Dynamic Spectrum Tracking through Quickest Detection Techniques: A Clustered Approach

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Abstract

Cognitive radio technology addresses the issue of spectrum scarcity and underutilization by using spectrum sensing to exploit the absence of the primary user. Sensing improvement of the secondary network can be measured by how quickly the absence or presence of a PU is determined. Delay in detection of a PU appearance causes harmful interference with the PU, whereas delay in detection of a PU disappearance reduces the spectrum access opportunity for secondary users. Thus, to achieve the quickest detection of PU appearances and disappearances, we propose a double-sided cumulative sum (DoSCuS) algorithm in a cluster-based cognitive radio network. At the SU level, the DoSCuS algorithm is used to promptly detect appearances and disappearances. At the cluster level, we propose the one-slot history (OSH)-based algorithm to maintain the history for each SU in order to consider only the SUs that observe a change in their adjacent timeslots. At the fusion center (FC), a global decision is made using a weighted decision fusion rule. By exploiting the advantages of the DoSCuS algorithm with the clustered base approach, the proposed scheme detects the status of the PU with minimum delay. The effectiveness of the proposed scheme is shown through simulations and comparisons to the conventional scheme.

Keywords: Change detection point, Cognitive radio, Detection delay, Log-likelihood ratio, Double-sided cumulative sum (DoSCuS)

1 Introduction

In the last decade, wireless technologies have grown rapidly, pushing the demand for increasing spectrum resources to support new services and applications. Various applications are used to monitor and track different types of information related to detection, latency, privacy, communication cost, and quality of service (QOS) [1-2]. Within the current spectrum regularity framework, a recent survey conducted by the federal communication commission (FCC) has indicated that a large number of spectrum resources are under-utilized in vast temporal and geographical spans [3]. Therefore, it has been proposed that unlicensed users be allowed to use under-utilized spectrums when unoccupied by licensed users.

Cognitive radio, as an agile technology, has been promoted for efficient use of the spectrum and to overcome the problems of under-utilization and spectrum scarcity in wireless communication [4]. In [5-6], the author discussed key techniques for efficient networking with cognitive radio to determine frequency spectrum usage and to actuate and utilize the frequency spectrum more efficiently. Several challenges for cognitive radio, such as false sensing information, low accuracy of primary user (PU) detection, and sensing errors, lead to decreased cognitive radio network performance. To overcome such inaccurate reports, the authors in [7] proposed a novel primary user localization algorithm based on compressed sensing in cognitive radio network in order to locate the source signal more accurately in authorized frequency band. In [8], authors proposed a context aware spectrum handoff scheme with multiple attributes decision making methods for preferred network selection in CR networks. Similarly, [9] proposed a model-based reinforcement learning method to extract false sensing reports. The goal is to allow an unlicensed or secondary user (SU) to use the available spectrum only in the absence of a licensed or primary user (PU). The availability of spectrum holes, which means the absence of the PU on a particular frequency band at a certain place and time, is obtained through a process called spectrum sensing. Spectrum sensing enables SUs to opportunistically utilize spectrum holes for their communication. To avoid any interference with the PU, the SUs must continuously sense the spectrum and vacate it as soon as the PU appears in the network.

The problem of spectrum sensing has been investigated using classical schemes such as energy detection, featured detection, and matched filtering [10-12]. In [13], authors proposed a novel clustered scheme for cooperative spectrum sensing to reduce cooperative sensing overhead, and improved sensing performance. In [14-15], a cooperative spectrums

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sensing scheme based on side information, and an efficient clustered algorithm is proposed to find the optimal distance and location of nodes as an application of internet of things. In these block-based detection schemes, an SU determines its test statistics from observations in a fixed window in order to maximize the probability of detection while maintaining a certain level of probability of false alarm. A change in PU activity should be sensed as soon as possible to maximize vacant spectrum utilization and minimize interference with the PU network. Thus, in addition to maximizing the probability of detection, detection delay should be minimized because it is also an important metric of efficient spectrum utilization. However, due to the block-based nature of classical detection schemes and the randomness of PU activity, detection delay has not been addressed in the existing methods.

A change in PU activity causes a change in the distribution of the signal at the SU. Therefore, sequential change point detection is an appropriate framework for spectrum sensing in a cognitive radio and has been extensively investigated in [16-19]. In sequential change detection, samples are observed sequentially. Initially, the samples are drawn from a certain distribution. At an unknown time, a PU state change occurs in the network; i.e., the distribution changes from one state to another, which prompts the SU to set an alarm as soon as possible in order to minimize the delay between the time when such a change occurs and the time when the alarm is raised. In [20], the authors implemented cumulative sum (CUSUM) for a single sensor node on the Aerospace Network Research Consortium (ANRC)'s hybrid cognitive radio test-bed, and they concluded that an algorithm based on the sequential change detector is more robust than an algorithm based on the snapshot energy detector, under low signal to noise ratio (SNR) conditions. In [21], the authors investigated detection delay for different types of information about the PU, and in [22], the authors studied the problem of fastest change with an additional constraint on the cost of observations used in the detection process. In [23], the authors considered a dual-CUSUM algorithm for spectrum sensing and developed the generalized likelihood ratio cumulative sum (GLR-CUSUM), which works with the imprecise estimates of channel gain. In [24], the authors developed a distributed algorithm for SUs to sense the channel cooperatively. In [25] authors studied a collaborative quickest detection scheme that utilizes a function of the eigenvalue of the sample covariance matrix for a spectrum sensing.

All the above approaches consider a flat network and a single-sided CUSUM, detecting only appearances of the PU.

In this work, we propose a double-sided cumulative sum (DoSCuS) algorithm for the quickest detection of PU activity. The double-sided cumulative sum approach considers both the appearances and the dis-appearances of the PU. We consider a cluster-based network where the DoSCuS algorithm runs at the SU level and a one-slot history (OSH) algorithm runs at the cluster level; the clustered approach provides the advantage of increased bandwidth utilization. The OSH algorithm maintains a one-slot history to consider only the SUs that observe changes in their distribution. This consideration of fewer SUs helps to minimize the detection delay. The cluster head (CH) receives the stopping times, the local decisions of users, and the user-IDs from the SUs. The CH combines the reports of the SUs and forwards a combined result to the FC, which declares a global decision about a PU appearance or dis-appearance. The main contributions of this paper are as follows.

- The double-sided cumulative sum (DoSCuS) is used at the user level to detect the PU appearances and dis-appearances.
- A one-slot history (OSH) algorithm at the cluster head is proposed to maintain the SUs' history for one time slot in order to consider only the SUs that observe changes in their distributions.
- A weighted fusion rule is applied at the fusion center (FC) to make a global decision. The proposed scheme is evaluated in comparison with the conventional scheme in terms of stopping time, collision probability, and percentage reporting.

The remainder of the paper is organized as follows. In Section 2 provides a description of the system. In Section 3, we discuss the double-sided cumulative sum (DoSCuS) algorithm employed for the quickest detection of a PU signal at the user level, the one-slot history (OSH)-based algorithm at the cluster level, and the global decision at the FC. In Section 4, we discuss the performance evaluation. Finally, the paper provides our conclusions in Section 5.

2 System Description

We consider a cognitive radio network that consist of C clusters, with each cluster having L SUs, as shown in Figure 1. We assume that each cluster experiences a different signal-to-noise ratio (SNR) because of the channel conditions.

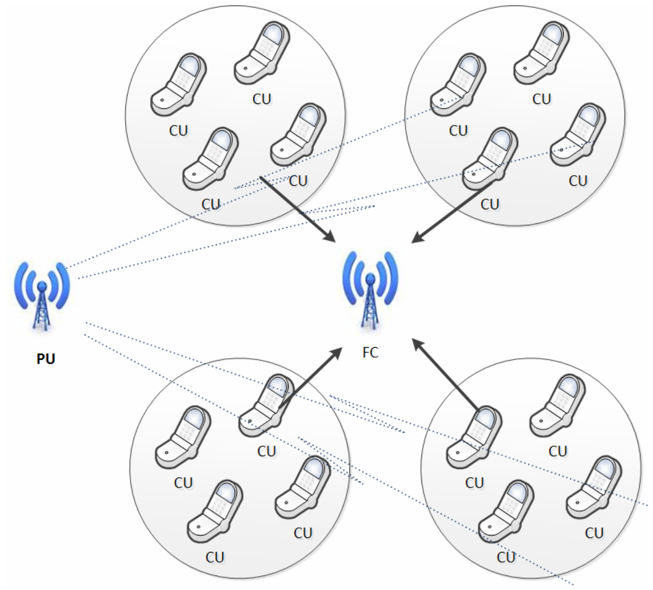

Figure 1. System model

3 Proposed Detection Scheme

The proposed scheme occurs on three levels: detection at the SU level using the DoSCuS algorithm, detection at the cluster level using the OSH algorithm, and global decision making at the FC. The proposed method minimizes the detection delay and reduces the bandwidth traffic load.

Overall flowchart of the proposed scheme is shown in Figure 2.

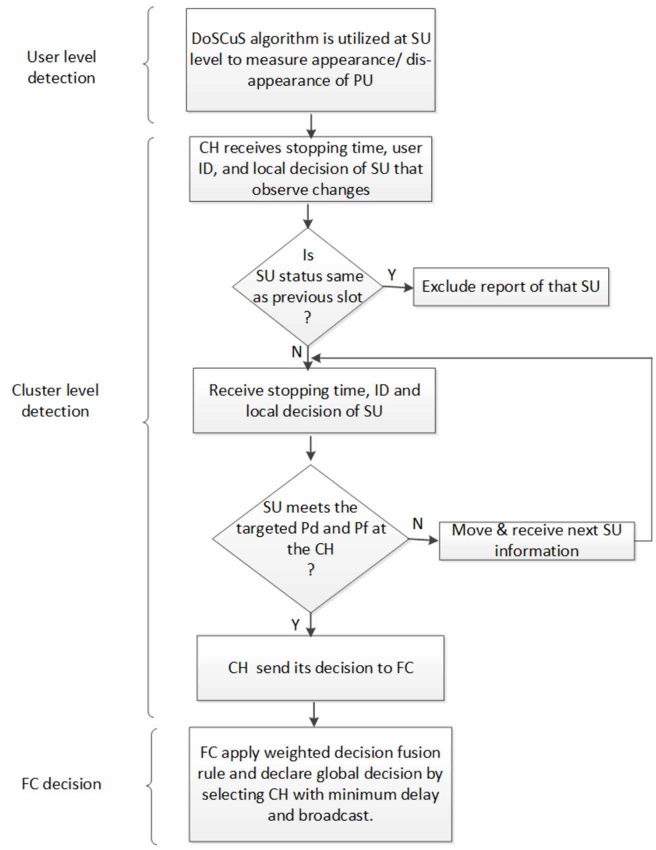

Figure 2. Flow chart of the proposed scheme

3.1 Detection at the SU Using DoSCuS Algorithm

The double-sided cumulative sum (DoSCuS) algorithm is performed at the SU level. We assume that the SUs operate in a slotted manner. The SUs periodically monitor the channel, and if a PU appears in the network, they must vacate the channel immediately. A delay in detection of the PU can cause harmful interference with the PU. Thus, detection delay plays an important role in the cognitive radio network. A PU appearance or dis-appearance can be modeled as a change point detection as shown in Figure 3.

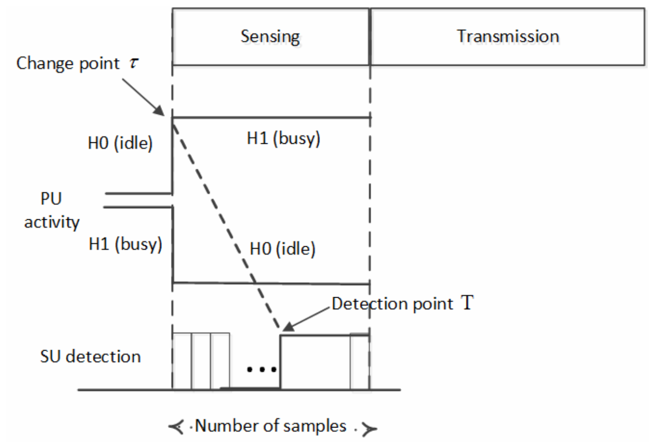

Figure 3. Change point detection of PU

Two scenarios can be considered for the PU signal: when the PU is using the channel and stops transmission, and when the PU is absent and suddenly appears on the channel. Most of the existing literature considers only a PU appearance [24, 26]. However, detection delays for both appearances and disappearances of the PU have significant impacts on the system performance. Thus, we propose a double-sided cumulative sum (DoSCuS) algorithm that quickly detects PU appearance and disappearance.

At a random time τ, when the state of the PU changes, the signal received by the l^{th} SU is given as

$$Y_l = \begin{cases} N_l & \mathrm{H}_0;\text{pre-change distribution} \\ X_l + N_l & \mathrm{H}_1;\text{post-change distribution} \end{cases} \tag{1}$$

where $X_l = h_l S$ is the product of the channel gain h_l and primary signal S, and N_l is white Gaussian noise with zero mean and σ^2 variance. X_l is assumed to be white Gaussian noise with zero mean and $\sigma_X{}^2$ variance. The value of $\sigma_X{}^2$ depends on the channel gain h_l and the power of the transmitter. S and N_l are independent and identically distributed (i.i.d) sequences and are independent of each other.

In the literature, there are two hypothesis about the pre-change and post-change distributions of Y_l [26-27].

In one hypothesis, the pre-change and post-change distributions are based on change in the mean of the Gaussian noise, whereas in the other hypothesis, the distributions are based on change in variance of the Gaussian noise. For this work, we use the variance change model.

Each SU in a cluster listens to the PU signal using the DoSCuS algorithm. The SUs send their observation $y_1, y_2 ..., y_L$ and stopping time to their respective cluster heads (CHs) as soon as a PU state change is observed. A CH forwards an aggregated result of the reports from the SUs to the FC. At the FC, a weighted decision fusion rule is applied to declare the PU's absence H_0 or presence H_1 in the network. If H_0 is declared by the FC, the SUs continue to use the channel, and if H_1 is declared by the FC, the SUs stop transmission.

The sequential change modeling problem is to detect such changes as soon as possible subject to false alarm when the PU appears in the network, and to the mis-detection when the PU disappears from the network. For the detection time T, if $T \geq \tau$, the detection delay is defined as $\Gamma = T - \tau$. The appearances and disappearances of the PU can be observed as the increases and decreases in variance, respectively. The detection delay of a PU appearance or dis-appearance is formulated as

$$\mathrm{Td}_l = \sup_{\tau \geq 1} \; E\left[T - \tau \mid T \geq \tau, W^a{}_{k,l}\right] \quad \textbf{(2)}$$

where Td_l is the stopping time when the state of the PU change is observed, $a \in (inc, dec)$ of the test statistic of the l^{th} SU in the current slot (k) when the PU appears in or dis-appears from the network. Minimizing the detection delay is highly desirable because it maximizes the opportunity for transmitting data and minimizes interference with the PU. For observation y_l, the likelihood ratio is given as

$$llr(\mathrm{y}_l) = \ln\left\{\frac{f_1(y_l)}{f_0(y_l)}\right\} = \frac{\sigma_X{}^2\, y^2{}_l}{2(\sigma_X{}^2 + \sigma^2)\sigma^2} + \frac{1}{2}\ln\left\{\frac{\sigma^2}{(\sigma_X{}^2 + \sigma^2)}\right\} \quad \textbf{(3)}$$

where $f_0(y_l)$ is the density of Y_l under H_0 and $f_1(y_l)$ is the density of Y_l under H_1.

Before and after a PU appearance, the average log-likelihood ratio can be measured, respectively, by using Equations (4) and (5):

$$E\left\{llr^{dec}(Y_l)\right\} = \int f_0(y) \ln\left\{\frac{f_1(y)}{f_0(\mathrm{y})}\right\} dy = -D\left(f_0 \,\|\, f_1\right) \leq 0 \quad \textbf{(4)}$$

$$E\left\{llr^{inc}(Y_l)\right\} = \int f_1(y) \ln\left\{\frac{f_1(y)}{f_0(\mathrm{y})}\right\} dy = D\left(f_1 \,\|\, f_0\right) \geq 0 \quad \textbf{(5)}$$

where $D\left(f_0 \,\|\, f_1\right) = \frac{\sigma_X{}^2}{2(\sigma_X{}^2 + \sigma^2)\sigma^2} + \frac{1}{2}\ln\left\{\frac{\sigma^2}{(\sigma_X{}^2 + \sigma^2)}\right\}$ is the Kullback-Leibler divergence of f_0 from f_1 and $D\left(f_1 \,\|\, f_0\right)$ is the divergence of f_1 from f_0. Thus, before a PU appearance in the network the expected value of $llr(\mathrm{y}_l)$ has a negative trend, whereas after the PU appearance, the KL divergence has a positive trend.

When the PU appears in the network, i.e., the variance increases, the test statistic for detection can be written as

$$W^{inc}{}_{k,l} = \max\left(0,\; (W^{inc}{}_{k-1,l} + llr^{inc}(\mathrm{y}_l))\right), W^{inc}{}_{0,l} = 0 \quad \textbf{(6)}$$

where $W^{inc}{}_{k,l}$ and $W^{inc}{}_{k-1,l}$ are the test statistics in the k^{th} (current) slot and the $(k-1)^{th}$ (previous) slot, respectively, and $llr^{inc}(\mathrm{y}_l)$ is the increase in variance when the PU appears in the network. When the PU disappears from the network, i.e., the variance decreases, the test statistic can be written as

$$W^{dec}{}_{k,l} = \max\left(0,\; (W^{dec}{}_{k-1,l} + llr^{d}(\mathrm{y}_l))\right), W^{dec}{}_{0,l} = 0 \quad \textbf{(7)}$$

where $W^{dec}{}_{k,l}$ and $W^{dec}{}_{k-1,l}$ are the test statistics in the k^{th} (current) slot, and $(k-1)^{th}$ (previous) slot, respectively. and $llr^{dec}(\mathrm{y}_l)$ is the decrease in variance when the PU disappears from the network. The local decision about appearances and dis-appearances of PU in the network can be represented as

$$Gd_{k,l} = \begin{cases} H_1 \;;\; if \;\; (W^{inc}{}_{k,l} > \lambda > 0) \cup (W^{dec}{}_{k,l} > \lambda > 0) \\ H_0 \;;\; otherwise \end{cases} \quad \textbf{(8)}$$

When test statistic is greater than the threshold λ, the local decision $Gd_{k,l}$ is made for H_1 i.e., a PU appearance in the network; otherwise, H_0, a PU disappearance, is declared. When a PU appearance or dis-appearance is observed, an SU reports the stopping time, and its ID to its respective cluster head (CH).

3.2 Cluster-Level Detection

At the cluster level, we propose a one-slot history (OSH)-based algorithm in which the CH maintains a one time-slot history for each SU, and only those SUs that observe changes from one state to another in two consecutive time slots are considered. The CH uses a time-based window to consider the local decision from the SU for a specific time to satisfy the targeted probability of detection and targeted probability of false alarm.

The CH in the j^{th} cluster receives the stopping time, local decision and ID from the SUs as:

$$CHD_j = (\mathrm{Td}_l, Gd_{k,l}, ID_l); \quad \mathrm{j} = 1,2,...\mathrm{C} \quad \textbf{(9)}$$

The CH compares the local decision received in the current time slot with that of the previously stored decision and ignores information from the SU if the decisions are the same; otherwise, information from the SU is considered. Considering only the SUs that exhibit changes in consecutive time slots reduces the control bandwidth from the CH to the FC. The set of such SUs is given below:

$$CHnet = (Gd_{k,1}, Gd_{k,2}, ...Gd_{k,M}) \quad \textbf{(10)}$$

where M is the set of SUs, that observed changes in their states in two consecutive slots.

The CH combines the reports from the SUs and makes a decision about the presence or absence of the PU using the half-voting rule:

$$CHD_j = \begin{cases} H_1; & No\ of\ H_1\ in\ CHnet > M/2 \\ H_0; & \text{otherwise} \end{cases} \quad \textbf{(11)}$$

The proposed one-slot history (OSH)-based algorithm at the cluster level is summarized in Table 1.

Table 1. Proposed One-slot History (OSH)-based algorithm at cluster level

Input: Stopping time Td_l, local decision of l^{th} user in the k^{th} slot ($Gd_{k,l}$), ID
Output: Cluster level decision CHD_j
If $(Gd_{k,l} == Gd_{k-1,l})$ then
exclude that SU from the decision (only save that users history)
else if $(Gd_{k,l} \neq Gd_{k-1,l})$ then
include the l^{th} user's, stopping time, and ID_l for making a decision
End
$Subject\ to: Q_d \geq P_{d_{t\arg}}{}^{*} and\ Q_f \leq P_{f_{t\arg}}{}^{*}$
- $CHnet = (Gd_{k,1}, Gd_{k,2}, ...Gd_{k,M})$
- Apply half voting rule to decide H0/H1 using eqn. (11).

In the next sub-section, the global decision at the FC is explained.

3.3 Global Decision at Fusion Center (FC)

At the cluster level, we propose a one-slot history (OSH)-based algorithm in which the CH maintains a one time-slot history for each SU, and only those SUs that observe changes from one state to another in two consecutive time slots are considered. The CH uses a time-based window to consider the local decision from the SU for a specific time to satisfy the targeted probability of detection and targeted probability of false alarm.

Finally, the CH decisions are combined using a weighted decision fusion rule at the FC, and a global decision is made about the presence or absence of the PU. Specifically, the FC adds weight w_{1j} to a CH decision that declares the presence of the PU, and adds weight w_{0j} to a CH decision that declares the absence of the PU. The clusters' decisions received at the FC are represented by the set $CHD = [CHD_1, CHD_2, ...CHD_C]$. The FC makes a global decision by using likelihood ratio test (LRT) as in [28-29]

$$\frac{\Pr[CHD_1, CHD_2, ...CHD_C \mid H1]}{\Pr[CHD_1, CHD_2, ...CHD_C \mid \mathrm{H}0]} \underset{H_0}{\overset{H_1}{\gtrless}} \frac{\mathrm{P}_0}{\mathrm{P}_1} \quad \textbf{(12)}$$

where $\mathrm{P}_0 = \Pr(H_0)$ and $\mathrm{P}_1 = \Pr(H_1)$ are the prior probabilities of the absence and presence of the PU, respectively. These probabilities are assumed to be known from the long term statistics of the PU activity.

Because the decision set {CHD} is independent, the log-likelihood ratio (L-LRT) corresponding to Equation (12) is as follows:

$$\log \frac{\prod_{j=1}^{C} \Pr[CHD_j \mid H_1]}{\prod_{j=1}^{C} \Pr[CHD_j \mid H_0]} \underset{H_0}{\overset{H_1}{\gtrless}} \log \frac{\mathrm{P}_0}{\mathrm{P}_1} \quad \textbf{(13)}$$

The weighted decision fusion rule can be written as

$$\sum_{j=1}^{C} \left[(1 - CHD_j) \log\left(\frac{1 - Q_d}{1 - Q_f}\right) + CHD_j \log\left(\frac{Q_d}{Q_f}\right) \right] \underset{H_0}{\overset{H_1}{\gtrless}} \log \frac{\mathrm{P}_0}{\mathrm{P}_1} \quad \textbf{(14)}$$

where Q_d is the target probability of detection and Q_f is the probability of false alarm. The weighted decision fusion rule can be re-written as

$$\sum_{j=1}^{C} \left[(1 - CHD_j) w_{0j} + CHD_j w_{1j} \right] \underset{H_0}{\overset{H_1}{\gtrless}} \log \frac{\mathrm{P}_0}{\mathrm{P}_1} \quad \textbf{(15)}$$

where

$$w_j = \begin{cases} w_{0j} = \log\left(\frac{1 - Q_d}{1 - Q_f}\right) & if\ CHD_j = 0 \\ w_{1j} = \log\left(\frac{Q_d}{Q_f}\right) & if\ CHD_j = 1 \end{cases} \quad \textbf{(16)}$$

4 Performance Evaluation and Discussion

This section presents, performance evaluation of the proposed scheme in comparison with other existing methods. The simulation parameters for the proposed scheme is presented in Table 2, and for the comparison, reference in [30] was considered as the conventional scheme.

Table 2. Simulation parameters

Parameters	Values
Number of clusters	05
Number of SUs in a cluster	10
Number of samples for PU detection	50
Number of PU	01
Targeted probability of detection	0.99
Targeted probability of false alarm	0.01

Figure 4 compares the proposed scheme with the conventional scheme in terms of the test statistics, i.e., the stopping time against the number of samples. As Figure 4 shows, the proposed scheme detects the PU state change based on fewer samples, compared to the conventional scheme. This is because the conventional scheme determines the presence of the PU by aggregating 50 samples, thus requiring a longer delay to determine the presence or absence of the PU signal. In contrast, the proposed scheme has a delay of using only 14 samples in the given scenario to make this determination. This earlier detection of the PU signal by the proposed scheme reduces the detection delay, the interference with the PU, and the energy consumption of the network.

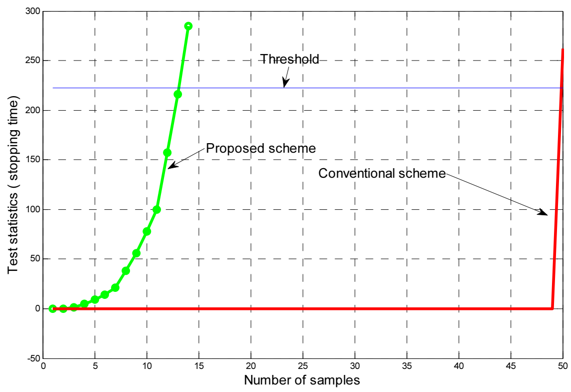

Figure 4. Test statistics vs number of samples

Figure 5 shows the collision probability versus the number of slots for the proposed and conventional schemes. When the PU is mis-detected, a collision occurs. Thus, in this scenario, the proposed scheme reports the presence of the PU as soon as a collision occurs, and it does so with fewer samples than the fixed number that the conventional scheme requires to declare the presence of the PU. Initially, the collision probability is high, and it decreases as the number of slots increases. As Figure 5 shows, the proposed scheme has lower collision probability than the conventional scheme, which shows the effectiveness of the proposed scheme compared with the conventional scheme.

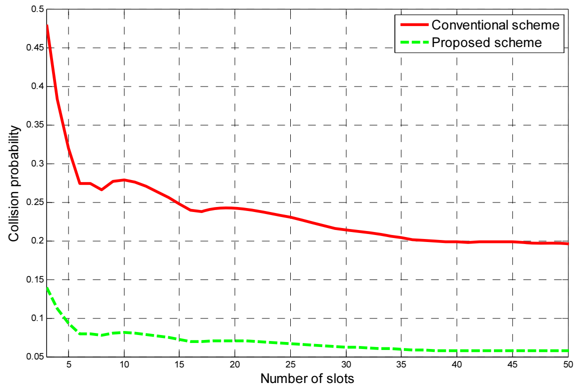

Figure 5. Collision probability vs. number of slots

In Figure 6, we compare the proposed and conventional schemes in terms of the percentage reporting versus the number of SUs in a cluster. We consider single reporting schemes. Therefore the total reporting for the conventional soft combination scheme is $Tr_{sc} = MCLt_s$, where M is the total number of samples an SU requires to declare its decision of the presence or absence, L is the number of SUs in the cluster, C is the number of clusters in the network, and t_s is the time each SU needs to send its report to the CH. The time that a CH needs to receive the sensing data from the SUs corresponds to the sum of the times that the SUs spend to send their sensing data to the CH. Thus, the total time a CH needs to receive the data from the other SUs is $M(L-1)t_s$. The time that the CH needs to compute the decision is assumed to be negligible, and the time a CH needs to send its results to the FC is t_{CH-FC} . Thus, in the investigated scenario, the total reporting time for the conventional scheme is $Tr_{conv} = MC(L-1)t_s + Ct_{CH-FC}$. However, in the proposed scheme, fewer samples are needed to determine and report the status of the PU; thus, the average number of samples needed in the proposed scheme to report the status to the FC is smaller than the conventional scheme. With the proposed scheme, $Tr_{prop} = D_s C(L-1)t_s$ $+Ct_{CH-FC}$, where D_s is the number of detection samples of the PU among the total samples M . It is noteworthy that, for a given bandwidth and transmission rate of the control channel, the more data an SU reports to the CH, the more transmission time it needs. As shown in Figure 6, the proposed scheme performs better than the conventional scheme. The proposed scheme requires about half as much time as the conventional scheme to determine the status of the PU, demonstrating the effectiveness of the proposed scheme.

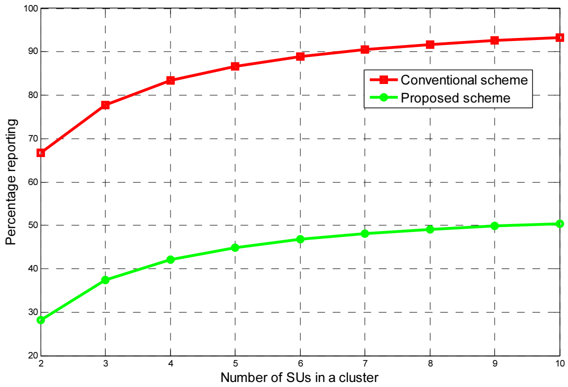

Figure 6. Comparison of the proposed and conventional schemes in terms of the percentage reporting versus the number of SUs in a cluster

5 Conclusion

Prompt detection of the PU's presence or absence is an important task in cognitive radio spectrum access. Delayed detection of a PU presence results in interference and delayed detection of a PU absence reduces the opportunity for the SU to access the channel. In this paper, we considered a cluster network and proposed the double-sided cumulative sum (DoSCuS) algorithm at the SU level to achieve the quickest detection of PU appearances and disappearances. We also proposed a one-slot history (OSH)-based algorithm at the cluster level to collect information only from the SUs that have observed change. We considered a time-based window method to collect the results from the SUs, which are then forwarded to the FC, where a weighted decision rule is applied to make a global decision about the presence or absence of the PU. The effectiveness of the proposed scheme is demonstrated in terms of detection delay time, collision probability, and percentage reporting.

Acknowledgments

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