. Energy detection does not require knowledge of the PU's signal and is robust to unknown dispersed channels and fading [9]. Although energy detection has low computational and implementation complexities, it is a less efficient detection technique because for instance, it is quite sensitive to noise uncertainty [9]. Coupled with strict PU interference constraints, energy detection based sensing algorithms typically warrant excessive sensing (time) which may potentially leave the SU with little or no time for actual data transmission in between PU transmissions.

In designing an optimal sensing strategy, therefore, the sensing time overhead and the achievable rate should both be taken into consideration. Further, for multi-radio multi-channel CR networks, it will be beneficial to additionally consider the number of transmitters on the SU in determining when is the best time for the SU to stop sensing and start transmission based on the channels that the SU has sensed idle. This is because, irrespective of the number of channels (and their possible rate of transmission) sensed idle by the SU, the number of channels that the SU can concurrently transmit on (and thus its effective achievable rate/throughput) is constrained by the number of transmitters it has.

Accordingly, we believe that it is smarter, more practical and optimal to explicitly consider the number-of-transmitters constraint in designing CR sensing schemes. To the best of our knowledge, this paper is the first to adopt this approach; our major motivation being the fact that in real networks, the number of available channels is usually greater than the number of transmitters on the nodes in the network. We consider that the RF front-end of the receiver has wideband architecture so the SU can sense/receive from a wideband channel, more specifically, it can simultaneously sense the multiple narrowband subchannels of the wideband channel so-called wideband joint detection [3]. In real network deployments, a node typically desires to transmit data to a specific remote node(s) over a specific channel(s) and so we consider that each of the SU's N transmitters will operate over single narrowband subchannels of the wideband channel. In other words, we consider that spectrum sensing is done over a wideband channel whereas data transmission is done over individual narrowband channels.

1.1. Related Work

In [1], an introduction to IEEE 802.22, which is the first wireless standard based on CRs is presented and in [2], a survey of spectrum sensing algorithms for cognitive radio networks is presented. For multi-channel CR systems, wideband spectrum sensing techniques for jointly detecting PU signals over multiple radio bands rather than over a single band at a time have been studied in [3]. In [3–5] and references therein, the optimal sensing stop problem and throughput maximization have been studied but the authors either did not explicitly consider the number of transmitters available on the individual SU [3, 4] or they assumed that the number of PU channels equals the number of transmitters on an individual SU [5], which we think is not realistic because, for instance, in the latter where the authors assumed the number of PU channels to be 10, a node (SU) with 10 radios will be required which will be highly cost and energy prohibitive. In real networks, the nodes typically have one or two transmitters while the number of available channels is much greater than two. Further, in [4] the authors consider that the SU senses each channel sequentially over a single band at a time whereas in [5], the authors considered that the SU senses all the channels simultaneously using one receiver per channel. In [6], the authors presented a narrowband real-time spectrum sensing algorithm whose decision threshold is independent of the noise level. Unlike the algorithms presented in [2–5], the algorithm presented in [6] was additionally implemented and demonstrated in a real hardware platform with controllable primary user devices. Accordingly, the algorithm which they called the FAR algorithm has been shown to be practical and implementable in a real network. In [8, 9], the authors similarly presented a narrowband spectrum sensing algorithm whose decision threshold is also noise-level independent. The algorithm presented in [9], which was called the CAV algorithm relies on the statistical covariances of the received signal and noise being different and so they can be used to differentiate between when the primary user's signal is present on the channel and when it is not. Unlike, [6] however, the CAV algorithm was not implemented in real hardware and so although its detection performance is comparable to the detection performance of the algorithm that we present in this paper, we do not know if it can also be easily implemented in real hardware as our algorithm can.

In summary, in this work, we adopt the wideband spectrum sensing approach developed in [3], where a receiver can jointly sense multiple channels simultaneously. We extend and then enhance the narrowband FAR algorithm [6], which has already been demonstrated and shown to be practical and implementable in real hardware, to our wideband sensing platform. More importantly, this work, improves on extant work by adopting a smarter, more practical and optimal approach to multi-radio multi-channel CR spectrum sensing by additionally considering the number-of-transmitters constraint in determining the optimal sensing stop time that maximizes the SU's throughput.

1.2. Contribution

The major contributions of this work are as follows:

- First, given an N-transmitters constrained SU, we develop an optimal sensing scheme that explicitly takes into account the sensing time overhead and maximizes the effective achievable throughput of the SU.
- Next, extending the FAR algorithm, which is a real-time narrowband spectrum sensing algorithm whose decision variable is SNR independent (unlike conventional energy detection algorithms where the decision variable is SNR dependent), we develop a wideband spectrum sensing algorithm, which we call the eFAR algorithm whose decision variable is also SNR independent. Further, using the fourth-moments rather than the second-moments, our eFAR algorithm provides better detection performance than the FAR algorithm.
- We formulate and solve the optimal sensing stopping problem and then we present numerical and simulation results which verify the efficiency of our spectrum sensing scheme.

A summary of the notations used in this paper is presented in Table 1 and the rest of the paper is organized as follows. In Section 2, we present the optimal sensing scheme and formulate the optimal sensing stop time problem. In Section 3, we present our enhanced spectrum sensing algorithm and show its detection performance. In Section 4, numerical and simulation results which verify the efficiency of the proposed spectrum sensing scheme are presented. And in Section 5, the paper is concluded.

Table 1. Summary of notations.

Notation	Description
N	Number of transmitters on the secondary user (SU)
M	Number of bands/channels in the CR system, $m \in \{1, 2, \ldots, M\}$
T	Frame duration of the CR system, seconds
τ	Sampling time interval, seconds
i	time epochs with equal distance in time equal to τ, $i = 0, 1, \ldots, T/\tau$
R^m	Maximum achievable transmit rate of the SU on channel m
r_i^m	Sample received on channel m at i, $i \in \{0, 1, \ldots, T/\tau\}$
z_i^m	i.i.d. real-valued Gaussian additive noise received on channel m at i
h_i^m	Channel gain on channel m at i
s_i^m	PU signal sample received by the SU on channel m at i
δ_i^m	Access decision variable: $= 1$ if at i, channel m is sensed idle; 0, otherwise
$\mathbb{G}_i(\cdot)$	Expected SU throughput (payoff) if sensing stops at i
λ	Energy detection threshold used by the energy detector
J	Segment size, i.e. number of frames in one segment
K	Number of samples per segment
P_{avg}	Average of the fourth-moment of J consecutive frames
P_{mean}	Mean of the average of the fourth-moment of J consecutive frames

2. DETERMINING OPTIMAL SENSING STOP TIME

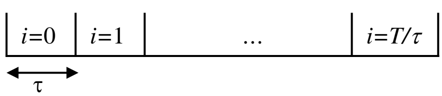
2.1. System Model

Consider a CR system with M-orthogonal AWGN channels opportunistically shared by PUs and SUs. For simplicity, without loss of generality, consider that the distance between the SUs is much large compared with the distance between an SU and the PUs so interference from other SUs is ignored. Alternatively, it may be considered that the MAC layer can guarantee that all SUs remain quiet during the spectrum sensing phase. Whichever way, we ignore interference from other SUs. In essence, we assume that in the CR system under consideration, there is information about SUs. Though it may be argued that availability of SU information does not quite agree with the term "*Cognitive*

Radio," the multitude of work available on cooperative sensing [2–5, 9] and references therein, which rely on the availability of SU information suggest that it is acceptable to assume that information about other SUs is available. In such cooperative CR networks, the SUs typically start and stop sensing at the same time. After sensing has stopped and channel access decisions taken, the SUs may then contend for access to the unoccupied channels which is where interference between SUs can clearly not be ignored. Contention schemes and techniques between SUs for channel access is beyond the scope of the current work and have been left for future work.

For the CR system under consideration, we consider that the SU receiver operates over a wideband channel which is divided into the M-orthogonal narrowband subchannels. Consider also that the SU with N-transmitters operates over a slot duration T, which is divided into a channel sensing phase and a data transmission phase. During T, actual PU occupancy of the M channels does not change but the presence of AWGN may mislead the SU to detect channel occupancy as changing during T. The objective of the SU is to correctly sense, select and then simultaneously transmit on N of the M bands ($N \leq M$) that are: (a) not in use (i.e., unoccupied) by PUs; and (b) it can achieve the highest effective rate on.

Let's consider that the SU can achieve a maximum transmit rate R^m on each subchannel $m \in \{1, 2, \ldots, M\}$. During T which is a finite time horizon, the aim is to minimize the time spent in the channel sensing phase and to maximize the time spent in the data transmission phase. In the channel sensing phase, the SU senses (takes samples from) the wideband channel[†] every τ time units. Based on the sample received on a subchannel, the SU can tell if that subchannel is busy (occupied) or idle (unoccupied). We consider a finite-state space with state $r_i^m \in \mathcal{X}$, $i \in \{0, 1, \ldots, T/\tau\}$ where parameters such as $\{\tau, T, N, M, R^m : \forall m\}$ are known.



For such a CR system, the received sample at i on subchannel m can be modeled by

$$r_i^m = \begin{cases} z_i^m, & \text{Channel } m \text{ is IDLE} \\ h_i^m s_i^m + z_i^m, & \text{Channel } m \text{ is BUSY} \end{cases} \tag{1}$$

where $\{h_i^m\}$ are the channel gains between the PU transmitter and the SU receiver, $\{s_i^m\}$ are the PU signal samples, and $\{z_i^m\} \sim N(0, \sigma^2)$ are

[†] More specifically, from each of the M subchannels.

independent and identically distributed real-valued Gaussian additive noise. We assume that the channel varies slowly such that the channel coefficients $\{h_i^m\}$ do not vary during T so, for instance, our sensing algorithm only needs to know $|h^m|^2, \forall i$. We define the channel access decision variable $\delta_i^m \in \{0, 1\}$, which says at i, the choice of action to be taken on channel m based on the observation r_i^m where $\delta_i^m = 1$, denotes that channel m was sensed IDLE and thus safe for SU data transmission whereas $\delta_i^m = 0$ denotes that it was sensed BUSY (occupied by PUs) and thus unsafe for SU data transmission.

If the N-transmitters SU stops sensing at i and proceeds to the data transmission phase, the maximum effective rate/throughput (i.e., the payoff for stopping at i) can be obtained by:

$$\mathbb{G}_i(\delta_i^m) = \frac{T - i\tau}{T} \sum_{m=1}^{N} R^m \delta_i^m, \quad m \in \{1, 2, \ldots, N, \ldots, M\},$$
$$\left\{R^1 \delta_i^1 \geq R^2 \delta_i^2 \geq \ldots \geq R^N \delta_i^N \geq \ldots \geq R^M \delta_i^M\right\}. \tag{2}$$

From Eq. (2), it can easily be seen that as i increases, $\frac{T-i\tau}{T}$ diminishes. The implication is that while increasing i may improve the SU's chance of correctly detecting more idle channels, it also reduces the time that the SU has for data transmission and thus its expected throughput (payoff). Consequently, the objective is to determine the "best" i at which to stop sensing that maximizes $\mathbb{G}_i(\cdot)$.

Interference Constraints: For the system under consideration, two constraints as follows must be met:

(1) The SU must ensure a low miss-detection probability, $\mathbf{P_{md}} = [P_{md}^1, P_{md}^2, \ldots, P_{md}^M]$, which is the probability that the SU detects the channel as IDLE and safe for use when in reality, the channel is BUSY. The miss-detection probability is the complement of the probability of detection ($\mathbf{P_d}$), that is, $\mathbf{P_{md}} = 1 - \mathbf{P_d}$. For the wideband channel under consideration, it is desired that $\mathbf{P_{md}}$ be kept below a small positive threshold, say β.

(2) Also, the SU must ensure a low false-alarm probability, ‡$\mathbf{P_{fa}}$ across the wideband channel. $\mathbf{P_{fa}}$ is the probability that the channel access decision says that the channel is BUSY when indeed the channel is IDLE. It is desired that $\mathbf{P_{fa}} = [P_{fa}^1, P_{fa}^2, \ldots, P_{fa}^M]$ be kept below a small positive threshold, say α.

‡ Note that because detection is done over the wideband channel, the $\mathbf{P_{md}}$ and $\mathbf{P_{fa}}$ are defined as the average miss-detect and false-alarm probabilities over the M subchannels respectively.

2.2. Optimal Solution of the Sensing Stopping Problem

The sensing stopping problem is a variation of the secretary problem, which is an optimal stopping problem that has been studied extensively in the fields of applied probability, statistics and decision theory [12]. It is most similar to the house-selling problem. More specifically to the case where a previous offer cannot be recalled.

Definition: The definition of the house-selling problem is as follows. Offers come in sequentially for a house that we wish to sell. While we do not know the values of the offers before they come in, we may assume that they are independent and have the same known distribution. Each offer cost an amount (discount/penalty etc.) to observe. When we receive an offer, we must decide whether to accept the offer or to wait under the expectation that a better offer will be made in the future. We know a better offer may eventually appear but the dilemma is in knowing if the increased size of the future offer will compensate for the observation costs we will have to pay.

In one variation of the classical house-selling problem, we will be able to recall and accept a previous offer after observing a subsequent one while in the other variation, after paying a cost to observe the current offer, we must either accept it or pay an additional cost to observe the next offer. The optimal sensing stopping problem is of the latter variation and in finding the solution, we follow the procedure outlined in [12]. Stopping problems of this kind are defined by two objects:

a) a sequence of random variables (e.g., the channel access decisions δ_i^m), and
b) a sequence of real-valued reward/payoff functions (e.g., $\mathbb{G}_i(\cdot), \quad i \in \{0, 1, \ldots, I\}$).

Further, the optimal stopping problem can be solved using an offline algorithm or an online algorithm.

Offline Solution: Using an offline algorithm, the observations of the random variables δ_i^m will first be taken and then using, for instance, the method of backward induction, the optimal stopping time i^* can be obtained as follows. Since sensing must stop at $i = I = T/\tau$, we first compute the payoff at stage $i = I - 1$ and then at stage $i = I - 2$, and so on back to the initial stage ($i = 0$). Next, we obtain the optimal payoff as:

$$\mathbb{G}^*(\cdot) = \max\left\{\mathbb{G}_0, \mathbb{G}_1, \ldots, \mathbb{G}_{I-1} | \mathbf{P_{md}} \leq \beta,\ \mathbf{P_{fa}} \leq \alpha\right\} \tag{3}$$

and then the optimal stopping time/stage (i^*) as the time/stage at which $\mathbb{G}^*(\cdot)$ was obtained.

Online Solution: Using an online algorithm, which is the interest of this work, the decision to stop or continue has to be taken at each stage i. Accordingly, at stage i, we compare the payoff for stopping ($\mathbb{G}_i$) with the payoff we anticipate to get by continuing. We compute expected future payoffs using the stopping rules defined for stages $i+1$ through to stage $I-1$. Let ϕ_i denote our non-randomized[§] stopping rule (so $\phi_i \in \{0,1\}$, $\phi_0 = 0$, $\phi_I = 1$). $\phi_0 = 0$ and $\phi_I = 1$ because for the CR system under consideration, the interference constraints require that at least one observation be made (so $\mathbb{G}_0 = 0$). Also, sensing must stop when $i = I$ and from Eq. (2), $\mathbb{G}_I = 0$. Additional stopping rules are formulated as follows.

The sensing scheme[‖] knows N, M, T, τ, I, and R^m which is sufficient information for it to know the maximum reward obtainable at each stage i. Consequently, we formulate the first optimal stopping rule $\phi^*_{i,1}$ as:

$$\phi^*_{i,1} = \begin{cases} 1, & \mathbb{G}_i = \mathbb{G}^*_i = \max\left(\frac{T-i\tau}{T}\sum_{m=1}^{N} R^m\right) \\ 0, & \text{otherwise} \end{cases}$$
$$i \in \{1, 2, \ldots, I-1\},\ \{R^1 \geq R^2 \geq \ldots \geq R^m\}, \quad (4)$$

which says to stop at i whenever the reward $\mathbb{G}_i$ is the maximum that can be achieved at i. Similarly, since the cost of observation at each stage i (i.e., $\frac{T-i\tau}{T}$) increases as i increases, we formulate the second optimal stopping rule $\phi^*_{i,2}$ as:

$$\phi^*_{i,2} = \begin{cases} 1, & \mathbb{G}_i \geq \mathbb{G}^*_{i+1} = \max\left(\frac{T-(i+1)\tau}{T}\sum_{m=1}^{N} R^m\right) \\ 0, & \text{otherwise,} \end{cases} \quad (5)$$

which says to stop at stage i whenever the reward at i is greater than the maximum reward that can be obtained at stage $i+1$. Finally, we define the general optimal stopping rule ϕ^*_i as:

$$\phi^*_i = \begin{cases} 1, & \mathbb{G}_i \geq \mathbf{E}\{G(i+1)\} \\ 0, & \text{otherwise} \end{cases} \quad (6)$$

where $G(i+1)$ is a random variable whose estimated value is generated at i ($\mathbb{G}_i$ is not, it is just a value). The expectation of $G(i+1)$ is:

$$\mathbf{E}[G(i+1)] = \max\{\mathbf{E}[\mathbb{G}_{i+1}], \mathbf{E}[\mathbb{G}_{i+2}], \ldots, \mathbf{E}[\mathbb{G}_{I-1}]\} \quad (7)$$

[§] For a randomized stopping rule, $0 \leq (\phi_1, \phi_2, \ldots, \phi_i) \leq 1$.

[‖] In this paper, we refer to the sensing algorithm as the procedure that produces the channel access decisions at each observation interval i, and to the sensing scheme as the procedure that uses the channel access decisions to compute the achievable payoff (throughput) at each i and then decides whether to stop or continue sensing.

and

$$\begin{aligned} \mathbf{E}[\mathbb{G}_{i+1}] &\leq \mathbb{G}^*_{i+1}, \\ \mathbf{E}[\mathbb{G}_{i+2}] &\leq \mathbb{G}^*_{i+2}, \\ \mathbf{E}[\mathbb{G}_{I-1}] &\leq \mathbb{G}^*_{I-1} \end{aligned} \tag{8}$$

At each observation stage i, the sensing scheme divides the set of M subchannels into three disjoints subsets:

- $\mathbb{I}(i)$: subchannels that are idle for sure
- $\mathbb{B}(i)$: subchannels that are busy for sure
- $\mathbb{U}(i)$: subchannels with an unsure status

The subchannels are placed in one of the three disjoint sets using the following procedure. At the initial stage (i.e., $i = 1$), all subchannels for which $\delta_1^m = 1$ are placed in $\mathbb{I}(i)$, all subchannels for which $\delta_1^m = 0$ are placed in $\mathbb{B}(i)$ while $\mathbb{U}(i)$ will be empty. In subsequent stages, a weighted function is applied in deciding the subset that a subchannel should be placed in. For instance, for stage $i = 2$, subchannels for which $\{\frac{\delta_1^m+\delta_2^m}{2}\} \geq 0.5$ will be placed in $\mathbb{I}(i)$. Those for which $\{\frac{\delta_1^m+\delta_2^m}{2}\} = 0$ will be placed in $\mathbb{B}(i)$ while $\mathbb{U}(i)$ will still be empty. If sensing continues to stage $i = 3$, subchannels for which $\{\frac{\delta_1^m+\delta_2^m+\delta_3^m}{3}\} \geq 0.67$ will be placed in $\mathbb{I}(i)$. Those for which $\{\frac{\delta_1^m+\delta_2^m+\delta_3^m}{3}\} < 0.67$ will be placed in $\mathbb{U}(i)$ while those for which $\{\frac{\delta_1^m+\delta_2^m+\delta_3^m}{3}\} = 0$ will be put in $\mathbb{B}(i)$ and so on until sensing stops. The overall aim is to ensure that subchannels that have mostly been detected as idle are put in the subset of idle channels while those that have mostly been detected as busy are put in the busy subset. For channels whose status frequently fluctuates between busy and idle, they will be put in the unsure subset. The subsets are populated based on the accumulated probability weights of their detected status as returned by the sensing algorithm at each observation stage. The motivation is to provide additional prevention against harmful interference to the primary users of the channels. Recall that the sensing algorithm which produces the access decision variables (δ_i^m) already ensures that specified miss detect and false alarm constraints are met.

Therefore, at each observation interval i, the sensing scheme will choose the best N subchannels in $\mathbb{I}(i)$ (or all the subchannels in $\mathbb{I}(i)$ if subset $\mathbb{I}(i)$ contains less than N subchannels) and use them to estimate $\mathbb{G}_i$. The set of stopping rules $\{\phi_0, \phi^*_{i,1}, \phi^*_{i,2}, \phi^*_i, \phi_I\}$ are conditioned on the set of disjoint subsets, which are themselves conditioned on $\mathbf{P_{md}}$, $\mathbf{P_{fa}}$.

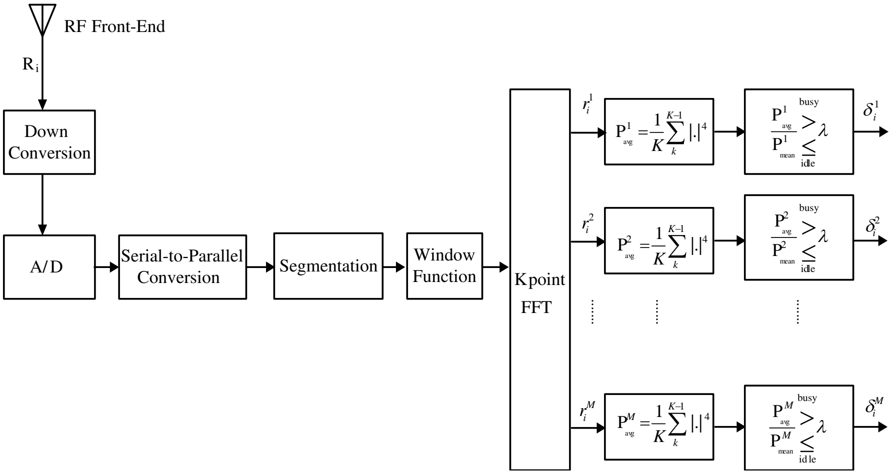


Figure 1. Schematic representation of the eFAR wideband spectrum sensing algorithm.

3. ENHANCED FFT-AVERAGING-RATIO (eFAR) SPECTRUM SENSING ALGORITHM

In this section, we present the spectrum sensing algorithm of our sensing scheme. Spectrum sensing is the first and most critical step in efficient cognitive radio networking as it can potentially make-or-break subsequent steps. Since energy detection is simple, has low computational complexity, is able to determine spectrum-occupancy information quickly and does not require prior knowledge of the PU signal, we use it as the building block of our algorithm. Our enhanced sensing algorithm, eFAR, is built on the FFT-Averaging-ratio (FAR) algorithm which is a real-time spectrum sensing algorithm whose decision threshold is independent of the noise level [6]. A schematic representation of our eFAR algorithm is given in Figure 1. A good spectrum sensing algorithm should be able to offer high probability of detection (P_d) at low probability of false alarm (P_{fa}) for a wide range of SNR [6].

The operational procedure of the eFAR algorithm is as follows. At each sensing interval i, the eFAR algorithm takes in a wideband discrete-time signal and produces as output, the decision variables δ_i^m for each m subchannel. The received signal is down converted and then passed through an analog-to-digital (A/D) converter. Thereafter, it goes through serial-to-parallel conversion where the single wideband signal is separated into multiple narrowband subsignals. Next¶, the sampled received signals of each subchannel are segmented into J frames of K samples each. Let's denote the j-th frame of a subchannel sample by $r_j(k)$, $j \in \{0, 1, \ldots, J-1\}$, $k \in \{0, 1, \ldots, K-1\}$. Then the segmented frames are multiplied by a window function:

$$r_{w,j}(k) = r_j(k)w(k), \quad j \in \{0, 1, \ldots, J-1\}, \ k \in \{0, 1, \ldots, K-1\}. \quad (9)$$

Note that in a multipath fading environment, the wideband channel exhibits frequency-selective features and its discrete frequency response can be obtained through a K-point FFT ($K \geq L$) [3]. The frequency spectrum of $r_{w,j}(k)$ is:

$$R_j(k) = \frac{1}{\sqrt{K}} \sum_{k=0}^{L-1} r_{w,j}(k) e^{-j2\pi kn/N},$$
$$j \in \{0, 1, \ldots, J-1\}, \ k \in \{0, 1, \ldots, K-1\}. \quad (10)$$

Next, we compute the trispectrum (trispectral density) of each frame by taking the fourth-moment of the received signal and then obtain the average of J consecutive frames as:

$$P_{avg}(k) = \frac{1}{J} \sum_{j=0}^{J-1} |R_j(k)|^4, \quad k \in \{0, 1, \ldots, K-1\}. \quad (11)$$

Thereafter, we compute the mean of $P_{avg}(k)$ as:

$$P_{mean} = \frac{2}{K+2} \sum_{k=0}^{K-1} P_{avg}(k). \quad (12)$$

Following this, the decision parameter is formed as the ratio of $P^m_{avg,i}$ to $P^m_{mean,i}$ and used to test against the preset decision threshold+ (λ) to generate the channel access decisions (δ^m_i):

$$\frac{P^m_{avg,i}}{P^m_{mean,i}} \underset{\mathrm{idle}(\delta_i^m=1)}{\overset{\mathrm{busy}(\delta_i^m=0)}{\gtrless}} \lambda \qquad i \in \{1, \ldots, I\}, \quad m \in \{1, 2, \ldots, M\}. \quad (13)$$

The operational procedure of the eFAR algorithm is similar to that of conventional energy detection based algorithms [3–8] except that to further improve detection performance, after the K-point FFT,

¶ For convenience, in the remainder of this section, we drop the notations for the observation interval i and the subchannels m. Accordingly, the following discussions refer to the processing of the samples received for a generic subchannel at a generic observation interval.

+ λ is obtained from the Eq. (4) in [7].

similar to [8], we use the fourth-order moments. In conventional algorithms, the second-order moments are used. The use of the fourth-moments allows for the AWGN to be further suppressed enabling the eFAR algorithm to perform better (in terms of improved detection performance at lower SNRs) than the FAR algorithm, especially given that the decision threshold is independent of the noise level. The second-moments describe the degree of dispersion around the mean while the fourth-moments depict the degree of centralization and decentralization. For more justifying arguments on the choice of the fourth-moments, the reader may see publications, e.g., [8, 10, 11]. Further, unlike in conventional energy detection where λ is noise level dependent and the total sum of the squared output of the K-point FFT of the frames are taken and then compared against λ to determine if the channel is occupied or not; in the eFAR algorithm (similar to the FAR algorithm), the ratio of the average trispectrums of the frames to the mean of the average is used to test against λ.

Figure 2 shows the detection performance of the eFAR wideband spectrum sensing algorithm under varying mean SNR values. We clarify that although the original FAR algorithm [6] was implemented over a narrowband channel, the FAR algorithm whose detection performance is shown in Figure 2 and Figure 3 is in reality, the extended FAR algorithm. In other words, it is our developed wideband version of the original FAR algorithm. This is to allow for a more fair comparison between the FAR and eFAR algorithms. The only difference between them being that for the FAR algorithm, the second-moments were used while for the eFAR algorithm, the fourth-moments were used. As Figure 2 shows, even at a low SNR of -20 dB, the detection probability of the eFAR algorithm is quite good. Also, it can be seen that the eFAR algorithm improves on the detection

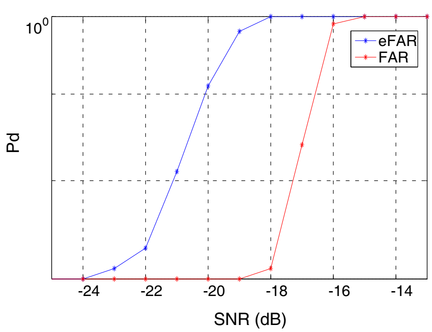


Figure 2. Probability of detection ($\mathbf{P_d}$) vs. SNR for $\mathbf{P_{fa}} = 0.01$.

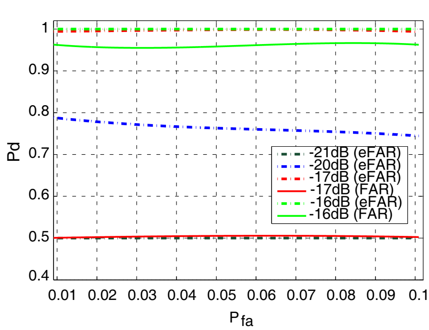


Figure 3. ROC curves for a wideband AWGN channel.

performance of the FAR algorithm. Using the eFAR detector rather than the FAR detector, therefore, the interference constraints of a CR network can be satisfied at lower SNRs. For instance, for the eFAR detector at an average SNR of $-20\,\mathrm{dB}$, $\alpha \leq 0.01$ and $\beta \leq 0.2$ can be satisfied whereas the FAR detector would require a minimum SNR of about $-17\,\mathrm{dB}$ to satisfy the same constraints. Considering that in the worst case, a detection probability of at least 0.5 is desirable, it can be seen that the eFAR algorithm brings a minimum of $3\,\mathrm{dB}$ improvement over the FAR algorithm yet the complexity/overhead of the eFAR algorithm is not any higher than that of the FAR algorithm. Just as the FAR algorithm has been demonstrated in [6] to be practical and implementable in real hardware, so also is the eFAR algorithm practical and implementable in real hardware. Further, just as we have demonstrated in this work that the FAR algorithm can easily work in a wideband environment, we believe that the eFAR algorithm will work as well in, for instance, a highly interfering environment where a narrowband frequency tunable antenna is used to sense the spectrum. Figure 3 shows the receiver operating characteristics (ROC) curves for both the eFAR and FAR algorithms under different mean SNR values.

The difference between the FAR and eFAR algorithms and those indicated in Section 1.1 is significant. First, the decision threshold employed by those algorithms are noise-level dependent and so a different decision threshold is required for each noise level (SNR). Further, while some were developed for wideband detection others are for narrowband detection. In terms of detection performance, the SNR range over which the FAR and eFAR algorithms give good detection performance is larger than the range over which those algorithms are able to give a similar level of detection performance. The only exception being the CAV algorithm [9], whose performance is quite similar to the performance of the eFAR algorithm. Moreover, the CAV algorithm is similar to both the FAR and eFAR algorithms in the sense that its decision threshold is independent of the noise level. Nonetheless, we do not know if (like the FAR and eFAR algorithm), it can easily be implemented in real hardware since only simulation results were presented in [9]. Given that the eFAR and CAV algorithms operate under different principles, it will be interesting to see how the CAV algorithm can be implemented over wideband channels and in a real hardware platform. Accordingly, it will also be interesting to compare both algorithms in terms of their practicality, complexity and ease of implementation. At first glance, however, the CAV algorithm appears to be more complex than the eFAR algorithm.

4. PERFORMANCE EVALUATION

In this section, we present the results of extensive simulation experiments conducted to evaluate our sensing algorithm. The results obtained confirm our belief that it is smarter, more practical and optimal to consider the N-transmitters constraint of the SU. We show results for scenarios with $M = 10$, $N = [1, 2]$, $T = 10$, $\tau = 1$, $K = 256$, $\alpha = 0.01$, $\beta = 0.2$. Rates $R^m = m$ for $m = 1, 2, \ldots, M$ were assumed while the PU occupancy was drawn from a random distribution with a 50% occupancy rate. The results presented were obtained from 1000 monte-carlo simulation runs.

Figure 4 shows the maximum achievable throughput at each observation interval for a) the case where the sensing time factors into the achievable throughput computation as given in Eq. (2) and b) the case where $\frac{T-i\tau}{T}$ is omitted from Eq. (2). It can easily be seen

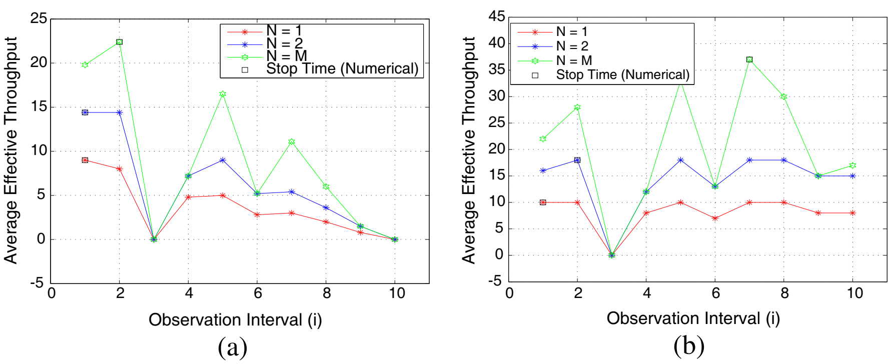


Figure 4. Throughput vs. observation interval.

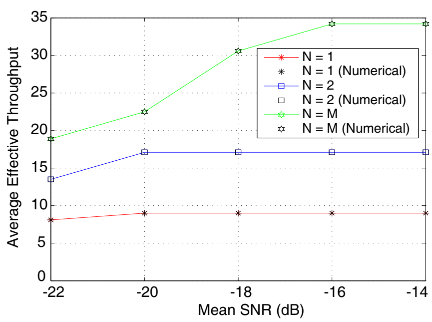


Figure 5. Throughput vs. mean SNR.

that irrespective of the number of channels sensed idle by the SU, the number of channels that the SU can concurrently transmit on (and thus its average achievable throughput) is constrained by the number of transmitters it has. Further, it can also be observed from Figure 4(a) that if the number of transmitters on the SU is not explicitly taken into consideration (as in the conventional algorithms), the sensing algorithm in this scenario will choose $i = 2$ as the optimal sensing stop time for the SU when in reality, an SU with only one transmitter achieves its maximum effective throughput at $i = 1$.

The impact of the N-transmitters constraint is more obvious in Figure 4(b) where conventional schemes will choose $i = 7$ as the best time to stop sensing while our algorithm will choose $i = 1/2$ for $N = 1/2$, which indeed, respectively represents the maximum achievable throughput of an SU that has only one/two transmitter(s). Accordingly, our sensing algorithm enables the SU to use the additional knowledge it has about its number of transmitters to stop sensing much earlier than conventional algorithms would.

Figure 5 shows the maximum achievable throughput as a function of the SNR. As the figure rather trivially confirms, an SU's maximum achievable rate is constrained by its number of transmitters. Accordingly, it justifies the need to explicitly consider the number-of-transmitters constraints in estimating the maximum achievable rate which in turn helps to determine the optimal time to terminate the spectrum sensing phase. Terminating the spectrum sensing phase at the most optimal time and proceeding to the transmission phase directly translates to throughput (data transmission time) optimization.

5. CONCLUSION

We have presented what we believe is a smart, practical and efficient sensing scheme for cognitive radio networks. Our sensing scheme, unlike existing work, explicitly takes into consideration, the number-of-transmitters constraint in determining the best time to stop sensing and proceed with data transmission. To the best of our knowledge, this work is the first to adopt this smart, practical and optimal approach. In addition, we have presented a new wideband spectrum sensing algorithm which we called the eFAR algorithm. Although the eFAR algorithm is mostly an enhancement of the FAR algorithm to spectrum sensing over wideband channels, the eFAR algorithm additionally gives improved detection performance over the FAR algorithm. The eFAR (just like the FAR) algorithm is a practical spectrum sensing algorithm that can easily be implemented in a real hardware platform and deployed in a real network that has primary users. This is a future plan for the present work.

Through the results of extensive simulation experiments conducted to evaluate the performance of our sensing scheme, we have demonstrated its efficiency and throughput benefits. The simulation results closely match the numerical analysis presented further validating our work. As future work, we will look at how to extend our sensing scheme to multi-SU scenarios where although each SU independently senses the channels, the channel access decisions are taken cooperatively, so-called cooperative spectrum sensing.

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