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PWAM: PENALTY-BASED WEIGHT ADJUSTMENT MECHANISM FOR COOPERATIVE SPECTRUM SENSING IN CENTRALIZED COGNITIVE RADIO NETWORKS

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Abstract. *Current static spectrum assignment policy leads to the shortage of the spectrum for launching newer telecom cooperation or enhancing the existing ones. To address this issue of inefficient spectrum utilization, a new term Dynamic Spectrum Access has emerged. Cognitive Radio is the most decisive technology for the successful deployment of Dynamic Spectrum Access. Spectrum sensing plays a vital role for cognitive radio to avoid interference with primary users by identifying unused portion of the spectrum. In practice, sensing is severely degraded by multipath fading and shadowing effects. To mitigate these impacts cooperative spectrum sensing is the most familiar technique. Cooperative spectrum sensing exploits spatial diversity by sharing sensing information among cognitive radios at the cost of additional bandwidth consumption and reporting time. This paper presents a fast convergent and adaptively adjusted weighted cooperative spectrum sensing scheme for centralized cooperative spectrum sensing scheme. In our method, the weight factor values are updated according to the cognitive users' performance history. Then, the weight factor is adjusted using a penalty mechanism based on current local decision made by secondary user. The final result is then computed by fusion of weighted soft decisions made by each cooperating secondary user. Simulation results show significant decrease in probability of error.*
Keywords: Cognitive radio networks, Primary user, Secondary user, Local decision, Global decision, Fusion center

1. **Introduction.** The spectrum regulatory authorities allocate the portion of spectrum exclusively to license holders for a large geographical region on a long term basis. As a result of the current spectrum assignment policy and drastic increase in wireless technologies, the world is facing severe spectrum deficiency problems. However, recent studies highlight that most of the spectrum is used intermittently in both the temporal and spatial domain substantiated by Federal Communication Commission [1]. Cognitive radio (CR) is the most promising solution to this spectrum scarcity by exploiting vacant spaces in an opportunistic manner without interfering with primary users (PUs). The distinctive ability of CR or secondary user (SU) is to autonomously interact with the radio environment and adapt its operational parameters such as frequency and power, according to the sensed information [2]. The SU system has to peacefully coexist in parallel with the PU System. However, PU has a sole privilege to access the spectrum, while the SU can access the white spaces opportunistically. These white spaces refer to the vacant spaces that may be in temporal, spatial or angle (in multiple input multiple output system) domain [3].

Spectrum sensing is an integral module in CR networks to discover white spaces. The two foremost concerns of spectrum sensing are: (1) SU's communication does not disturb PU's transmission and (2) Efficient identification of white spaces for required throughput and quality of service [8]. The performance of spectrum sensing is primarily measured in terms of the probability of detection and the probability of false alarm. The probability of detection is the probability that a channel is announced as occupied when it is actually occupied, whereas the probability of false alarm is the probability that a channel is announced as occupied when it is actually empty. Robust spectrum sensing scheme seeks to attain a high probability of detection and low probability of false alarm, because a faulty detection caused by false alarm will lead to the reduction in spectral utilization, and a misdetection will cause interference with PU [4].

Conventional spectrum sensing techniques impose highly stringent constraints on the SU. SU must be versatile, support multiple radio bands, identify diversified wireless access technologies and have soaring detection sensitivity. Here, detection sensitivity means the minimum SNR at which PU may still be accurately detected by the SU. These demands add on to the complexity and cost of the SU. Additionally, over a huge stretched spectrum, sensing consumes more time, which pushes towards the high service latency and leads to throughput reduction as well as more power consumption at the SU [5].

Besides the above-mentioned issues, under fading or shadowing, SU requires higher detection sensitivity in order to prevail over the uncertainty induced by channel arbitrariness. The resultant detection sensitivity may be too complicated for an individual SU to maintain. Multipath and shadowing are highly dependent on the SU's location, and these effects can be mitigated by allowing different SUs to share their sensing results and cooperatively decide on the licensed spectrum occupancy. The diversity gain achieved through cooperation improves over the probability of detection without imposing higher detection sensitivity requirement on the individual SU [6,8]. According to recent rules documented in [9], Federal Communication Commission (FCC) has acknowledged the relevance of cooperative spectrum sensing for improving the sensing reliability by stating "unlicensed TV band devices communicating in a local area network, either directly with one another or linked through a common base station, share information on channel occupancy determined by sensing".

In this paper, we propose a Penalty-based Weight Adjustment Mechanism (PWAM) for cooperative spectrum sensing (CSS) to enhance the adaptability of SU in time-varying environments. To do this, the proposed algorithm adjusts the weights using current local decision of every cooperating SU rather than just considering its past experience. For instance, if a cooperating SU performed very well in the past but now its performance is suddenly degraded due to shadowing or fading effects, it would be better that its contribution is lesser now in the final decision. The key contribution of our scheme is that it reduces the contribution of such SU swiftly by adjusting its weight via introducing the proposed penalty-based mechanism.

The remaining paper is organized as follows. In Section 2, various weighted cooperative spectrum sensing schemes proposed in the past few years are discussed briefly. Section 3 presents the system model and the network architecture chosen for the simulation. Section 3 also presents the proposed framework. Section 4 presents simulation results and their detailed analysis, and Section 5 concludes this paper.

2. **Related Work.** Two steps for the CSS are local spectrum sensing and aggregation of the local spectrum sensing results. In the local spectrum sensing, each SU scans the spectrum and gathers information from the RF environment. Based on the collected information, each SU employs signal processing techniques to decide the channel availability.

Several signal processing techniques, having their own pros and cons, have been proposed for the local spectrum sensing. They are energy detection, matched filter detection and cyclo-stationary feature detection. The energy detector is most widely used due to its low computational complexity and easy implementation. However, the energy detector cannot differentiate between noise power and signal power [7]. Besides, it is also possible that a single SU decides incorrectly due to some factors such as deep multipath fading and shadowing. CSS has attracted much attention in view of the limitation of the local spectrum sensing. In CSS, local decisions from multiple SUs are combined also known as data aggregation to form a better decision. Several techniques for data aggregation among wireless nodes have been proposed in studies on wireless networks [10-18] including CR networks but CR network still have a room for more sophisticated data aggregation scheme to increase its sensing reliability.

A half voting or majority rule is explored in [11] in which the author proposed that a channel is occupied if N out of K votes are in favor of occupied status, where N is greater than $K/2$. The OR rule and AND rule are special cases of voting rule with $N = 1$ and $N = K$, respectively. As far as this rule is concerned, the author assumed that all SUs participating in the cooperative decision must have the same threshold which is a very hard requirement to meet in reality. The author in [12] introduced a fuzzy based logic CSS in which a phase of training is augmented along with the local spectrum sensing and data fusion phases of CSS. In the training phase, fuzzy logic is applied to have the credibility of each SU. After collecting the result of local sensing from different SUs, the access point (AP) fuses the various results by assigning weights to each SU decision depending on its pre-calculated credibility. This approach outperforms OR and AND rules, but it assumes that credibility of each SU is invariant, which is impractical for a changing RF environment.

A weighted cooperative spectrum sensing scheme, using clustering, is proposed in [13] where CR terminals are first divided into clusters using a distributed clustering algorithm based on the assumption that all SUs within the cluster are very close to each other. After clustering, a SU within each cluster is chosen as the cluster head based on the strongest reporting channel, which is the SU with the highest SNR. In [14], S. Wu et al. studied a SNR-based weighted CSS in cognitive radio networks, in which local decisions from cooperating users are assigned weights based on the SNR with which they receive the PU signal. A SU receiving PU signal with higher SNR contributes more in the final decision. However, in [15], it is mentioned that the SU cannot improve the performance under a certain threshold ($\mathrm{SNR}_{\mathrm{wall}}$), thus SNR may not be a good candidate for assigning weights. In [16], a cooperative spectrum sensing scheme using fuzzy logic for cognitive radio network was proposed. Every SU participating in cooperation estimates the presence possibility of PU using fuzzy inference rules based on observed energy and estimated SNR value. The final decision is deducted by aggregating the possibilities of the presence of PU received from each SU at the fusion center, compared with a certain threshold. An adaptive cooperative spectrum sensing algorithm proposed by L. Chen et al. in [17] focuses on the use of probability of detection and probability of false alarm instead of using SNR to characterize each participating user. Probabilities of detection and false alarm are computed by storing the local decision received from each SU and comparing it against the final decision. The author, looking at the memory requirements, proposed an aging concept to erase the older observation either by windowing mechanism or multiplying them with a forgetting factor.

A weighted cooperative spectrum sensing framework (WCSSF) proposed by Y. Zhao et al. in [18] states that every cooperative user sends both measured energy of PU signal as well as probability of error. The probability of error can be thought as the summation of the probability of false alarm and probability of misdetection. In order to compute probability of error, each SU takes the probability of detection, probability of false alarm as well as primary user activity into account. At the fusion center (FC), each participating user is assigned a weight corresponding to its probability of error, i.e., a SU with higher probability of error is assigned lower weight. This scheme performs very well if the system parameters remain constant like noise power but slow to respond to fast changing RF environment.

In the past few years, various weight-based techniques have been proposed for the cooperative spectrum sensing in the CR network. Most of the earlier mentioned techniques assign weights to the local decisions from SUs based on their past performance. Computing weights just on the basis of previous track record is not a good solution for a fast changing RF environment. For example, although a SU performed reasonably well in the past, it may be affected by shadowing effect due to the change of geographical location of either PU or SU. Even then, its contribution is higher in the final decision due to its past record. In this paper, we present a technique in which a user is characterized by its probability of error, but the current decision is also closely monitored. On each wrong decision, i.e., local decision mismatching global decision made by the fusion center (FC), which is either false alarm or misdetection, its weight decreases by a certain decaying factor.

3. **System Model and Framework.** The Cognitive Radio Network (CRN) considered in this paper has a centralized network entity such as a base station or access point in infrastructure-based network. This centralized entity can communicate with all SUs within its coverage range and can decide the availability within this geographical region. Furthermore, the network comprises of N SUs and one PU. For example, in our system model depicted in Figure 1, the PU corresponds to a device using a digital/analog TV channel. The SUs are customer-premises equipments (e.g., smart phones, laptop computers and PDAs) in a Wi-Fi zone and the fusion center is the access point (AP).

The system model that we assume is an infrastructure-based cognitive radio network in which a central entity known as FC collects the local sensing decision from multiple SUs over the reporting channel and fuses these local decisions to make a final decision about the presence or absence of the PU. The channel between PU and SU is known as

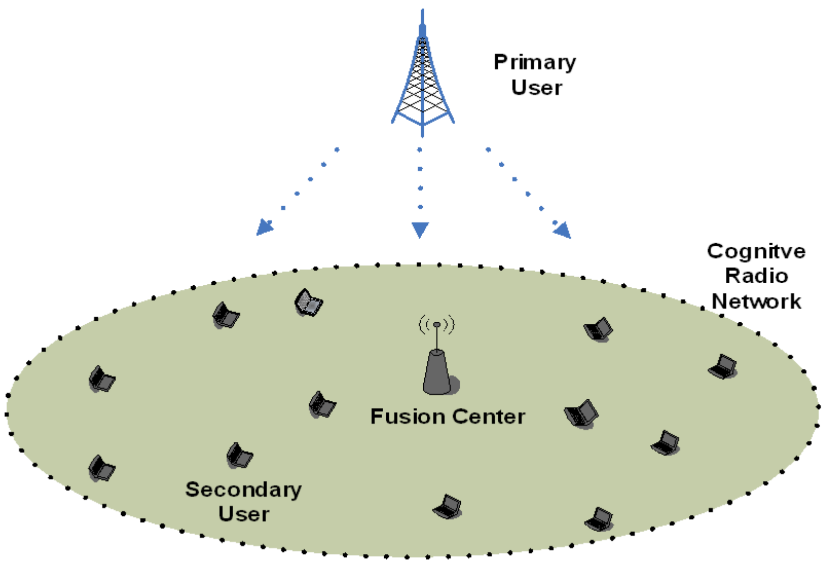

FIGURE 1. System model for centralized cooperative spectrum sensing

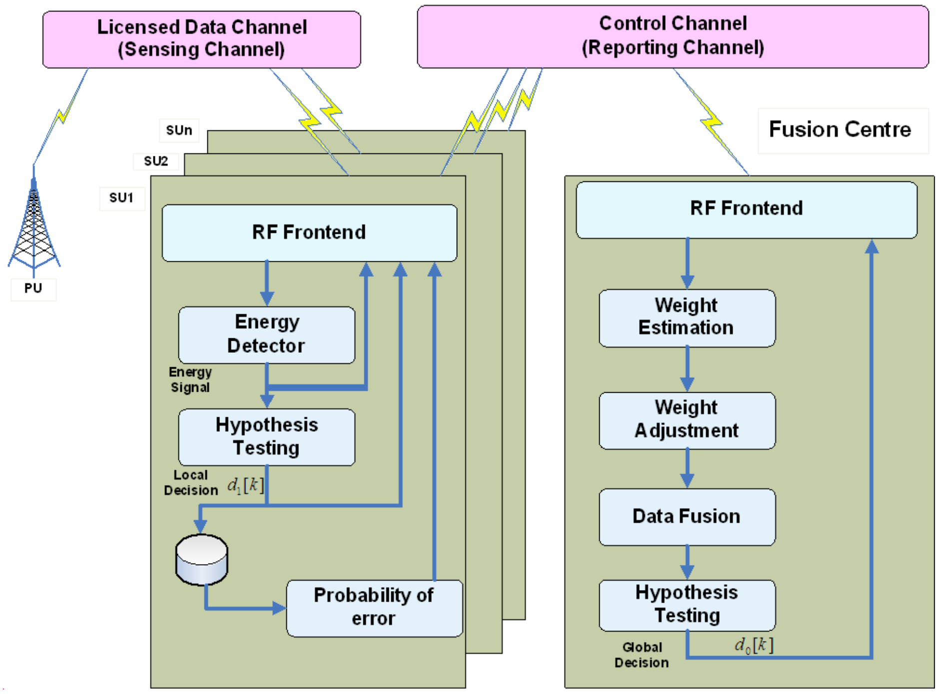

FIGURE 2. Framework of PAWM (CSS)

a sensing channel, and the channel between SU and access point is known as a reporting channel. The reporting channel is assumed to be accessed using a contention-free mechanism examined by the FC [21]. Each SU receives PU signals with different SNRs. SU, in an opportunistic way, shares the licensed channel with PU for data transmission. From the concept of SU, the transmission channel switches between idle (PU is absent) and occupied state (PU is present). The major objective of CRN is to utilize portion of spectrum where PU is absent without harmfully interfering with PU in the vicinity. On the other hand, PU networks have no condition to change their infrastructure [8].

As shown in Figure 2, the process of our proposed Penalty-based Weight Adjustment Mechanism (PWAM) for cooperative spectrum sensing (CSS) in infrastructure CRN is broken down into two phases. In the first phase, every SU performs local spectrum sensing independently to computes energy signal, probability of error and decides the presence or absence of PU (local decision). In the second phase, every SU sends its estimated energy signal, local decision and error probability to the FC through a common reporting channel [19]. The FC makes a final global decision by assigning weights to the soft decisions computed with the previous track record of the SUs as well as the current local decision. After computation, the FC broadcasts the global decision.

Let $d_j[k]$ denote the jth SU's local decision at the kth sensing period and $d_0[k]$ denote the global decision made by the fusion center in the kth sensing iteration, then we have

$$d_j[k] = \begin{cases} 1, & \text{if } H_1 \text{ is declared,} \\ 0, & \text{if } H_0 \text{ is declared,} \end{cases} \tag{1}$$

where H_0 is the null hypothesis which means the absence of the PU, whereas H_1 is the alternate hypothesis which means the presence of the PU.

In FC, the global decision is made every kth duration by aggregating the energy signals $E_j[k]$ obtained from all the SUs ($j = 1, \ldots, N$). Computation using the energy detection algorithm will be discussed later. Their corresponding weights $w_1, w_2, \ldots, w_N$ are illustrated in Figure 3. To implement FC, we need to know the weight value first.

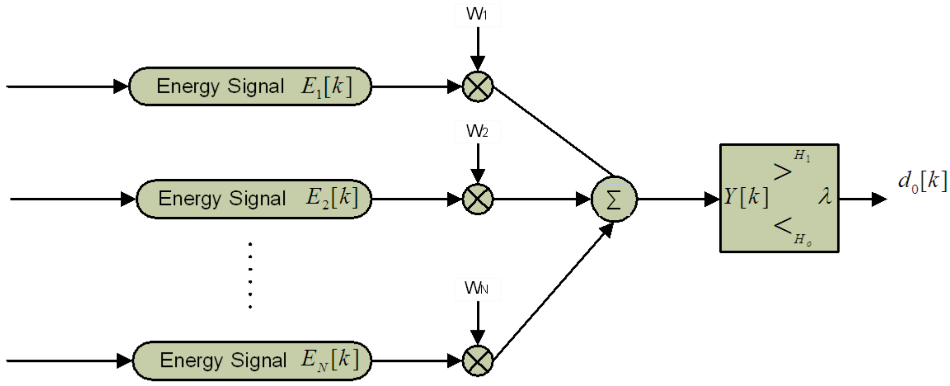

FIGURE 3. Aggregation at fusion center

The weight assigned to each jth SU is estimated using its probability of error P_e^j, local decision $d_j[k]$ and global decision $d_0[k]$. The probability of error P_e^j is given by

$$P_e^j = P(H_0)P_f^j + P(H_1)(1 - P_d^j) \tag{2}$$

where P_f^j and P_d^j denote the probability of false alarm and probability of detection of the jth user, respectively. $P(H_0)$ and $P(H_1)$ denote the probability of channel being idle and occupied, respectively. Let d_{occu} and d_{idle} denote the mean occupied and idle duration of the channel, then $P(H_0)$ and $P(H_1)$ can be determined by following formulae:

$$P(H_0) = \frac{d_{idle}}{d_{occu} + d_{idle}}, \quad P(H_1) = \frac{d_{occu}}{d_{occu} + d_{idle}}. \tag{3}$$

In the cooperative spectrum sensing, global decision $d_0[k]$ is more reliable than local decision $d_j[k]$. Therefore, we can use the global decision as a supervisor to estimate the probabilities of detection and false alarm. If the local decision is the same as the global decision, it is assumed to be correct. Otherwise, it is assumed to be incorrect. By just counting the global and local decision agreement as given in (4) and (5) as

$$P_d^j = P(d_0[k] = 1)P(d_j[k] = 1|d_0[k] = 1), \tag{4}$$

$$P_f^j = P(d_0[k] = 0)P(d_j[k] = 1|d_0[k] = 0), \tag{5}$$

we can have the estimated probability of false alarm and probability of detection for a particular SU as described by Algorithm 1.

In the above mentioned algorithm, $d_j[k]$ is used as local decision of jth SU in kth sensing duration. For the convenience of analysis, local decision is computed using the energy detection algorithm. The problem of the local spectrum sensing can be expressed by a binary hypothesis function as presented by Yue and Zheng in [20], given by

$$r[k] = \begin{cases} n[k], & \text{if } H_0, \\ s[k] + n[k], & \text{if } H_1, \end{cases} \tag{6}$$

where $r[k]$ is the received signal by SU in the kth sensing duration, $s[k]$ is the primary user signal and $n[k]$ is the additive white Gaussian noise (AWGN). Channel gain is ignored, because it is assumed to be constant during the detection interval. After receiving $r[k]$, each SU computes the energy signal $E[k]$ as demonstrated by

$$E[k] = \sum_{i=1}^{M} |r[k]|^2 \tag{7}$$

Algorithm 1: Probability of Detection and False Alarm Computation of SU

```
Input: d_0[k] for k = 1, 2, 3...n          n is the number of sensing periods
P_d^j <--- 0, P_f^j <--- 0
for j = 1 to N do                           N is the number of secondary users
count1<---1, count2<---1, correctcount<---0, falsecount<---0
    for k = 1 to n
        If d_0[k] = 1
            If d_j[k] = 1
                correctcount = correctcount + 1
                P_d^j = correctcount/count1
            endif
            count1 = count1 + 1
        else
            If d_j[k] = 1
                falsecount = falsecount + 1
                P_d^j = falsecount/count2
            endif
            count2 = count2 + 1
        endif
    end
end
```

P_d^j	Probability of detection of jth user
P_f^j	Probability of false alarm of jth user

where $r[k]$ is the received signal in kth sensing duration at jth SU and M is the total number of samples, i.e., equal to $2TW$, where T and W represent the detection time and signal bandwidth, respectively. Based on the output of the energy detector, i.e., energy signal $E[k]$, the SU determines if hypothesis is either H_0 or H_1.

Initially, jth SU is assigned equal weight W_j where j is from 1 to N and N is the number of cooperating secondary users. Once we have the probability of error P_e, local decision d_j and global decision d_0, we can calculate the weight for the corresponding SU. The idea of weight assignment presented in [16] is mainly based on the probability of error P_e. In our proposed scheme, besides simply depending on the probability of error of SU, we introduce weighted penalty. In this penalty-based weight adjustment mechanism, if the local decision reported by a SU is not consistent with the global decision, its weight is reduced by the penalty θ. The value of θ is chosen as $1/N$, where N is the number of users participating in the cooperative decision. The penalty-based weight adjustment mechanism is illustrated in Algorithm 2.

With the assigned weight W_j for each SU and energy signal E_j obtained from local sensing at each SU, the FC can compute the output signal $Y[k]$ as

$$Y[k] = \sum_{j=1}^{N} W_j[k] \times E_j[k]. \tag{8}$$

The FC then compares $Y[k]$ with a predetermined threshold λ. If $Y[k]$ is larger than the predetermined threshold, FC will assert the presence of the PU. Otherwise, it will deny the presence of the PU.

4. **Experimental Results and Discussions.** In this section, the performance comparison between the weighted cooperative spectrum sensing framework (WCSSF) introduced in [18] and our proposed technique is presented. In order to validate the efficiency of the

Algorithm 2: Penalty-based Weight Adjustment Mechanism	
Input: $d_0[k]$, $d_j[k]$, P_e^j $j = 1, \ldots, N$,	*at kth detection moment*
1. $\theta = 1/N$	*penalty factor*
2. for $j = 1$ *to* N *do*	
3. $W_j^* = 1/P_e^j$	
4. end	
5. for $j = 1$ *to* N *do*	
6. $W_j = W_j^* \Big/ \sum_{j=1}^{N} W_j^* - \theta(d_0[k] \oplus d_j[k])$	
7. end	

proposed spectrum sensing scheme, Monte Carlo simulations are carried out. Simulation is conducted under the following system settings: It is assumed that 10 SUs are participating in cooperative decision, and each SU receives the primary signal with randomly distributed SNR ranging from −10 to 30 dB under randomly generated Gaussian noise distribution with zero mean and variance 1. The sum of the probability of channel being idle $P(H_0)$ and being occupied $P(H_1)$ is 1 as

$$P_H = P(H_0) + P(H_1) = 1. \tag{9}$$

Figure 4 shows the impact of PU activity on total error probabilities for WCSSF and PWAM by varying the probability of absence of a primary user from $0 \sim 1$ with a step interval of 0.1. Total error probability refers to the probability of error computed for the FC. It is computed using (2), where the probability of false alarm and probability of detection are calculated using global decision $d_0[k]$ and actual absence or presence of the PU. The performance gain of PWAM is higher, because it is more robust against malfunctioning nodes than WCSSF.

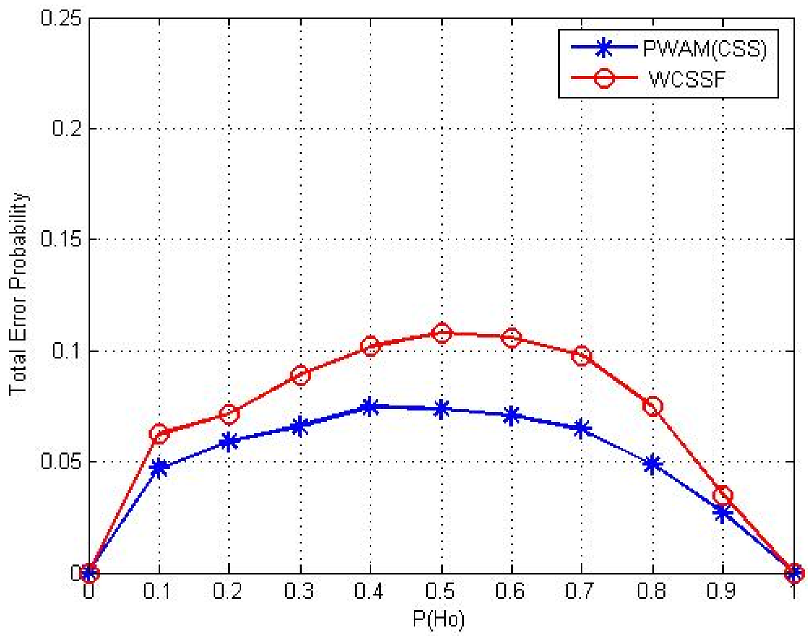

Figure 4. Impact of primary user activity on total error probability

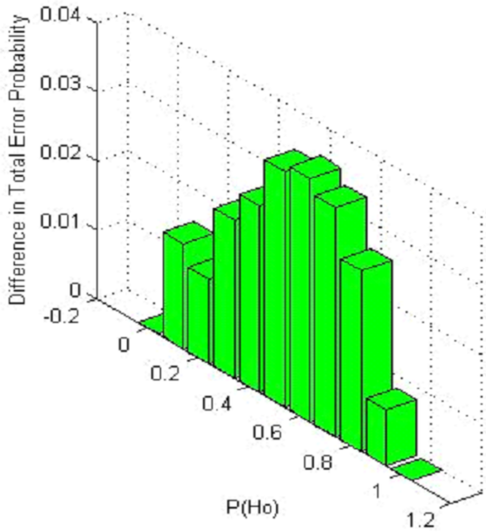

FIGURE 5. Difference in total error probability of WCSSF and PWAM

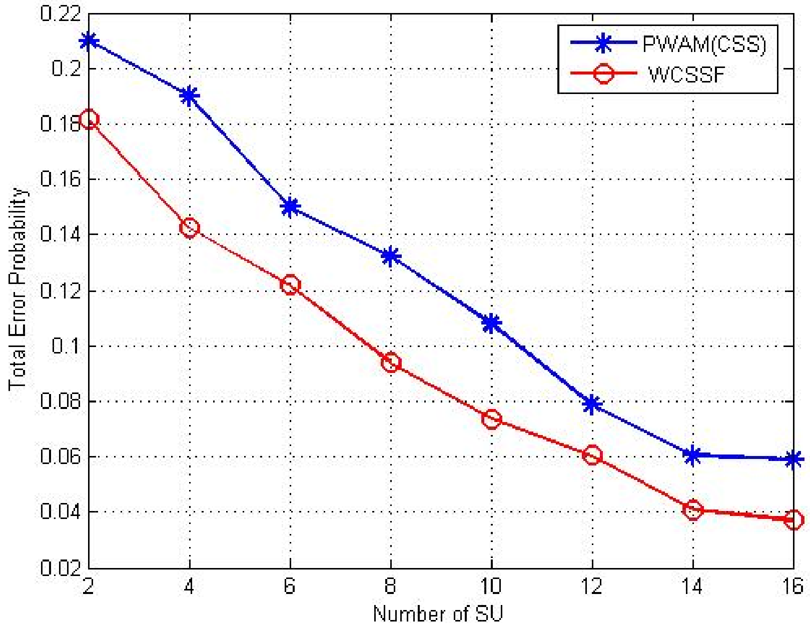

FIGURE 6. Impact of the number of cooperating SUs on total error probability

Figure 5 shows the reduction in total error probability achieved by PWAM with reference to WCSSF. From the result, one can see that PWAM is superior to WCSSF due to the significant difference in total error probabilities of two techniques.

To examine the impact of the number of SUs participating in cooperation on the total error probability, experiments are carried out under given value of $P(H_0) = 0.5$. Figure 6 shows that the error probability decreases remarkably by increasing the number of SUs participating in the cooperation. PWAM exhibits the same error probability with quite fewer participating SUs than required by WCSSF.

Table 1 shows the more elaborative view of the impact of increasing or decreasing cooperating users on the total error probability. One can see that there is a clearly significant difference in the error probability against the same number of users in WCSSF and our proposed penalty based CSS.

TABLE 1. Impact of number of cooperating SU on total error probability

	Total Error Probability							
Number of SUs	2	4	6	8	10	12	14	16
PAWM	0.21	0.19	0.15	0.13	0.10	0.08	0.06	0.057
WCSSF	0.18	0.14	0.12	0.09	0.07	0.06	0.04	0.039
Difference	0.03	0.05	0.03	0.04	0.03	0.02	0.02	0.018

To examine the behavior of PWAM under different values of SNR, we simulated the system model with the system settings as discussed earlier except considering one SU as a reference user whose SNR varies from $-10 \sim 10$ dB. Figures 7 and 8 show the observed curves of probability of detection and false alarm for both WCSSF and PWAM, respectively. As far as the probability of detection is concerned, both techniques exhibit almost similar performance. PWAM shows a significant improvement in terms of the probability of false alarm when compared with WCSSF.

5. **Conclusion.** The spectrum sensing is a prerequisite for CRs. To achieve higher sensing efficiency, the cooperative sensing is the most beneficial strategy. In the cooperative spectrum sensing, it is critical how to fuse the data to make a global decision about the presence or absence of primary user. In this paper, we proposed an improved noise-immune fusion approach for the cooperative spectrum sensing scheme in CRN. The simulation results show that our proposed scheme, PWAM, exhibits a low probability of error in comparison with other cooperative spectrum sensing techniques. A fusion scheme this paper proposed improves the sensing reliability of cooperating SUs. In the future, this

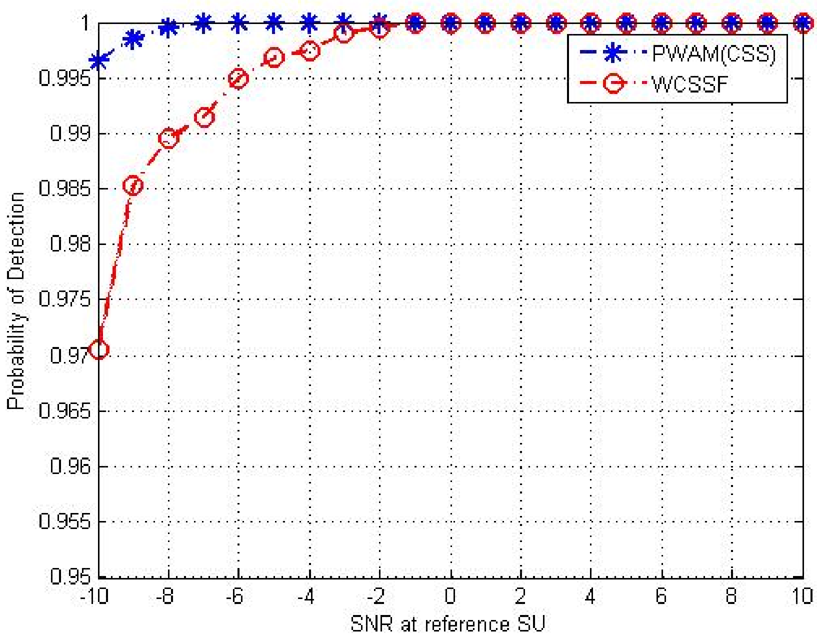

FIGURE 7. Probability of detection vs. SNR

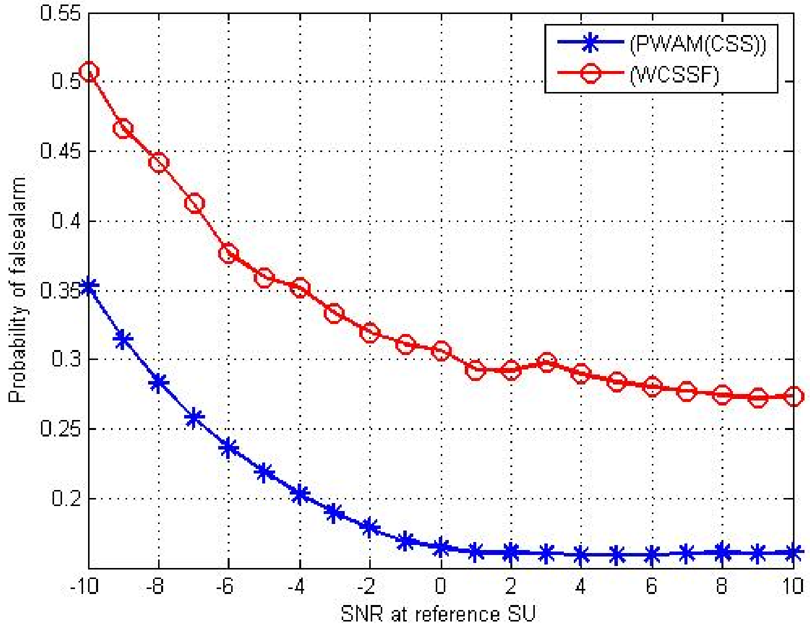

Figure 8. Probability of false alarm vs. SNR

work can be extended to reduce the overhead incurred in achieving spectrum sensing reliability.

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