

國立交通大學

電信工程研究所

碩士論文



在感知無線電網路中使用權重式

匯整規則做合作式頻譜感測

Cooperative Spectrum Sensing Using a Weighted

Fusion Rule for Cognitive Radio Networks

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指導教授：李程輝 教授

中華民國一百年六月

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Advisor: Prof. Tsern-Huei Lee



A Thesis
Submitted to Institute of Communication Engineering
Collage of Electrical Engineering and Computer Science
National Chiao Tung University
in Partial Fulfillment of Requirements
for the Degree of
Master of Science
in
Communication Engineering
June 2011
Hsinchu, Taiwan, Republic of China

中華民國一〇一年六月

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中文摘要

在感知網路中，每個感知使用者和主要使用者距離不盡相同，可能受到訊號干擾及衰減影響其感測能力，而硬體故障、駭客攻擊，也會導致錯誤的判定。合作式頻譜感測是一種能讓失敗偵測機率及錯誤預警機率降低的辦法，因此匯整規則就顯得相當重要，好的匯整規則足以因應感知網路的各種環境，讓判定錯誤率降到極低。現存一些匯整規則，譬如OR規則、AND規則、多數決規則，它們的錯誤率仍非令人滿意，因此權重式匯整規則因應而生，給予信賴度較高的感知使用者較高的權重，即使於不穩定的網路環境，仍有較正確的判定機率。因此在這篇學位論文裡，我們提出一種新的權重式匯整規則，有別於之前提出的匯整規則，更能在未知多變的網路環境，使得誤判率下降，進而讓感知使用者在不影響主要使用者的前提下，得到更高的吞吐量。

Cooperative Spectrum Sensing Using a Weighted Fusion Rule for Cognitive Radio Networks

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Abstract

In cognitive radio (CR) networks, because the distance of every CR user and the primary user is different, a signal may have interference and attenuation that affect the sensing ability of CR users. A CR user in mal-function or being hacked also results in wrong decision. Cooperative spectrum sensing is a way to decrease the probability of miss detection and the probability of false alarm. Therefore, the fusion rule is remarkably important. A good fusion rule is suitable for various circumstances because it can decrease significantly error probability. The error rate of existing data fusion techniques, such as OR rule, AND rule, and Majority rule, are still not satisfactory. Consequently, a weighted fusion rule is proposed so that reliable CR users are given higher weights. It still makes better decision under unstable networks. Hence in this thesis, we propose a weighted fusion rule that differs from previous weighted fusion rule. It can decrease the probability of wrong decision in unknown and changing networks. Furthermore, CR networks have higher throughput under the promise of avoiding interference to the primary user.

誌謝

感謝我的指導教授—李程輝老師，在研究所的求學過程中悉心地指導我。您無比的研究熱忱和適時給予我的鼓勵，讓我對研究產生了興趣和信心。在您的教誨下，我學習到了做研究應有的態度與嚴謹的思維，在做研究和撰寫論文的過程，我得到了許多寶貴的經驗，實在是獲益匪淺。平時您的親和力和幽默感，更拉近了師生間的距離，讓實驗室的氣氛既溫暖又歡樂。

感謝郭耀文教授，在網路的另一端，陪我們走過每一個的春夏秋冬，每次meeting時，都能獲得您的珍貴意見，讓我對於做研究有了更多的動力和熱情。

感謝 NTL 實驗室整個大家庭的成員，尤其同是 CR組的承潔、順閔，於撰寫計劃時的交流，讓我學習怎樣團隊工作。也感謝熱心辦活動的實驗室大總管book，讓實驗室更顯蓬蓬朝氣。感謝坐在我旁邊的梓洋學長，以過來人分享些很受用的經驗。也感謝郁文、啟賢學長，你們都是我做研究的模範。

感謝交大單車社的夥伴、三腳貓鐵人隊的夥伴、清大攀岩場的夥伴，你們證明了有強壯的體魄能做更多事情，更重要的是，學業、事業的表現並不比其他人差。有夢最美，築夢踏實。

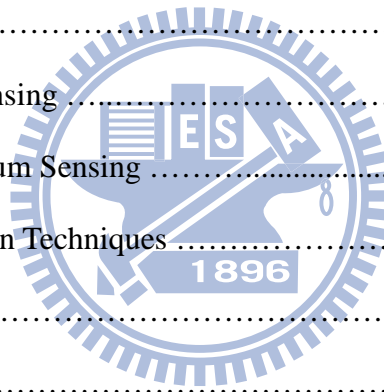
最後，更要特別感謝我的父親李癸和先生與母親林美貴女士，謝謝您們對我從小無微不至的養育照顧與支持，讓我無後顧之憂地完成學業。感謝我所有的親朋好友，謝謝您們平時對我的關心和勉勵。因為您們，才能讓我求學之路走得如此堅定踏實！

謹將此論文獻給所有愛我與我愛的人！

2011 年 6 月 於風城交大

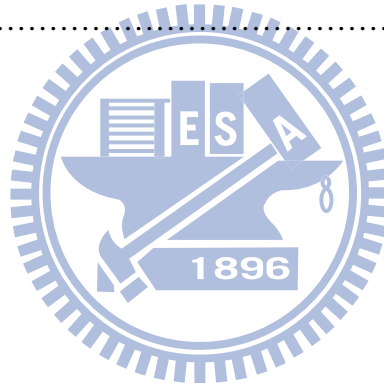
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Notation

N : the number of CR users

x : sensing round

E_i : energy of detecting the primary user at a CR user

W_n : decision variable

λ : a threshold of a CR user

$I_i(x)$: a decision of a CR user

$\omega_i(x)$: a weight of a CR user's decision

β : the proportion of historical decisions

ε : the threshold of the fusion center

$B(x)$: a decision of the fusion center

$T_i(x)$: decide if $I_i(x)$ equals $B(x)$

$R(x)$: the throughput of CR users

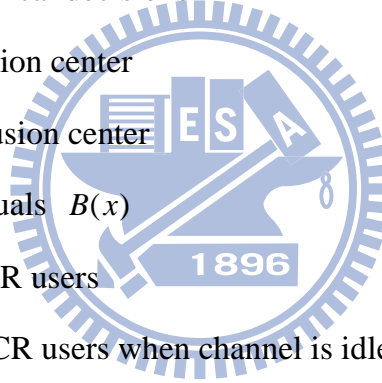
$R_0(x)$: the throughput of CR users when channel is idle

$Q_m(x)$: the probability of miss detection at the fusion center

$Q_f(x)$: the probability of false alarm at the fusion center

$Q_d(x)$: the probability of detection at the fusion center

\bar{Q}_d : the lowest bound of the probability of detection



Chapter 1

Introduction

In recent years, the demand of spectrum is increasing that results in cram of some spectrum bands and poor spectrum efficiency. Therefore, spectrum is a precious resource. The CR technique [1], [2] that has the ability of spectrum sensing was proposed in order to utilize as idle spectral resources as possible.

This technique divides users in a CR network into the primary (licensed) users and secondary (CR) users. CR users sense a certain spectrum segment first before transmitting data. If CR users sense no primary users using this spectrum segment, they are allowed to utilize this spectral resource only when they do not cause interference to the primary users. Otherwise, if CR users find the primary users using this spectrum segment, they must quit this spectrum segment and search another available spectrum segment. This idle spectrum segment is called spectrum hole [3], we can detect it to improve spectrum efficiency by spectrum sensing technique.

However, the sensing ability of a single CR user is limited since signals may be interfered by noise and attenuated by distance. In addition, shadowing effect in wireless network and hardware's condition of CR users may cause poor sensing ability of CR users. Thus, we need to combine CR users together to sense spectrum that can promote the whole sensing ability of a CR network. The way is called cooperative spectrum sensing (CSS) [4].

Merely, a simple CSS using OR rule, AND rule, and Majority rule of which error rate are still not satisfactory under an unstable network. Consequently, a weighted fusion rule is proposed so that reliable CR users are given higher weights. It has a better performance than a simple CSS.

A CR user in mal-function and being hacked may cause incorrect reports. These incorrect reports are sent to the fusion center that results in wrong global decision. Therefore, we design a weighted algorithm that is more robust than other weighted algorithms against hackers.

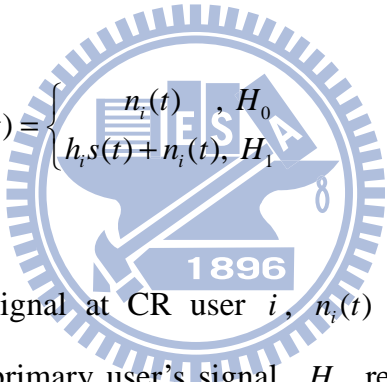
The rest of this thesis is organized as follows. In Chapter 2, we formulate the problem of signal detection of the primary user in a CR network. Then we investigate some weighted fusion rules in Chapter 3 and propose our weighted algorithm in Chapter 4, respectively. Next, we give some simulations about the previous weighted fusion rule and ours in Chapter 5. Finally, conclusions are given in Chapter 6.

Chapter 2

Background

2.1 Local Spectrum Sensing

The purpose of local spectrum sensing is to decide if the primary user exists and do binary hypothesis test of CR users based on received the primary user's signal. We assume that the sensing channel is time-invariant during the sensing process. Then we can represent local spectrum sensing to the following binary hypothesis test [4] :

$$y_i(t) = \begin{cases} n_i(t), & H_0 \\ h_i s(t) + n_i(t), & H_1 \end{cases} \quad (1)$$


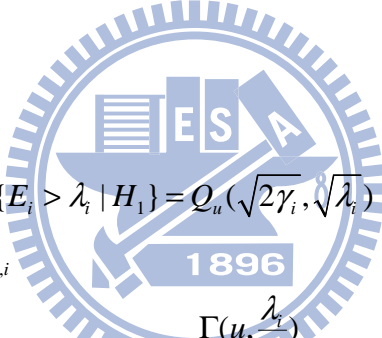
where $y_i(t)$ is received signal at CR user i , $n_i(t)$ is the channel noise, h is the channel gain, $s(t)$ is the primary user's signal. H_0 represents that the primary user is absent in the sensing channel; otherwise, H_1 represents that the primary user is present in the sensing channel. We define the probability of detection $P_{d,i}$, the probability of miss detection $P_{m,i}$, the probability of false alarm $P_{f,i}$ at CR user i :

$$\begin{aligned} P_{d,i} &\triangleq \text{Prob}\{H_1 | H_1\} \\ P_{m,i} &\triangleq \text{Prob}\{H_0 | H_1\} = 1 - P_{d,i} \\ P_{f,i} &\triangleq \text{Prob}\{H_1 | H_0\} \end{aligned} \quad (2)$$

We assume that CR users perform local spectrum sensing with energy detector [5] :

$$E_i = \begin{cases} \chi_{2u}^2, & H_0 \\ \chi_{2u}^2(2\gamma_i), & H_1 \end{cases} \quad (3)$$

where E_i is received signal energy at CR user i , χ_{2u}^2 is central chi-square distribution, $\chi_{2u}^2(2\gamma_i)$ is non-central chi-square distribution. For CR user i with energy detector, the average probability of detection $P_{d,i}$, the average probability of miss detection $P_{m,i}$, and the average probability of false alarm $P_{f,i}$ over AWGN channels are given, respectively, by [5] :



$$\begin{aligned} P_{d,i} &= \text{Pr ob}\{E_i > \lambda_i | H_1\} = Q_u(\sqrt{2\gamma_i}, \sqrt{\lambda_i}) \\ P_{m,i} &= 1 - P_{d,i} \\ P_{f,i} &= \text{Pr ob}\{E_i > \lambda_i | H_0\} = \frac{\Gamma(u, \frac{\lambda_i}{2})}{\Gamma(u)} \end{aligned} \quad (4)$$

where $u = TW$ is the time-bandwidth product and γ_i is instantaneous signal-to-noise ratio (SNR) of received signal at CR user i . Q_u is the Generalized Marcum

Q -function by $Q_u(a, x) = \frac{1}{a^{u-1}} \int_x^\infty t^u e^{-\frac{t^2+a^2}{2}} I_{u-1}(at) dt$, $I_{u-1}(\cdot)$ is modified Bessel function, and

$\Gamma(a, x)$ is incomplete gamma function by $\Gamma(a, x) = \int_x^\infty t^{a-1} e^{-t} dt$.

2.2 Cooperative Spectrum Sensing

CR networks may happen shadowing effort and signal attenuation. To solve this issue, multiple CR users perform local spectrum sensing together. The way is called cooperative spectrum sensing [4]. As is shown in fig. 1, reports I_i from different CR users is combined at the fusion center to decide whether the primary user is present in the sensing channel. A global binary decision B is made by the fusion center. The procedure is as follows :

- Step 1 : Every CR user i performs local spectrum sensing, then makes a binary decision $I_i \in \{0,1\}$.
- Step 2 : All CR users report I_i to the fusion center.
- Step 3 : The fusion center combines these reports to make a global binary decision $B \in \{0,1\}$ that indicates whether the primary user is present in the sensing channel.

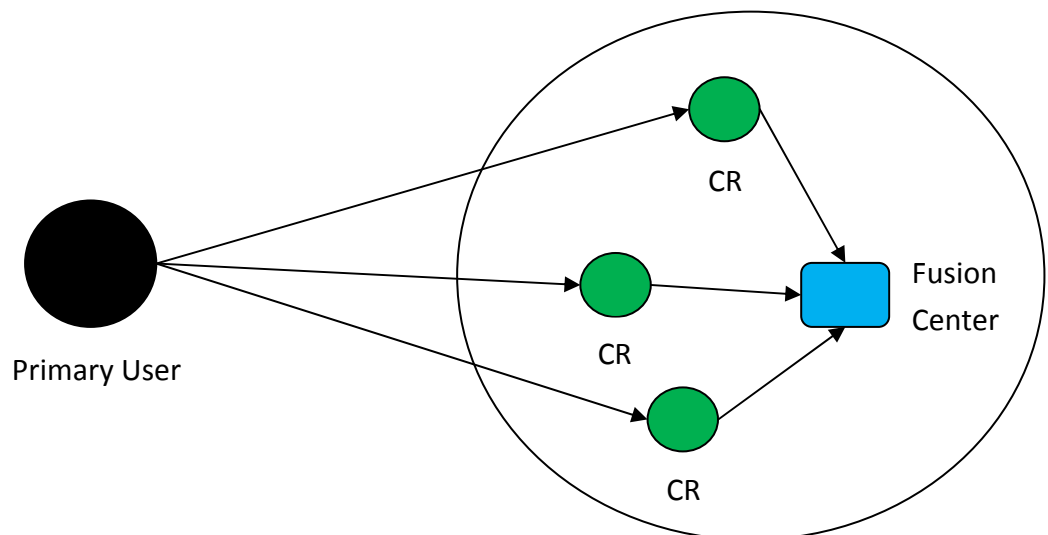


Fig. 1. System model of cooperative spectrum sensing in a cognitive network.

2.3 Existing Data Fusion Techniques

As the above mentioned, CR user i performs local spectrum sensing and reports a local decision I_i to the fusion center. The fusion center makes a global decision B based on the fusion rule. Most general fusion rule is k -out-of- n rule :

$$\begin{cases} \sum_{i=1}^n I_i \geq k, B=1 \\ \text{Otherwise, } B=0 \end{cases} \quad (5)$$

OR rule and AND rule are special cases of $k=1$ and $k=n$, respectively. From (5), we know that every CR user owns equal weight for k -out-of- n rule. A final global decision is based on how many CR users report that the primary user is present in the sensing channel. For k -out-of- n rule, if more than or equal k CR users report that the primary user is present in the sensing channel, a global decision B is 1. The paper [4] discusses how to select an optimal k value to minimize total error probability ($Q_f + Q_m$). Usually, if the probability of false alarm P_f and the probability of miss detection P_m for CR users are the same order, an optimal k value is $\left\lfloor \frac{n}{2} \right\rfloor + 1$ that is Majority rule. When $P_f \ll P_m$, the threshold λ of a CR user should be very large, it implies that k value approaches 1, thus OR rule is optimal; otherwise, when $P_m \ll P_f$, the threshold λ of a CR user should be very small, it implies that k value approaches n , thus AND rule is optimal. They can be verified by fig. 2.

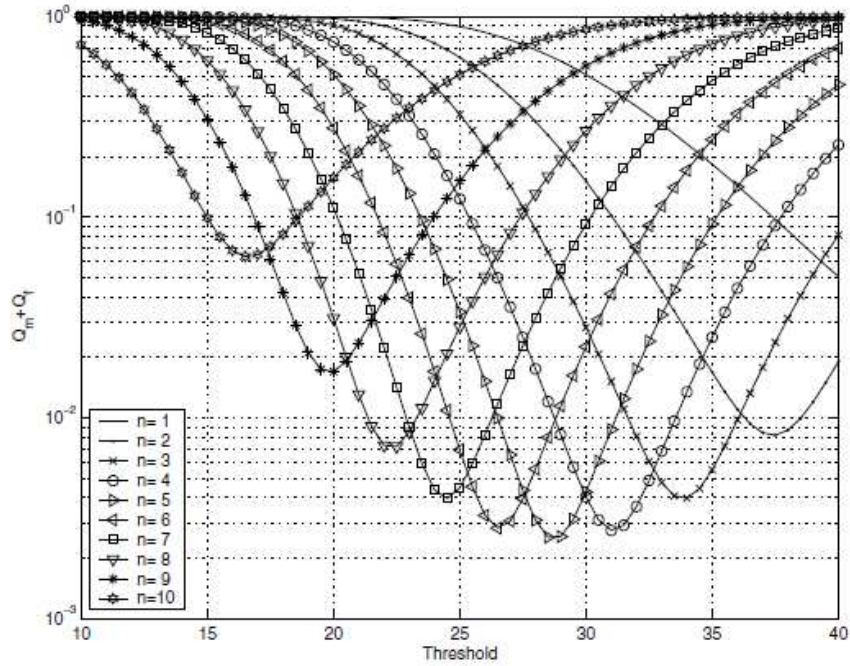
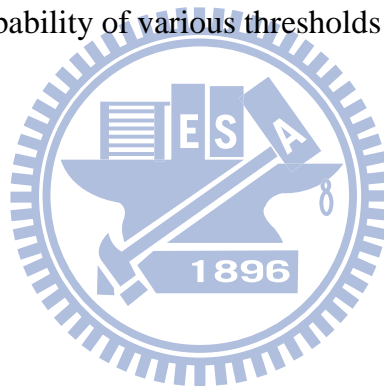


Fig. 2. Error probability of various thresholds for k -out-of- n rule [4]



2.4 Throughput

The framework of 802.22 is shown in fig. 3, the length of a frame is T . The beginning part of a frame is the sensing time τ , then the sensing result decides that a CR user keeps silent or processes data transmitting during the following $T - \tau$. As the sensing time is shorter, the transmitting time is longer. However, the sensing time is too small to decrease the probability of miss detection and the probability of false alarm. The paper [6] discusses how to set the sensing time τ that makes a CR network have an optimal throughput when the probability of detection Q_d is more than the lowest bound of the probability of detection $\overline{Q_d}$.

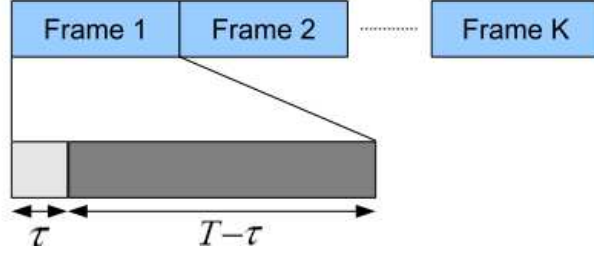


Fig. 3. The framework of 802.22 [6]

Next, we want to calculate the throughput R of a CR user during a frame time. If the primary user is absent in the sensing channel and a CR user does not happen the condition of false alarm, the throughput is R_0 , by contrast, if the primary user is present in the sensing channel and a CR user does not detect the primary user, the throughput is R_1 . We can formulate an optimal throughput :

$$\begin{aligned}
 & \max_{\tau} R(\tau) = R_0(\tau) + R_1(\tau) \\
 & \text{subject to} \\
 & Q_d(\tau) \geq \overline{Q_d}
 \end{aligned} \tag{6}$$

where

$$\begin{aligned}
 R_0(\tau) &= r_0 P(H_0)(1 - Q_f(\tau)) \\
 R_1(\tau) &= r_1 P(H_1)(1 - Q_d(\tau))
 \end{aligned} \tag{7}$$

r_0 , r_1 of the above formulation are the throughputs when the primary user is absent and the primary user is present in the sensing channel respectively. Moreover, $P(H_0)$, $P(H_1)$ are the probabilities when the primary user is absent and the primary user is present in the sensing channel respectively, and $\overline{Q_d}$ is the lowest bound of the probability of detection. Because $r_1 \ll r_0$ and Q_m is limited under 0.1 according to 802.22 standard, we can neglect $R_1(\tau)$ in $R(\tau)$. Simple the problem formulation of an optimal throughput :

$$\begin{aligned}
& \max_{\tau} R_0(\tau) \\
& \text{subject to} \\
& Q_d(\tau) \geq \overline{Q_d}
\end{aligned} \tag{8}$$

The paper [6] proves that the throughput of a CR network can arrive optimization under an ideal sensing time. This result is as the following fig. 4 :

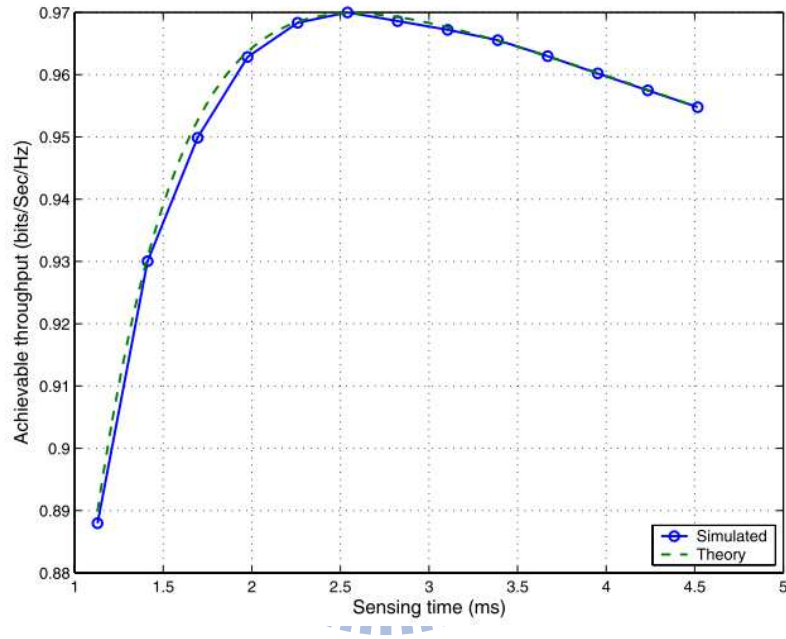


Fig. 4. The relation of the throughput and the sensing time. [6]

From equation (7), we modify equation (8) as follows :

$$\begin{aligned}
& \min_{\tau} Q_f(\tau) \\
& \text{subject to} \\
& Q_d(\tau) \geq \overline{Q_d}
\end{aligned} \tag{9}$$

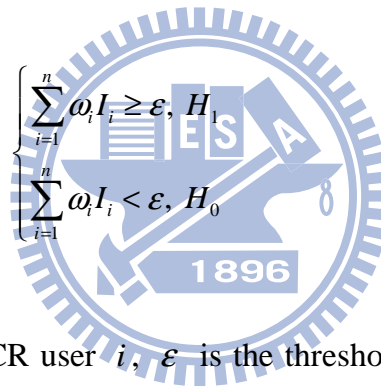
Therefore, equation (9) is the problem formulation of an optimal throughput in a CR network.

Chapter 3

Related Work

3.1 Weighted Fusion Rule

However, because the distance and channel SNR of every CR user and the primary user are different, the sensing ability of every CR user is also different. Therefore, weighted fusion rules emerge to decrease the probability of false alarm under avoiding interference to the primary user. In this paper [7], a weighted fusion rule is defined :

$$\begin{cases} \sum_{i=1}^n \omega_i I_i \geq \varepsilon, H_1 \\ \sum_{i=1}^n \omega_i I_i < \varepsilon, H_0 \end{cases} \quad (10)$$


where ω_i is a weight of CR user i , ε is the threshold of the fusion center. The paper [12] represents that ω_i is the function of distance ℓ_i and SNR γ_i , as follows :

$$\begin{aligned} \omega_i &= af(\ell_i) + b \\ \omega_i &= a\gamma_i + b \end{aligned} \quad (11)$$

where a 、 b are constant. $f(\ell_i)$ is a non-increasing function. Usually, closer to the primary user and higher channel SNR γ_i of CR user i result that the sensing accuracy is also higher. When the accuracy of a CR user is high, we give it a high weight.

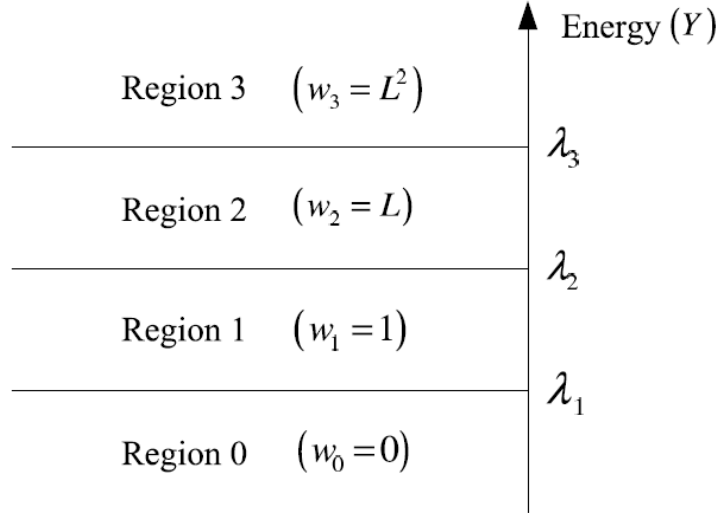


Fig. 5. Four weights are generated due to three thresholds [8]

Furthermore, the paper [8] also proposed a weighted fusion rule that differs from the above mentioned. In this paper [8], a CR user using 2 bits has four kinds of weights. As is shown in fig. 5, we can separate four regions due to three thresholds based on the value of received energy. Every region has its corresponding weight. Moreover, received energy of a CR user locates in a higher region so that the CR user owns a higher weight. The summation of product of a weight and the number of CR users locate in Region i is represented to N_c :

$$N_c = \sum_{i=0}^3 \omega_i N_i \quad (12)$$

where N_i is the number of CR users locate in Region i . This paper set the threshold of a global decision L^2 . When $N_c \geq L^2$, we decide that the primary user is present in the sensing channel; otherwise, when $N_c < L^2$, we decide that the primary is absent in the sensing channel. For example, we assume that there are j CR users in Region 2, $i - j$ CR users in Region 1, and received energies of the rest $N - i$ CR users locate in Region

0, it means $N_3 = 0$, $N_2 = j$, $N_1 = i - j$, $N_0 = N - i$. If $N_c = (i - j)\omega_1 + j\omega_2 < L^2$, we can decide that the primary user is absent in the sensing channel.

3.2 SPRT and WSPRT

Although the above mentioned weighted fusion rules help CR networks promote the throughput, they are still worth improving in many aspects. For example, there may be hackers in CR networks. In the paper [9], it proposed Weighted Sequential Probability Ratio Test (WSPRT) algorithm to improve this problem. WSPRT is derived from Sequential Probability Ratio Test (SPRT).

SPRT collects more local spectrum sensing reports even if CR users have low spectrum sensing accuracy. We define the following likelihood ratio as the decision variable :

$$S_n = \prod_{i=0}^n \frac{P[I_i | H_1]}{P[I_i | H_0]} \quad (13)$$

where the number of collecting samples n is a variable. The fusion rule is based on the following criterion :

$$\begin{cases} S_n \leq \eta_0 \Rightarrow H_0 \\ S_n \geq \eta_1 \Rightarrow H_1 \\ \eta_0 < S_n < \eta_1 \Rightarrow \text{take another observation} \end{cases} \quad (14)$$

η_1 and η_0 are upper threshold and lower threshold, respectively. The proposed new decision variable in WSPRT is :

$$W_n = \prod_{i=0}^n \left(\frac{P[I_i | H_1]}{P[I_i | H_0]} \right)^{\omega_i} \quad (15)$$

where ω_i is defined as a weight of CR user i that is the function of reputation value κ_i :

$$\omega_i = f(\kappa_i) = \begin{cases} 0 & \kappa_i \leq -g \\ \frac{\kappa_i + g}{\max(\kappa_i) + g} & \kappa_i > -g \end{cases} \quad (16)$$

$\omega_i \in [0,1]$

where $f(\cdot)$ is a non-decreasing function, $g(>0)$ is a variable that let ω_i be not zero for the first $(g-1)$ reputation.

This paper [9] describes WSPRT fusion rule using the following algorithm :

- 1: $\forall i, \kappa_i = 0.$
- 2: For each spectrum sensing attempt made by fusion center{
- 3: $i = 0, W_n = 1.$
- 4: Get a spectrum sensing report I_i from CR user i
- 5: $W_n \leftarrow W_n \left(\frac{P[I_i | H_1]}{P[I_i | H_0]} \right)^{f(\kappa_i)}$
- 6: If $\eta_0 < W_n < \eta_1, i \leftarrow (i+1) \bmod N.$ Go to step4.
- 7: If $W_n \geq \eta_1,$ accept $H_1,$ i.e., output $B = 1.$ Go to step9.
- 8: If $W_n < \eta_0,$ accept $H_0,$ i.e., output $B = 0.$
- 9: For each sampled $I_i,$ set $\kappa_i \leftarrow \kappa_i + (-1)^{I_i+1}$
- 10: }

Chapter 4

Proposed Weighted Fusion Rule

However, the above weighted fusion rules only consider a little real circumstances of CR networks. For example, both power attenuation and mal-function of CR users, and notorious hackers in CR networks result in decay of the sensing ability. Consequently, assignment of a dynamic weight is suitable for reality. In order to arrive assignment of a dynamic weight, the fusion center needs to refer historical records of CR users to make up current weight. Moreover, CR users with higher reliability are given a higher weight; otherwise, poor CR users are given a lower weight. We proposed an improved weighted fusion rule, it gives various weights based on conditions of CR users. As a result, using our proposed weighted fusion rule can promote the sensing ability and the throughput of CR networks. On the basis of the above discussion, we can formulate the design of a weighted fusion rule as the following optimal problem :

$$\begin{aligned} & \max \{R_0(x)\} \Rightarrow \min\{Q_f(x)\} \\ & \text{subject to} \\ & Q_d(x) \geq \overline{Q_d} \end{aligned} \quad (17)$$

where

$$Q_f(x) = P\left(\sum_{i=1}^N \omega_i(x-1)I_i(x) \geq \varepsilon \mid H_0\right) \quad (18)$$

Based on the above mentioned concept, we propose an algorithm that designs a dynamic weight to promote the throughput of the whole CR network. The system model is shown in fig. 6.

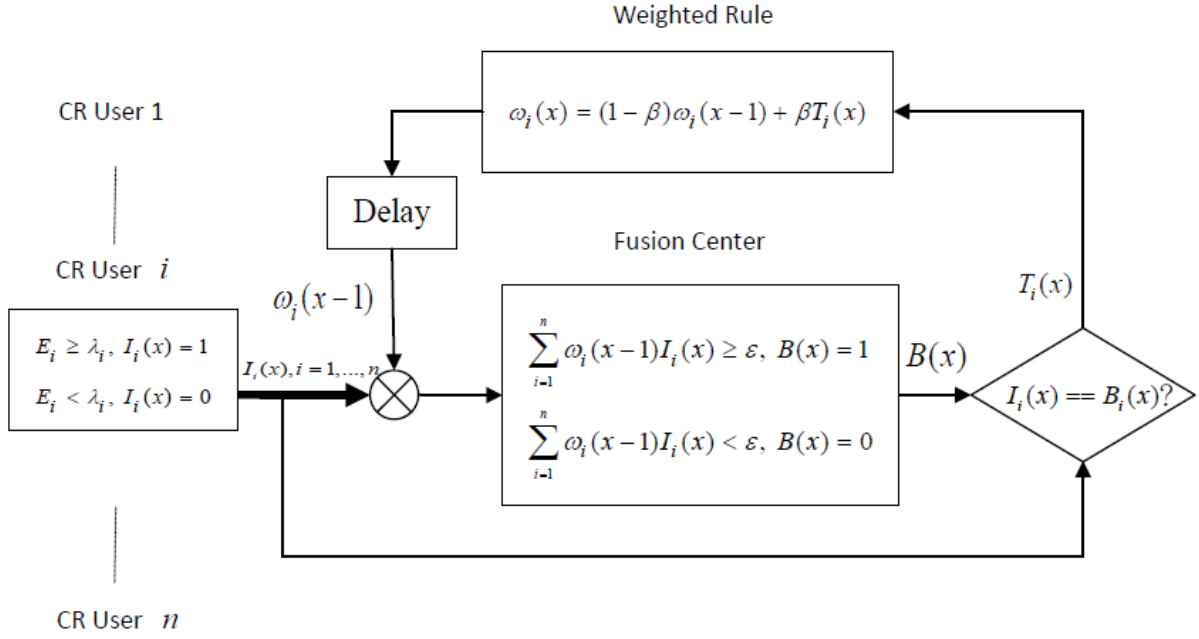


Fig. 6. The system model of the proposed weighted fusion rule.

Using components discussed above, we describe our proposed weighted fusion rule using the following algorithm :

- 1: $\forall N, x = 1, \omega_i(0) = 1.$
- 2: For each spectrum sensing round x attempt made by fusion center{
- 3: $i = 1.$
- 4: Get a spectrum sensing report $I_i(x)$ from CR user i
- 5: decision variable $W_n = \sum_{i=1}^N \omega_i(x-1) I_i(x)$
- 6: If $W_n \geq \varepsilon$, accept H_1 , i.e., output $B = 1$. Go to step7
- 7: If $W_n < \varepsilon$, accept H_0 , i.e., output $B = 0$.
- 8: Compare $I_i(x)$ with B , get $T_i(x) = \begin{cases} 0, & \text{if } I_i(x) \neq B(x) \\ 1, & \text{if } I_i(x) = B(x) \end{cases}$
- 9: $\omega_i(x) \leftarrow (1 - \beta)\omega_i(x-1) + \beta T_i(x)$
- 10: }

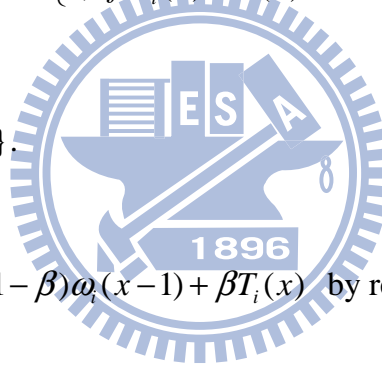
The update weight is

$$\omega_i(x) = (1 - \beta)\omega_i(x-1) + \beta T_i(x) \quad (19)$$

in the above formulation, x is the sensing round, the initial $\omega_i(0)=1$, moreover, a weight of x -th round is composed of a weight of $(x-1)$ -th round and $T_i(x)$ based on proportion β , $0 \leq \beta \leq 1$, an optimal β is obtained by simulation. $T_i(x)$ is an indicator that shows if a local spectrum sensing report of CR user i is equal to a global decision of the fusion center.

$$T_i(x) = \begin{cases} 0, & \text{if } I_i(x) \neq B(x) \\ 1, & \text{if } I_i(x) = B(x) \end{cases} \quad (20)$$

where $I_i(x) \cdot B(x) \in \{0,1\}$.



We derive $\omega_i(x) = (1 - \beta)\omega_i(x-1) + \beta T_i(x)$ by recursive :

$$\begin{aligned} \omega(x) &= (1 - \beta)\omega(x-1) + \beta T_i(x) \\ &= (1 - \beta)^2 \omega(x-2) + \beta(1 - \beta)T_i(x-1) + \beta T_i(x) \\ &= (1 - \beta)^3 \omega(x-3) + \beta(1 - \beta)^2 T_i(x-2) + \beta(1 - \beta)T_i(x-1) + \beta T_i(x) \\ &= \dots \\ &= (1 - \beta)^x \omega(0) + \beta \sum_{k=1}^{x-1} [(1 - \beta)^{x-k} T_i(k)] + \beta T_i(x) \\ &= (1 - \beta)^x \omega(0) + \beta \sum_{k=1}^{x-1} [(1 - \beta)^{x-k} T_i(k)] + \beta T_i(x) \\ &= (1 - \beta)^x + \beta \sum_{k=1}^{x-1} [(1 - \beta)^{x-k} T_i(k)] + \beta T_i(x) \end{aligned} \quad (21)$$

The above formulation is generated by recursive procedure of a weight shown in fig. 7.

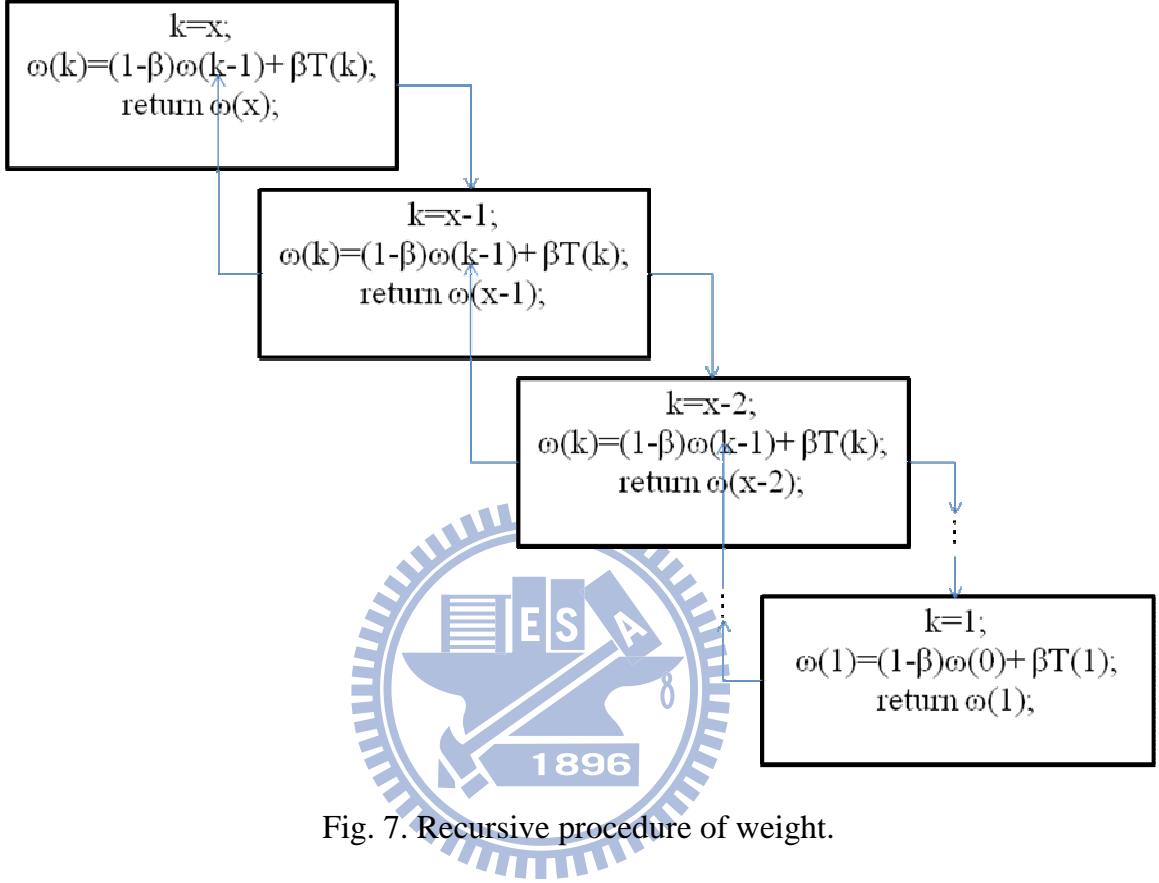


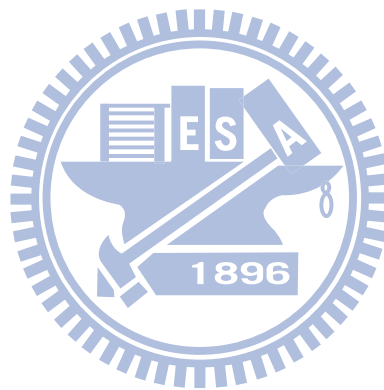
Fig. 7. Recursive procedure of weight.

Therefore, we substitute equation (21) to equation (18) :

$$\begin{aligned}
 Q_f(x) &= P\left(\sum_{i=1}^N \omega_i(x-1)I_i(x) \geq \varepsilon \mid H_0\right) \\
 &= P\left(\sum_{i=1}^N ((1-\beta)^{x-1} + \beta \sum_{k=1}^{x-2} [(1-\beta)^{x-1-k} T_i(k)] + \beta T_i(x-1))I_i(x) \geq \varepsilon \mid H_0\right)
 \end{aligned} \tag{22}$$

The threshold ε of the fusion center depends on average weight $\sum_{i=1}^N \frac{\omega_i(x)}{N}$ of CR users due to the decision variable $W_n = \sum_{i=1}^N \omega_i(x-1)I_i(x)$. Therefore, we suppose that the

threshold ε of the fusion center is about $\frac{N}{2} \sum_{i=1}^N \frac{\omega_i(x)}{N}$. The factor $\frac{N}{2}$ is the threshold of Majority rule. However, real threshold ε of the fusion center remains to be simulated in next chapter.



Chapter 5

Simulation Results

In our proposed algorithm, we must find an optimal β to decrease Q_f by simulation. The circumstance of the CR network is the number of CR users $N=500$, the sensing rounds $x=1000$, and CR users are separated into two groups, one group is CR users with 90% sensing accuracy, another group is CR users with 40% sensing accuracy. Here, both CR users with good sensing accuracy and CR users with bad sensing accuracy account for half of CR users in the CR network. In the simulation shown in fig. 8, we get an optimal $\beta = 0.4$ so that the CR network has maximal throughput. .

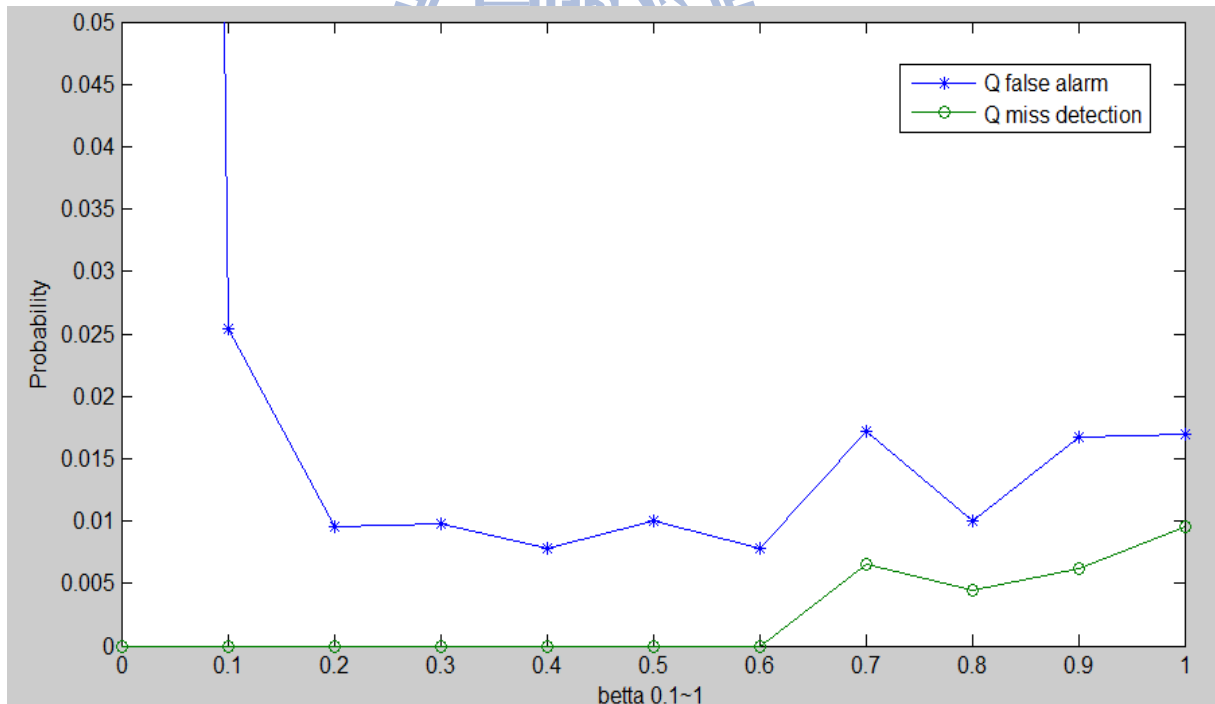


Fig. 8. Error probability under different proportion β .

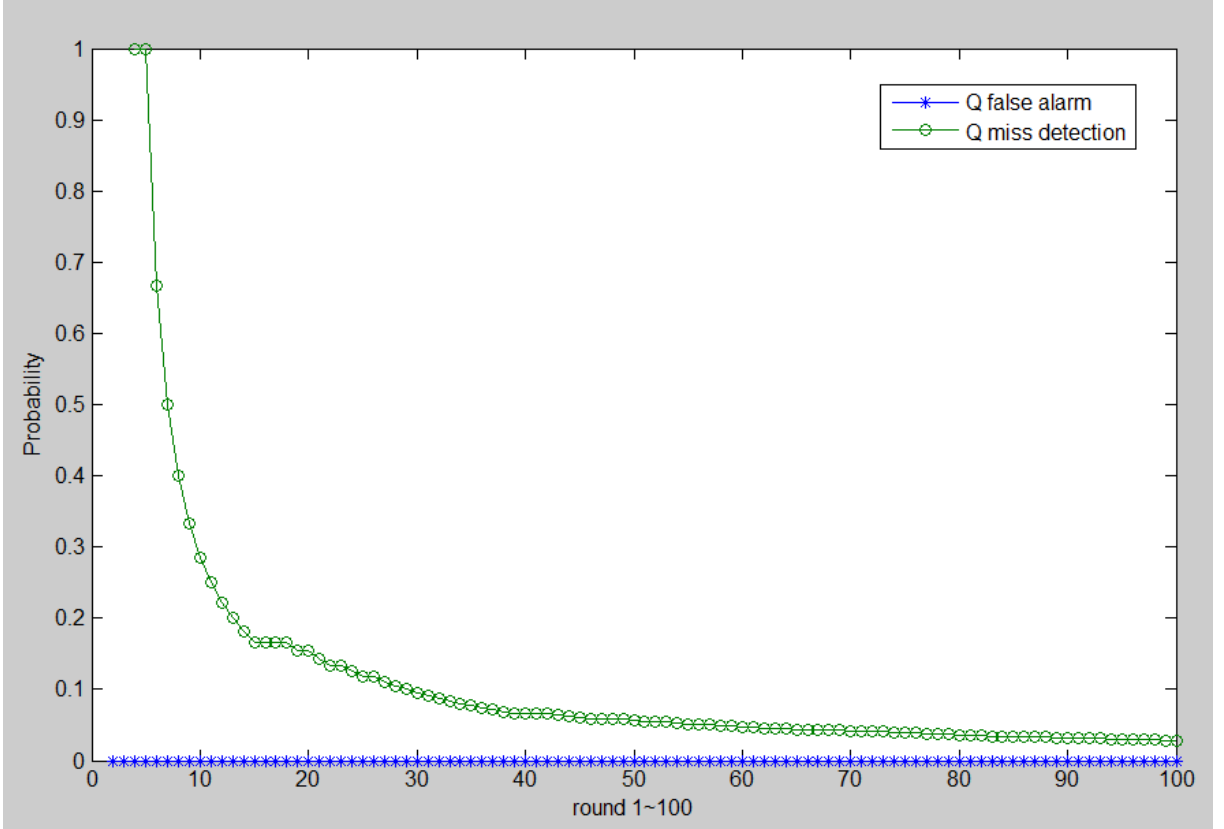


Fig. 9. Error probability when the threshold $\varepsilon = \frac{N}{2} \sum_{i=1}^N \frac{\omega_i(x)}{N}$ of the fusion rule.

The threshold ε of the fusion center can be decided as $\frac{N}{2} \sum_{i=1}^N \frac{\omega_i(x)}{N}$ and $\frac{N}{3} \sum_{i=1}^N \frac{\omega_i(x)}{N}$ by simulation shown fig. 9. and fig. 10, respectively. After 28 rounds in fig. 9, we discover that the probability of miss detection just decreases to an acceptable value. Otherwise, fig. 10 shows that the probability of miss detection is almost 0 and the probability of false alarm also has remarkable decrease. In order to guarantee that CR users do not affect the primary user, we select $\frac{N}{3} \sum_{i=1}^N \frac{\omega_i(x)}{N}$ as the threshold ε of the fusion center.

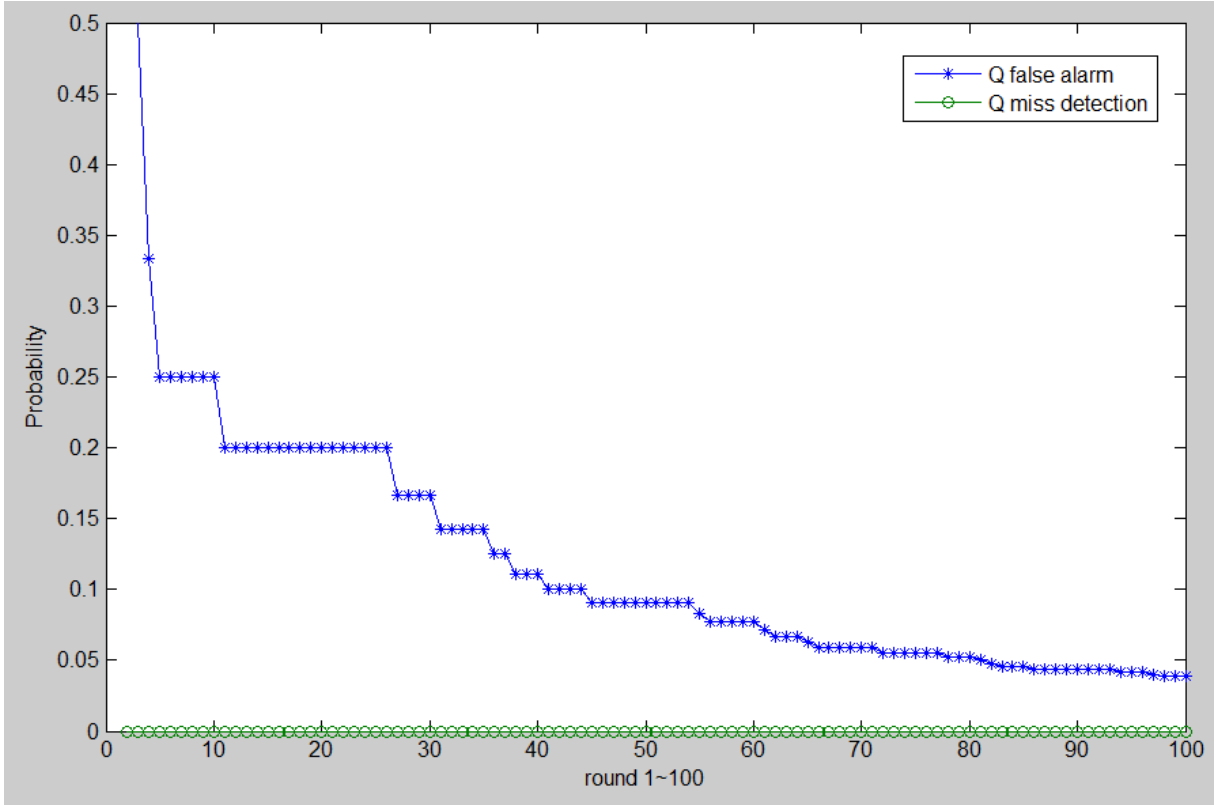


Fig. 10. Error probability when the threshold $\varepsilon = \frac{N}{3} \sum_{i=1}^N \frac{\omega_i(x)}{N}$ of the fusion rule.

We assume several conditions that simulate various circumstances of a CR network. In a CR network, we set that one group has good sensing accuracy and another group has bad sensing accuracy. Here, CR users with good sensing accuracy account for 0~100% of CR users in a CR network, and CR users with bad sensing accuracy account for the rest of CR users in a CR network. Parameters are $\beta = 0.4$, $N = 500$, $x = 100$. First, CR users are separated into group 1 with 90% sensing accuracy and group 2 with 40% sensing accuracy. Second, CR users are separated into group 1 with 90% sensing accuracy and group 2 with 10% sensing accuracy. Third, CR users are separated into group 1 with 80% sensing accuracy and group 2 with 10% sensing accuracy. We display the above mentioned three cases of network circumstances in fig. 11, fig. 12, and fig. 13, respectively.

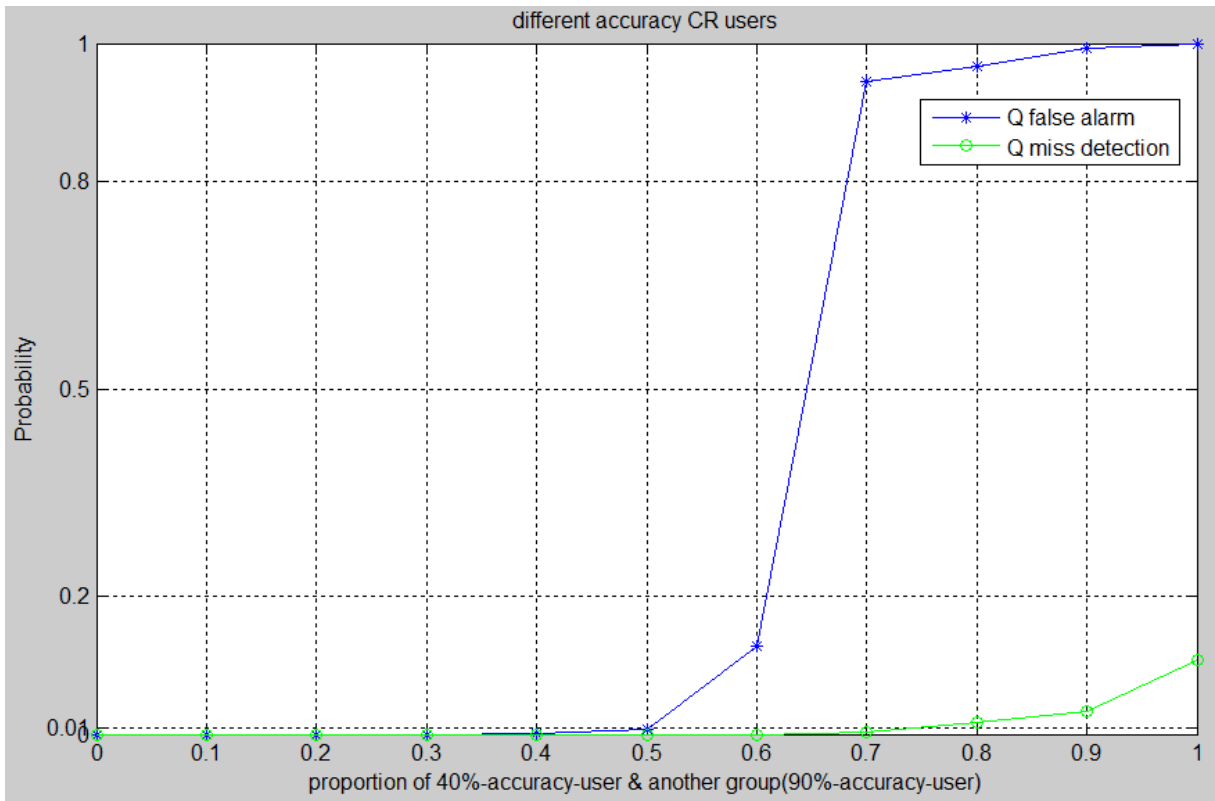


Fig. 11. Error probability of CR users with 90% and 40% sensing accuracy.

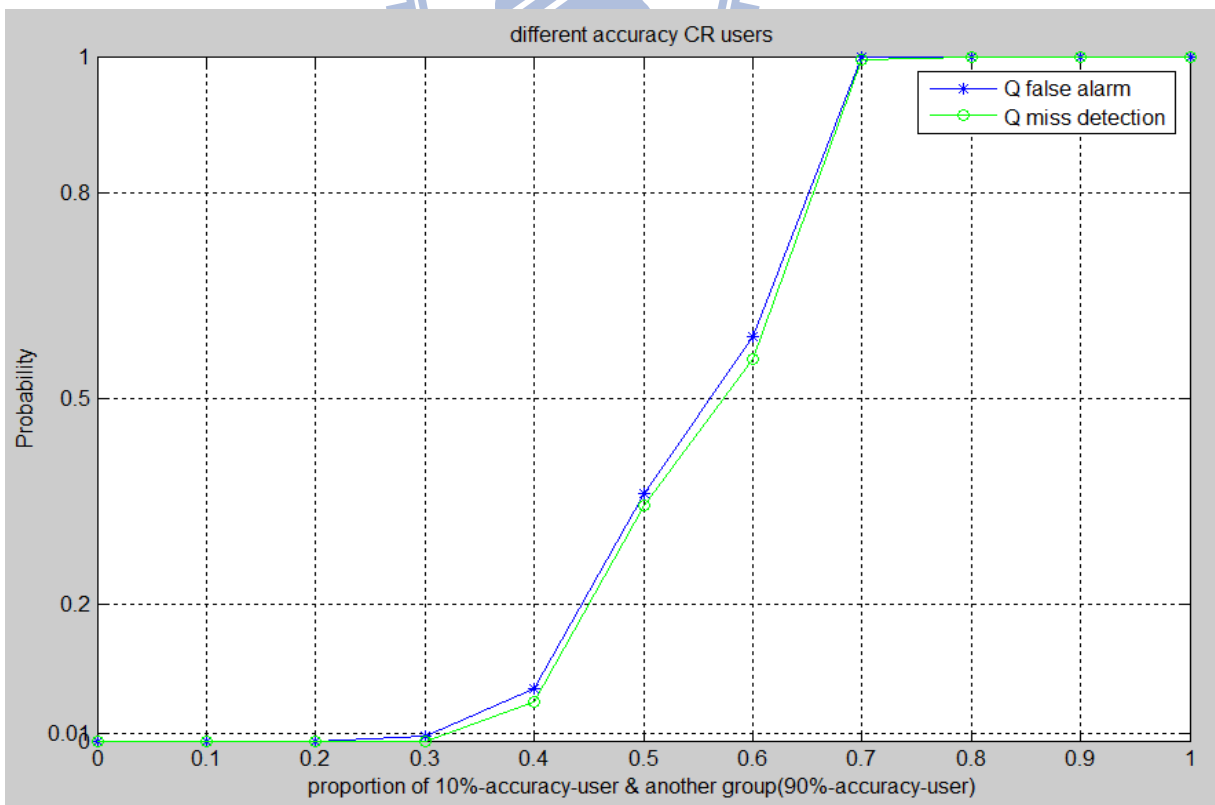


Fig. 12. Error probability of CR users with 90% and 10% sensing accuracy.

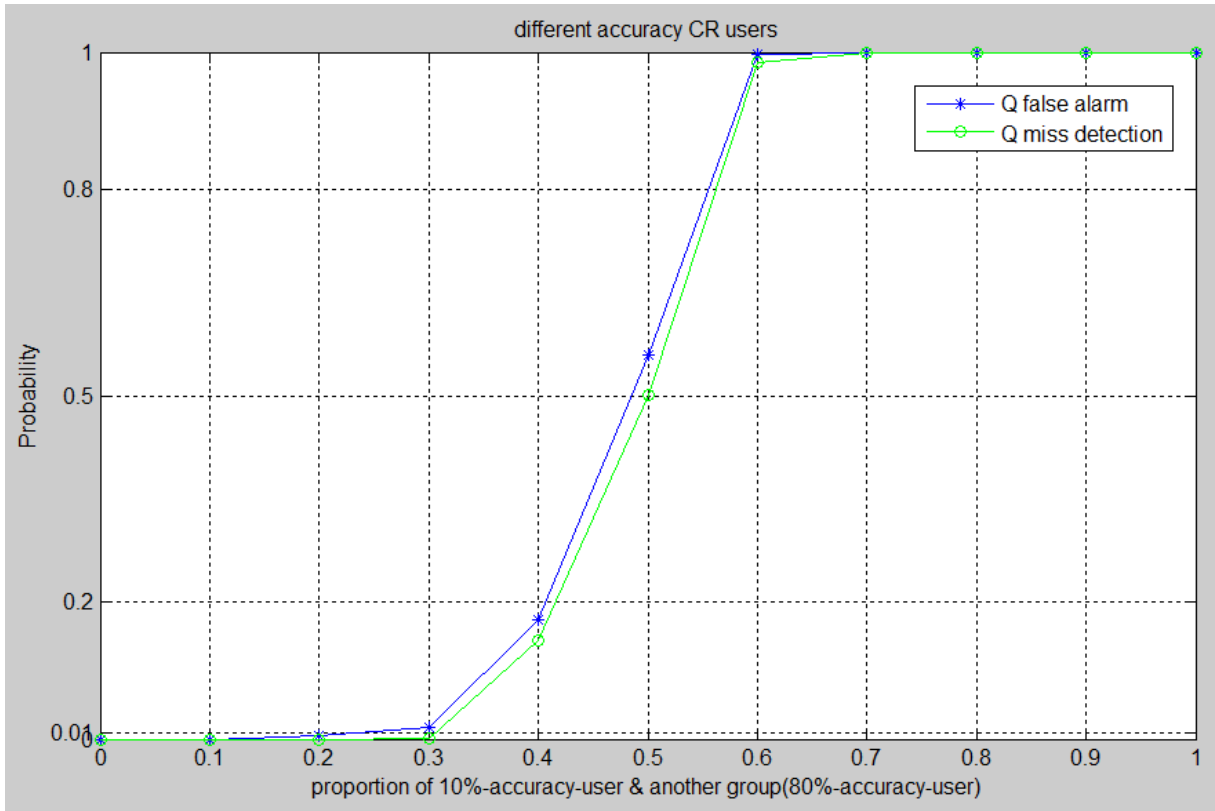


Fig 13. Error probability of CR users with 80% and 10% sensing accuracy.

When both CR users with good sensing accuracy and CR users with bad sensing accuracy are higher such as fig. 11(90% and 40%), error probability is lower. It means that the CR network has higher throughput. In addition, CR users with bad sensing accuracy also help CR users with good sensing accuracy promote the whole throughput of a CR network together. It can be observed from fig. 11 ~ fig. 13.

On the basis of the above discussion, we list three tables for different proportions of CR users with good sensing accuracy and CR users with bad sensing accuracy. First in table 1, CR users with good sensing accuracy account for 50% of CR users in a CR network, and CR users with bad sensing accuracy account for 50% of CR users in a CR network. Second in table 2, CR users with good sensing accuracy account for 60% of CR users in a CR network, and CR users with bad sensing accuracy account for 40% of CR

users in a CR network. Third in table 3, CR users with good sensing accuracy account for 70% of CR users in a CR network, and CR users with bad sensing accuracy account for 30% of CR users in a CR network. From three tables, when CR users with good sensing accuracy account for higher proportion of CR users in a CR network, the throughput of a CR network is higher. It can be observed that error probability of table 3 is lowest between table 1~table 3.

Table 1. Error probability of different group accuracies under good-sensing-accuracy CR users accounting for 50% of CR users and bad-sensing-accuracy CR users accounting for 50% of CR users.

Group Accuracy	0%	10%	40%
100%	$Q_f = 0.3470$ $Q_m = 0.3574$	$Q_f = 0.1040$ $Q_m = 0.0869$	$Q_f = 0.0003$ $Q_m = 0$
90%	$Q_f = 0.5365$ $Q_m = 0.5240$	$Q_f = 0.3622$ $Q_m = 0.3454$	$Q_f = 0.0073$ $Q_m = 0$
80%	$Q_f = 0.6995$ $Q_m = 0.6754$	$Q_f = 0.5595$ $Q_m = 0.5009$	$Q_f = 0.7269$ $Q_m = 0$

Generally, if the proportion of CR users with bad sensing accuracy is less than 40% (table 2) in a CR network and accuracies of two groups are only not terrible, our proposed weighted fusion rule will have an excellent performance about the probability of miss detection and the probability of false alarm.

Table 2. Error probability of different group accuracies under good-sensing-accuracy CR users accounting for 60% of CR users and bad-sensing-accuracy CR users accounting for 40% of CR users.

Group Accuracy	0%	10%	40%
100%	$Q_f = 0.1094$ $Q_m = 0.1186$	$Q_f = 0.0683$ $Q_m = 0.0527$	$Q_f = 0$ $Q_m = 0$
90%	$Q_f = 0.1402$ $Q_m = 0.1285$	$Q_f = 0.0756$ $Q_m = 0.0562$	$Q_f = 0.0007$ $Q_m = 0$
80%	$Q_f = 0.4326$ $Q_m = 0.4282$	$Q_f = 0.1732$ $Q_m = 0.1434$	$Q_f = 0.0992$ $Q_m = 0$

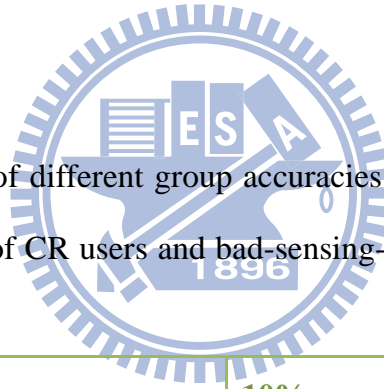


Table 3. Error probability of different group accuracies under good-sensing-accuracy CR users accounting for 70% of CR users and bad-sensing-accuracy CR users accounting for 30% of CR users.

Group Accuracy	0%	10%	40%
100%	$Q_f = 0$ $Q_m = 0$	$Q_f = 0$ $Q_m = 0$	$Q_f = 0$ $Q_m = 0$
90%	$Q_f = 0.0492$ $Q_m = 0.0406$	$Q_f = 0.0060$ $Q_m = 0$	$Q_f = 0$ $Q_m = 0$
80%	$Q_f = 0.0829$ $Q_m = 0.0686$	$Q_f = 0.0163$ $Q_m = 0.0012$	$Q_f = 0.0043$ $Q_m = 0$

Next, we compare our weighted fusion rule with WSPRT. The circumstance of the simulation exists 0~100% of hackers in a CR network. Parameters are $\beta = 0.4$, $N = 500$,

$x=100$. We assume that hackers have 0% sensing accuracy and the rest CR users have 100% sensing accuracy. In fig. 14, when the proportion of hackers is less than 40%, the performance of our proposed weighted fusion rule is superior to WSPRT. Otherwise, when the proportion of hackers is more than 50%, the performance of our proposed weighted fusion rule is inferior to WSPRT. However, regardless of any great fusion rules, data are not worthy to be referred under more than 50% CR users with bad sensing accuracy because both Q_f and Q_m must be too high to be acceptable.

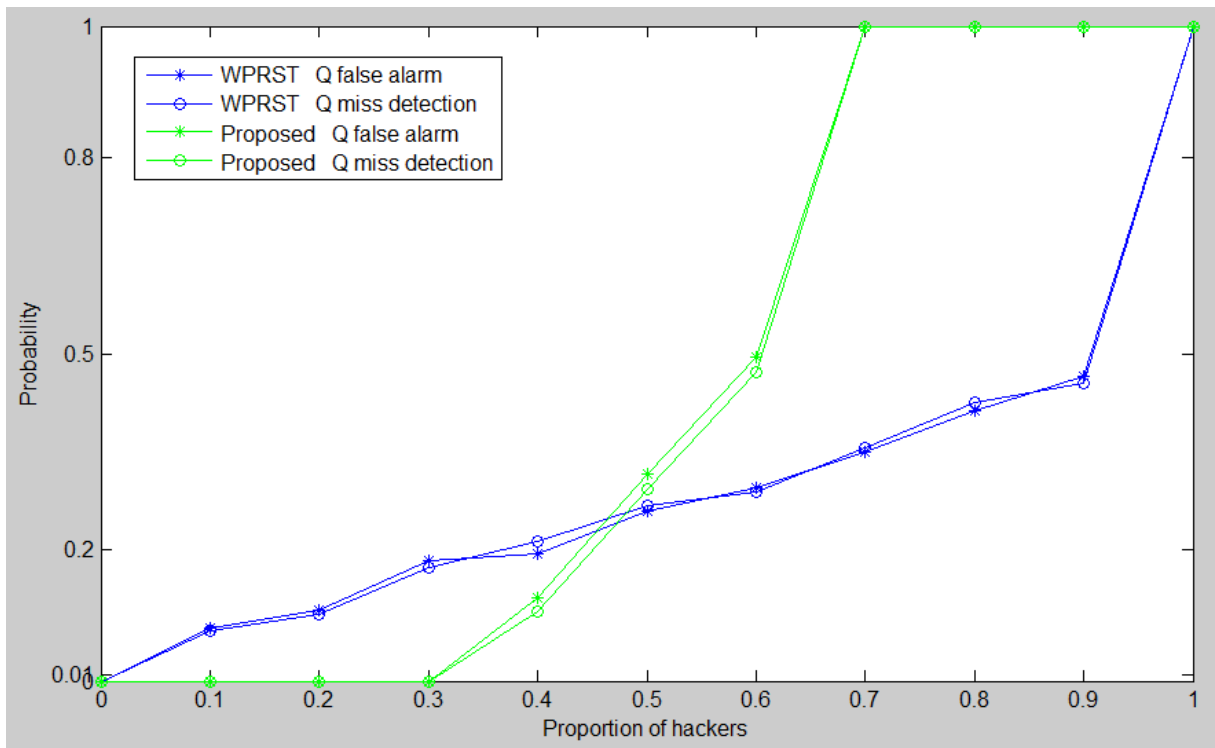


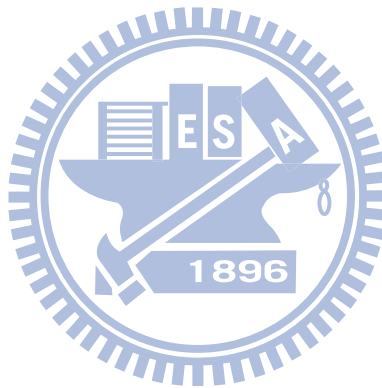
Fig. 14. The performance of WSPRT and our proposed weighted fusion rule under different proportion of hackers.

Chapter 6

Conclusion

In this thesis, we propose a simple model and an algorithm for spectrum sensing in CR networks. Our main concern here is to design an algorithm for weights of CR users based on historical records. We have shown that not only miss detection is in our control, but also false alarm has a significant improvement. Specifically, our proposed model still keep robust for CR networks with hackers.

However, our proposed model only takes the fusion center terminal into consider. How to combine cluster skills of CR users to promote more throughput remains to be further studied.



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