Sensing Optimization Considering Sensing Capability of Cognitive Terminal in Cognitive Radio System

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Abstract—Cognitive radio is a promising technology to overcome the insufficiency of available communication spectrums. In the cognitive radio system, many important issues exist. Spectrum sensing is one of the important issues, which has been studied throughout recently. In this paper, we propose a new distributed spectrum sensing scheme which considers the difference of sensing capabilities among cognitive terminals. By using our proposed scheme, we can effectively measure the sensing capability of a cognitive terminal and optimize the performance of the spectrum sensing by differentiating the number of spectrum sensing that each cognitive terminal performs. Through performance analysis and numerical results, we show that our proposed scheme can achieve desired performance in view of the probability of false alarm and the probability of miss detection compared to a conventional scheme.

I. INTRODUCTION

In these days, the number of wireless standards is increasing, and this reduces the amount of available spectrums which can be used by communication systems, while data rate that users demand increases. While the communication system has suffered from the insufficiency of available spectrums, many licensed spectrums are unused [1] [2]. To solve the problem of the insufficient amount of spectrums, the concept of cognitive radio has been proposed by J. Mitola [3], [4].

There are a lot of issues in cognitive radio technology. One of the most important issue in the cognitive radio technology is spectrum sensing [5], because in cognitive radio system, the system recognizes the radio environment by the spectrum sensing. If the spectrum sensing does not work properly, the cognitive radio system will have wrong information about the radio environment, and the system will try to use the spectrum which a primary user uses and does not use the spectrum which the primary user does not use. It results in the several performance degradation of the cognitive radio system and the primary user, as we mentioned previously.

A cognitive radio system is composed of many cognitive terminal(CT)s which are distributed in a network. Each CT will observe different radio signals, because the CTs are located at the different location. So, by the cooperation of spectrum sensing between CTs, the performance of the spectrum sensing can be improved. The distributed spectrum sensing has been studied throughout [2], [10], [11], [12], [13], [14]. In [10], the performance of collaborative spectrum sensing which is based on energy detection when shadow fading and multipath exist is studied. In [11], a new cooperative spectrum sensing is proposed which uses a relay node, and authors show that by using proposed sensing scheme, the probability of detection is increased and the time required for the detection is decreased. In [12], a new robust spectrum sensing to sense RF spectrum which is locally unused is proposed and authors show that the performance of sensing can be increased by cooperation. In [13], authors show that the sensing requirements of secondary user is changed by the transmission range of a primary user and also show that a cognitive sensor network is needed in the IEEE 802.22 system to appropriately detect part 74 users. In [2], a new distributed spectrum sensing scheme which can detect overlapped primary users is proposed, and authors show that the proposed sensing scheme can detect and distinguish primary users when the Bluetooth and IEEE 802.11b system are the system of primary users and they are in the same place. In [2], cooperation between CTs is achieved by sharing a sensing model where the results of spectrum sensing are shared in other cooperative spectrum sensing schemes. In [14], the trade-off among spectrum sensing and throughput and the optimal duration of energy detection have been studied. And the cooperative sensing has been studied.

II. PROBLEM DESCRIPTION

The sensing capability of a CT can be different from that of other CTs due to the geographical location of the CT, antenna gain or the performance of a RF amplifier. But the majority of the spectrum sensing schemes do not consider the difference of sensing capabilities among CTs. In [14], the sensing capability of a CT has been considered but cooperative sensing scheme which considers the sensing capability has not been studied. We will show that the sensing capability of the CT can be different.

The sensing capability of a CT depends on antenna characteristics, average channel attenuation and RF amplifier characteristics [19] and these are distinct to all the CTs. Antenna characteristics can be varied by the size of a conducting box [15], and the type of the antenna and they are effected by the human body who uses the CT [17]. RF amplifier characteristics can be varied [16]. The sensing capability can be varied by the location of the CT. For example, if a concrete
wall exists between the CT and a primary user, the received signal power of the CT emitted from the primary user will decrease by 13dB [19]. And if the height of CT A is 1m and the height of CT B is 10m, then the received signal power of CT A from the primary user will be lower by 8.74dB compared to the received signal of CT B in case of using Hata pathloss model [19].

So, from the discussion above, we can conclude that the sensing capability of a CT can be different from other CTs. Moreover, if the CT has a MIMO antenna, the performance of spectrum sensing can be improved by using multiple antennas [18]. So we should consider the sensing capability of a CT to optimize spectrum sensing because the sensing capability are distinct to all CTs. In this paper, we find an optimal distributed spectrum sensing scheme which considers the sensing capability.

In this paper, we use two metrics to describe the sensing capability of the CT. One is the probability of false alarm($P_{FA}$) and the other is the probability of miss detection($P_{MD}$). $P_{FA}$ means the probability that a CT detects a primary user when the primary user is absent. $P_{MD}$ means the probability that a CT does not detect the primary user when the primary user occupies a spectrum.

III. PROPOSED SCHEME

In this paper, we propose a new distributed spectrum sensing scheme, which considers the sensing capability of a CT. In our proposed scheme, we optimize spectrum sensing by changing the number of sensing that each CT performs and we assume that user $i$ senses the spectrum $N_i$ times. $N_i$ is chosen based on $P_{FA}$ and $P_{MD}$ which mean the $P_{FA}$ and $P_{MD}$ of user $i$, respectively. In our proposed scheme, each CT makes a final 1-bit decision on the presence of a primary user for each sensing attempt. If the CT decides that a primary exists, it chooses 1 and otherwise it chooses 0. Each CT shares only final 1-bit decision to minimize the communication overhead due to the spectrum sensing [8], [10]. The system makes a decision via OR operation on these 1-bit decisions, so if a primary user is detected at least once, the system concludes that the primary user exists. In this paper, we also assume that the system is static and parameters which are related to spectrum sensing such as sensing time do not change.

Next, we formulate the optimization problem to find optimal $N_i$ and solve the problem by using Karush-Kuhn-Tucker(KKT) conditions [21]. In the optimization problem, we assume that a cognitive radio system has $K$ users and each user has different sensing capabilities. In this paper, we also assume that $N_i$ is larger than or equal to zero because it cannot be a negative value. But in a real cognitive radio system, it is more desirable to use $N_i \geq 1$ instead of $N_i \geq 0$, because there can be a primary user which can be detected by only one CT. So, it is desirable that every CT senses the primary user at least once. But in this paper, we simply limit $N_i$ to be a nonnegative integer.

In this paper, we assume the objective of our proposed scheme is to minimize $P_{FA}$ when $P_{MD}$ is restricted. This minimization problem can be written as follows:

\[
\begin{align*}
\text{minimize} \quad & P_{FA}^\text{total} \\
\text{subject to} \quad & P_{MD}^\text{total} \leq P_{FA}^\text{thr}, \quad 0 \leq N_i
\end{align*}
\]

(1)

where $P_{FA}^\text{thr}$ means the maximum allowable $P_{MD}$ and $P_{FA}^\text{total}$ and $P_{MD}^\text{total}$ mean $P_{MD}$ and $P_{FA}$ of the system, respectively.

By using our assumptions, we can formulate $P_{FA}^\text{total}$ and $P_{MD}^\text{total}$ as follows [20]:

\[
\begin{align*}
P_{FA}^\text{total} &= (1 - \prod_{i=1}^{K} (1 - P_{FA}^i)^{N_i}) \\
P_{MD}^\text{total} &= \prod_{i=1}^{K} \left( 1 - P_{\text{sense}} + P_{\text{sense}} \cdot (P_{MD}^i)^{N_i} \right)
\end{align*}
\]

(2)

where $P_{\text{sense}}$ means the probability that a primary user can be detected by a certain CT. Since CTs are located at the different position, some CTs are located at the position where the primary user can be detected while the other CTs are located at the position where the primary user cannot be detected.

From eq.(2), we can see that as the number of spectrum sensing increases, $P_{FA}^\text{total}$ increases while $P_{MD}^\text{total}$ decreases. So there is a trade-off between $P_{FA}^\text{total}$ and $P_{MD}^\text{total}$ [14].

The minimization problem defined in eq.(1) is an integer programming because variables $N_i$ should be integer. And since the minimization problem is the integer programming, it is hard to find a closed form solution. So, we relax this constraint so that $N_i$ can be real number larger than zero.

Next, we use the KKT conditions to solve the optimization problem. To solve the problem, we modify original problem from minimization problem to maximization problem. Then, the objective function can be changed as follows:

\[
\text{maximize} \quad \prod_{i=1}^{K} (1 - P_{FA}^i)^{N_i}
\]

(3)

And next, we take log for $P_{FA}^\text{total}$ and $P_{MD}^\text{total}$ and change the problem into minimization problem. Since log function is monotonically increasing function, the solution does not change. By taking log for $P_{FA}^\text{total}$ and $P_{MD}^\text{total}$ and changing the maximization problem to the minimization problem, the problem is changed as follows:

\[
\begin{align*}
\text{minimize} \quad & -\sum_{i=1}^{K} N_i \cdot \log(1 - P_{FA}^i) \\
\text{subject to} \quad & \sum_{i=1}^{K} \log(1 - P_{\text{sense}} + P_{\text{sense}} \cdot (P_{MD}^i)^{N_i}) \\
& \leq \log(P_{FA}^\text{thr}) \\
& 0 \leq N_i
\end{align*}
\]

(4)

The objective function and the constraint on $N_i$ in eq.(4) are affine function. So, if a constraint on $P_{MD}$ is convex, then the minimization problem becomes a convex problem and a point which satisfies the KKT conditions becomes an optimal solution [21]. To check that the constraint is convex function, we calculate the second derivative of the function and check that the Hessian of function is a positive semi definite(PSD).

Let the first constraint of eq.(4) be $g(x)$, then the second derivative of the constraint can be calculated as follows:

\[
\begin{align*}
g(x) &= \sum_{i=1}^{K} \log(1 - P_{\text{sense}} + P_{\text{sense}} \cdot (P_{MD}^i)^{N_i}) \\
\frac{\partial g(x)}{\partial N_i} &= \frac{P_{MD}^i \cdot \log(P_{MD}^i)}{(1 - P_{\text{sense}} + P_{\text{sense}} \cdot (P_{MD}^i)^{N_i})} \\
\frac{\partial^2 g(x)}{\partial N_i^2} &= \frac{\left( \frac{P_{MD}^i \cdot \log(P_{MD}^i)}{(1 - P_{\text{sense}} + P_{\text{sense}} \cdot (P_{MD}^i)^{N_i})} \right)^2 + \frac{1}{(1 - P_{\text{sense}} + P_{\text{sense}} \cdot (P_{MD}^i)^{N_i})^2} \cdot (1 - (P_{MD}^i)^{N_i})}{(1 - P_{\text{sense}} + P_{\text{sense}} \cdot (P_{MD}^i)^{N_i})^2} \\
&\geq 0
\end{align*}
\]

(5)
From the eq.(5), we can see that the Hessian of $g(x)$ is a diagonal matrix and every element is positive. So the Hessian of $g(x)$ is PSD and the constraint of minimization problem becomes convex. So, the problem is a convex optimization problem.

Next, we calculate the derivative of a lagrangian function, which can be written as follows:

$$\frac{\partial L(x, \mu)}{\partial N_i} = \log(1 - P_i(x)) + \lambda \frac{(P_i(x))^N_i \log(P_i(x))}{(1 - P_i(x))^N_i \log(P_i(x)) - P_i(x)} + \mu_i$$

where $\lambda$ and $\mu_i$ should be non-negative real value. And, a KKT condition is the point which satisfies following condition:

$$0 = \log(1 - P_i(x)) + \lambda \frac{(P_i(x))^N_i \log(P_i(x))}{(1 - P_i(x))^N_i \log(P_i(x)) - P_i(x)} - \mu_i$$

$$0 = \mu_i N_i$$

$$0 = \lambda \cdot \left( \frac{P_{th}^{MD} - \sum_{i=1}^{K} \log(1 - P_i(x))}{(1 - P_i(x))^{N_i} \log(P_i(x))} \right)$$

$$0 \leq \left( \frac{P_{th}^{MD} - \sum_{i=1}^{K} \log(1 - P_i(x))}{(1 - P_i(x))^{N_i} \log(P_i(x))} \right)$$

From eq.(7) we can derive the following function:

$$0 = \frac{-\log(1 - P_i(x)) + \lambda (P_i(x))^N_i \log(P_i(x))}{(1 - P_i(x))^N_i \log(P_i(x)) - P_i(x)} \cdot N_i$$

If the optimal number of spectrum sensing for CT $i$ is larger than zero, then $\lambda$ and $(P_{MD}^{i})^{N_i}$ for CT $i$ can be derived from eq.(8) as follows:

$$(P_{MD}^{i})^{N_i} = \frac{(1 - P_i(x)) \log(1 - P_i(x))}{\lambda \log(1 - P_i(x)) - P_i(x) \log(1 - P_i(x))}$$

$$\lambda = \frac{(P_{MD}^{i})^{N_i} \log(P_i(x))}{(1 - P_i(x))^{N_i} \log(P_i(x))} \cdot (1 - P_i(x))^{N_i}$$

And constraint on the $P_{MD}$ can be written as follows:

$$P_{th}^{MD} \geq \prod_{i=1}^{K} (1 - P_i(x) + P_i(x) \cdot (P_{MD}^{i})^{N_i})$$

If the $P_{FA}$ and the $P_{MD}$ are not zero nor one, $\lambda$ is a positive real value. In this case, the equality in eq.(10) should be holded according to eq.(7). Let $U$ be the set of CTs which have the number of spectrum sensing larger than zero and $U_{num}$ be the number of the element of set $U$. $P_{total}^{MD}$ of a CT $i$ which is not the element of set $U$ is 1 because it will not sense the spectrum. If we combine eq.(9) with eq.(10), we can get following equation:

$$P_{th}^{MD} = \prod_{i \in U} \left[ (1 - P_i(x) + P_i(x) \log(1 - P_i(x))) \right]$$

$$\lambda = \frac{(P_{MD}^{i})^{N_i} \log(P_i(x))}{(1 - P_i(x))^{N_i} \log(P_i(x))} \cdot (1 - P_i(x))^{N_i}$$

where equality holds because $\lambda$ is positive. And since $P_{FA}$ and $P_{MD}$ are close to 0 in real system, we can approximate the eq.(11) as follows:

$$P_{th}^{MD} \approx (1 - P_i(x))^{U_{num}} \prod_{i \in U} (1 + \frac{P_i(x) \log(1 - P_i(x))}{\lambda \log(1 - P_i(x))})$$

And eq.(12) can be approximated further as follows if $P_{FA}$ and $P_{MD}$ are close to 0:

$$P_{th}^{MD} \approx \frac{(1 - P_i(x))^{U_{num}}}{\lambda \log(1 - P_i(x))}$$

Also, from eq.(13), we can get the value of $\lambda$ as follows:

$$\lambda \approx P_i(x) \cdot \left( P_{th}^{MD}(1 - P_i(x))^{-U_{num} - 1} \right)$$

And by combining eq.(14) with eq.(9), we can get the function for $N_i$ as follows:

$$N_i \approx \frac{\log(1 - P_i(x))}{\log(1 - P_i(x))} \cdot \left( \frac{\sum_{i \in U} \gamma_i}{(\sum_{i \in U} \gamma_i)^{U_{num} - 1}} \right)$$

where $\tau_i = \log(1 - P_i(x))$. From the definition of $\tau$, we can easily check that the inverse of $\tau$ is proportional to the sensing capability of a CT. If a CT has high sensing capability, then the CT will have small $\tau$. Also, it will have large $\tau$ if the CT has low sensing capability.

From eq.(15), we can see that the number of spectrum sensing which a CT should perform is proportional to the sensing capability of the CT. It is intuitively true because $P_{total}^{MD}$ and $P_{total}^{FA}$ will be lower when a CT which has high sensing capability senses more compared to the case when the CT which has high sensing capability does not sense more than other CTs.

From eq.(14), the minimum allowable value of $P_{th}^{MD}$ can be found as follows:

$$P_{th}^{MD} \geq (1 - P_i(x))^{K}$$

If the condition in eq.(16) is not satisfied, then the value of $\lambda$ become less than 0. So, the solution of the problem cannot be found. eq.(16) can be easily derived from the definition of eq.(2). When $N_i \to \infty$ for all $i$, then $P_{FA}^{MD} \to 0$ since $P_{FA}^{MD} \leq 1$, and therefore $P_{total}^{MD} \to (1 - P_i(x))^{K}$. So $P_{total}^{MD}$ cannot be less than $(1 - P_i(x))^{K}$.

Next, we should find the element of set $U$. For $N_i$ in eq.(15) to be a non negative real number, the following inequality should be holded:

$$0 \leq \left( ((P_{th}^{MD}(1 - P_i(x))^{-U_{num} - 1}) \cdot \sum_{j \in U} \gamma_j) - \tau_i \right) \forall i \in U$$

Eq.(17) is derived from the fact that real logarithm function should have positive domain. According to the value of $(P_{th}^{MD}(1 - P_i(x))^{-U_{num} - 1})$, eq.(17) can be satisfied for all CTs which are in the system. If the following condition is satisfied, eq.(17) is satisfied for all CTs with any sensing capability:

$$1 \leq \left( ((P_{th}^{MD}(1 - P_i(x))^{-K} - 1)^{-1} \right)$$

Then, eq.(18) can be simplified as follows:

$$K \geq \frac{\log(P_{FA}^{MD})}{\log(1 - P_i(x))}$$

So if eq.(19) is satisfied, all CTs will have the positive number of spectrum sensing. If eq.(19) is not satisfied, then all the
elements which satisfy the following condition is the element of set $U$.

$$
\tau_i \leq \frac{(P_{FA}^h)^{N_i}(1-P_{sense})^{U_{num}} - 1}{1 - (P_{MD}^i(1-P_{sense})^{U_{num}} - 1)^{-1} \cdot \sum_{j \in U, j \neq i} \tau_j}
$$

(20)

This equation can be easily derived from eq.(17). And the $\tau_i$ which is not the element of set $U$ should be larger than the element of set $U$. So, by using eq.(20), we can find the element of set $U$ easily by sequentially removing the element.

For CT $i$ whose number of spectrum sensing is zero, following equation should be satisfied.

$$
0 \leq ( - \log(1-P_{FA}^i) + \lambda \cdot (P_{MD}^i)^{N_i} \cdot \log(P_{MD}^i) ) \cdot \\
= ( - \log(1-P_{FA}^i) + \lambda \cdot \log(P_{MD}^i))
$$

(21)

Eq.(21) can be rewritten as follows:

$$
\tau_i \leq P_{sense} \cdot (P_{MD}^h)^{1-P_{sense}} - U_{num} - 1) \cdot \sum_{j \in U} \tau_j
$$

(22)

Eq.(22) is satisfied for all CT $i$ whose number of spectrum sensing is zero due to eq.(20) and due to the fact that $P_{sense}$ is smaller than 1. So, $N_i$ which is defined in eq.(15) is a KKT condition and is the optimal solution to the problem defined in eq.(4).

Since $N_i$ in eq.(15) is a positive real value, we need to quantize this value to determine the number of spectrum sensing. In this paper, we propose two methods to quantize $N_i$, which are Method 1 and Method 2. Method 1 is to round $N_i$ for quantization. By using this method, we can get quantized value but there is no guarantee that $P_{MD}^i$ is less than $P_{MD}^h$. The constraint may not be satisfied. Method 2 is to set the number of spectrum sensing to be the smallest integer which is larger than $N_i$. By using this method, we can satisfy the constraint that $P_{MD}^i$ is less than $P_{MD}^h$, but it can be away from the optimal solution.

Although we derive the optimal number of spectrum sensing by using KKT conditions and some approximations, the optimal solution can be directly calculated by solving the problem (1), which is an integer programming. If the number of CTs is small, then it is feasible to find the optimal number of spectrum sensing by directly solving the problem defined in (1). And if the number of CTs is large, using eq.(15) to find the optimal number of spectrum sensing is better due to computational complexity.

IV. NUMERICAL AND SIMULATION RESULTS

In this section, we analyze the performance of proposed method. In this paper, major performance metrics are $P_{MD}^h$ and $P_{FA}^h$.

First, we calculate $P_{MD}^h$ and $P_{FA}^h$ of spectrum sensing in case of using various schemes. In this calculation, we assume that the sensing capability of CTs is known. We use Method 1 and Method 2 to quantify the number of spectrum sensing which can be obtained from eq.(15). We also calculate the performance of spectrum sensing when we do not quantize the number of sensing to see the effect of quantization. We also calculate the performance of spectrum sensing by using the number of spectrum sensing which is obtained by directly solving the integer programming defined in eq.(1). For comparison, we calculate the performance of spectrum sensing when the number of spectrum sensing of each CT is the same. And also, we calculate the performance when the number of spectrum sensing of each CT is chosen randomly.

First, we calculate $P_{MD}^h$ and $P_{FA}^h$ when the number of CTs is 10 and $P_{sense}$ is 30%. And we choose the value of $P_{MD}^h$ from uniform random variable which is distributed from 0 to 30%, and we choose the value of $P_{FA}^h$ from uniform random variable which is distributed from 0 to 2%. We set $P_{MD}^h$ to be much larger than $P_{FA}^h$, because in our proposed scheme, $P_{MD}$ monotonically decreases as the number of user increases while $P_{FA}$ monotonically increases [8], [10]. If we use energy detection for spectrum sensing, we can adjust $P_{MD}$ and $P_{FA}$ by changing the threshold of energy detection.

We set $P_{MD}^h$ to be 2.91% and it is achievable due to eq.(16), since $100 \cdot (1 - 0.30)^{10} = 2.82 \leq 2.91$. For the calculation of the performance when the number of spectrum sensing of each CT is the same, we vary the number of spectrum sensing from 1 to 4. And, for the calculation of the performance when the number of spectrum sensing of each CT is chosen randomly, we choose the integer from uniform random variable which is distributed from 1 to 5. Results are summarized in Table I, where the word "Optimal" means that the number of spectrum sensing is found by solving an integer programming defined in eq.(1).

As we can see from Table I, our proposed scheme shows better performance compared to the performance of other cases. Either using Method 1 or Method 2, or directly solving the integer programming, the performance of proposed scheme is better than the other schemes. For example, to satisfy the constraint on $P_{MD}^h$, all CTs should sense the channel 3 times. The value of $P_{FA}^h$ in this case is by 30% larger than that of $P_{FA}^h$ when the optimal number of spectrum sensing is used.

We can see from the results that the performance of our proposed scheme when Method 1 is used is close to the optimal performance which can be obtained by solving an integer programming defined in eq.(1). We can check this by comparing the performance of Method 1 with the performance of optimal case. But, in general, the $P_{MD}^h$ is larger than $P_{MD}^h$ when Method 1 is used, due to the characteristic of exponential function which appears in $P_{MD}^h$. But when Method 2 is used, the constraint on $P_{MD}^h$ is always satisfied, because the number of spectrum sensing of each CT is always larger than the optimal number of spectrum sensing. However, the number of spectrum sensing is increased and hence the $P_{FA}^h$ of spectrum sensing is degraded.

<table>
<thead>
<tr>
<th>$P_{MD}^h$ (%)</th>
<th>$P_{FA}^h$ (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Optimal</td>
<td>2.91</td>
</tr>
<tr>
<td>Method 1</td>
<td>2.91</td>
</tr>
<tr>
<td>Method 2</td>
<td>2.87</td>
</tr>
<tr>
<td>w/o quantization</td>
<td>2.91</td>
</tr>
<tr>
<td>Number of sensing = 1</td>
<td>4.93</td>
</tr>
<tr>
<td>Number of sensing = 2</td>
<td>3.17</td>
</tr>
<tr>
<td>Number of sensing = 3</td>
<td>2.90</td>
</tr>
<tr>
<td>Number of sensing = 4</td>
<td>2.84</td>
</tr>
<tr>
<td>Random select</td>
<td>3.41</td>
</tr>
</tbody>
</table>
sensing increases, too, as shown in Table I.

It is noticeable that the performance of proposed scheme is better when quantization is not used to decide the number of spectrum sensing compared to the performance of optimal case. This is due to the fact that the number of spectrum sensing is integer in optimal case while the number of spectrum sensing is not integer when quantization is not used.

Next, we calculate $P_{\text{total}}^i$ and $P_{\text{total}}^f$ by varying the number of CTs from 2 to 8. Since the minimum value of $P_{\text{MD}}^i$ varies with the number of CTs, we set the $P_{\text{MD}}^i = 1.1 \cdot (1 - P_{\text{sense}})^K$, so that $P_{\text{MD}}^i$ varies with the number of CTs. In this performance evaluation, $P_{\text{FA}}^i$ is chosen from uniform random variable which is distributed from 0 to 2% and $P_{\text{FA}}^f$ is chosen from uniform random variable which is distributed from 0 to 20%. Other parameters are the same as above calculation. We calculate the performance of spectrum sensing when Method 1 or Method 2 quantization is used and when quantization is not used. We also calculate the performance of spectrum sensing when the number of spectrum sensing is chosen optimally and when the number of spectrum sensing is randomly chosen from 1 to 5. Results are shown in Fig.1 and Fig.2.

As we can see from Fig.1 and Fig.2, our proposed scheme shows better performance compared to the sensing performance when the number of sensing is randomly chosen. We can also find that the performance of spectrum sensing when Method 1 or Method 2 is used, is close to optimal performance and the spectrum sensing when the quantization is not used shows the best performance due to the same reason that we stated above.

From Fig.1, we can find that $P_{\text{MD}}^i$ decreases as the number of CTs increases because as the number of CTs increases, $P_{\text{MD}}^i$ decreases. $P_{\text{MD}}^f$ when quantization is not used coincides with the $P_{\text{MD}}^f$ but $P_{\text{MD}}^i$ of optimal case is smaller than $P_{\text{MD}}^f$ because in optimal case, the number of spectrum sensing is constrained to integer value and in this case to satisfy the constraint on $P_{\text{MD}}^i$ defined in eq.(1), $P_{\text{MD}}^i$ should be smaller than $P_{\text{MD}}^i$. When quantization is not used, the number of sensing is not constrained to integer value and the constraint on $P_{\text{MD}}^i$ can be met with equality.

We can also find from Fig.1 that the constraint on $P_{\text{MD}}^i$ is not satisfied only when Method 1 is used due to the characteristic of exponential function in round operation as we denoted in the analysis of Table I. But $P_{\text{MD}}^i$ is minimized when Method 1 is used. We can also find that $P_{\text{MD}}^i$ when Method 2 is used is always smaller than $P_{\text{MD}}^i$ of other cases due to the same reason that we have observed previously. But from Fig.2, we can also find that $P_{\text{MD}}^i$ when Method 2 is used is always larger than $P_{\text{MD}}^i$ of other cases due to the same reason that we stated above. From this, we can observe the trade-off between $P_{\text{MD}}^i$ and $P_{\text{MD}}^f$. And we can also observe that $P_{\text{MD}}^i$ and $P_{\text{MD}}^f$ when Method 1 or Method 2 is used is always larger than $P_{\text{MD}}^i$ and $P_{\text{MD}}^f$ shown in Fig.3 and Fig.4.

As we can see from Fig.3 and Fig.4, as the number of spectrum sensing samples increases, the performance of our proposed scheme converges, because $P_{\text{FA}}$ and $P_{\text{MD}}$ of each CT which are known to the system is close to real $P_{\text{FA}}$ and $P_{\text{MD}}$ as the number of spectrum sensing samples increases. From the results, we can see that more than 3000 samples are needed to find the sensing capability of a CT. If the spectrum sensing is performed every 100ms, it will take 300 seconds to find the capability of each CT, which is quite large.
optimal solution, we proposed a new distributed spectrum sensing scheme and from numerical results, we show that our proposed scheme minimizes $P_{\text{total}}^{\text{MD}}$ while satisfying the constraint on $I_{\text{total}}^{\text{MD}}$.

In this paper, we have not considered the variation of the sensing capability of each CT. However, when a CT moves or when the environment around the CT changes, the sensing capability of each CT changes. So, the variation of the sensing capability of CTs should be further studied.

REFERENCES


