Optimized Reliable Data Combining Cooperative Spectrum Sensing Method in Cognitive Radio Networks

**Masoud Moradkhani · Paeiz Azmi ·
Mohammad Ali Pourmina**

Abstract Spectrum sensing is one of the most important tasks of each cognitive radio network. Cooperation among secondary users, by increasing the sensing accuracy can improve the network throughput, but also increases the energy consumption of cognitive radio network. In this paper, we propose the reliable data combining method for cooperative spectrum sensing, according to which the fusion center by using two threshold values, makes the final decision only if it is confident enough in validity of received local data. Otherwise, an additional sensing will be performed. Throughput maximization problems under interference constraints are formulated for both soft and hard fusion schemes and the optimal sensing time and threshold values are obtained. Simulations show that for all SNRs, higher absolute throughput and also higher throughput per energy consumption are accessible, rather than conventional cooperative sensing. Moreover, for a large range of SNRs the less energy is consumed.

1 Introduction

Current wireless communication networks are following the fixed spectrum assignment policy. According to the federal communications commission (FCC) report, major portions of

M. Moradkhani (✉) · M. A. Pourmina
Department of Electrical Engineering, Science and Research Branch,
Islamic Azad University, P.O. Box 14515-775, Tehran, Iran
e-mail: m.moradkhani@srbiau.ac.ir

M. A. Pourmina
e-mail: pourmina@srbiau.ac.ir

P. Azmi
Department of Electrical and Computer Engineering, Tarbiat Modares University,
P.O. Box 14115-143, Tehran, Iran
e-mail: Pazmi@ieee.org

licensed spectrum is underutilized across time and space [1]. The limited spectrum resources, low spectrum efficiency and growing demands for spectrum, reveal the need for dynamic spectrum management. Cognitive radio (CR) is an emerging advanced radio technology that enables a secondary user (SU), intelligently monitor its radio frequency environment to detect both busy and idle communication channels and move into idle channels, while avoiding busy ones [2]. This technology increases the spectrum efficiency by adapting its operating characteristics based on idle channel conditions and engaging in communication through them [3].

At any CR network, normally the following operations are performed, spectrum sensing, spectrum decision, spectrum sharing and spectrum mobility [4]. Spectrum sensing which aims at detecting idle frequency channels at a specific time or location, is considered as the most important function of CR [5]. Spectrum sensing is done by different techniques like matched filter detection, cyclostationary based detection and energy detection. In this paper we consider energy detection, which is a simple method with low computational cost and free from prior knowledge of primary user (PU) signal [6]. If each SU performs sensing by itself, fading and shadowing effects may degrade the detection performance. Cooperative spectrum sensing has been proposed as a solution for such harmful effects [7,8].

In CR networks, the fusion scheme which is applied at the FC to make the final decision, plays a decisive role in the performance of cooperative spectrum sensing [9]. It affects the probabilities of missed detection and false alarm, which determine the amount of interference and CR network throughput, respectively [9,10]. There are two commonly used fusion schemes in cooperative spectrum sensing, soft fusion and hard fusion. In Soft fusion, the observation of any SU is forwarded to a common receiver often called fusion center (FC), through a control channel and then all the observations are fused together to make the final decision. In hard fusion, each SU makes a binary local decision regarding the presence of PU and sends its decision to the FC, in which the final decision is made. It is well known that soft fusion scheme for cooperative spectrum sensing, outperforms the hard fusion one, but at the cost of more bandwidth requirement for the control channel and more communications overhead [11–13]. Nevertheless, in the case of participating a large number of SUs in the cooperation, it is shown that the performance of hard fusion can be as good as soft fusion [14].

Cooperative spectrum sensing can reduce both the general false alarm and missed detection probabilities, resulting in throughput improvement and better immunity of PUs against interference. On the other hand, as the number of SUs increases, the network energy consumption is also increased, which is a critical factor in battery powered sensor networks. This paper presents the so called reliable data combining (RDC) method, for both soft and hard fusion schemes which aims at joint enhancing the network throughput and energy efficiency, while sufficient protection of PUs is guaranteed. In the proposed method the sensing process is performed again, whenever the local decisions or observations gathered in the FC, are not reassuring for making the final decision.

The optimum soft fusion data combining is the Chair–Varshney rule, which is based on log-likelihood ratio test and needs the channel state information [15]. For widely used energy detection spectrum sensing, various soft combining schemes, like square-law combining (SLC) and square-law selection (SLS) are explained over AWGN, Rayleigh and Nakagami-m channels [16–18]. In [19], the authors optimize a linear combination of local statistics measured by SUs, for minimizing the interference to PU, while enhancing the spectrum efficiency. In [20], a weighted combining method for cooperative spectrum sensing is proposed. In [11], a maximum ratio combining method (MRC) is adopted. It needs prior knowledge of the channels gains and assigns greater weights to local energy statistics with higher SNRs. The equal gain combining (EGC) scheme is considered in [21]. Based on EGC, the local observed energies after passing through the control channel, will be multiplied by an identical

weights, which are assigned based on the number of cooperative SUs and then added together at the FC. The performance of this scheme is near-optimal and independent of channel information, thus it is a tradeoff between complexity and performance and widely used as an soft fusion technique [11]. From energy consumption point of view, the recent work [22], indicates the better performance of EGC rather than other soft combining schemes.

Regarding the hard combining scheme, various fusion rules have been considered in the literature. Counting rule or K out of N rule, is investigated in [23–25]. In this case, the FC votes in favor of PU activity if at least K out of N SUs, have made decision on the activity of PU. As the special cases of counting rule, Ghasemi and Sousa [26] adopts the OR fusion rule cooperative spectrum sensing. In [23], the AND rule is also investigated. The optimization of counting rule is considered in [9] to minimize the sum of missed detection and false alarm probability. It is shown that the entitled HALF-VOTING rule is optimal. Authors of [10] aim at adopting the counting rule to maximize throughput, while the sensing accuracy is guaranteed. In [27], based on hard fusion scheme, the throughput maximization of an energy limited CR network is studied. Recently, a method for linear combination of local decisions is proposed in [28] and the performance of K out of N fusion rule under erroneous reporting channels is investigated in [29].

With the goal of performance enhancement, choosing a number of SUs for cooperation, known as sensing user selection, has attracted much attention in the literature. It is shown in [23] and [30] that cooperation of all SUs, no matter what combination scheme applied at the FC, is not necessarily meant to achieve the maximum performance. According to the results of [23], selecting a subset of SUs with highest SNRs, leads to a lower false alarm and missed detection probabilities. In [30], a sensing user selection scheme is presented to minimize the average detection Bayesian risk. A cluster-based method is considered in [31], in which all the SUs are divided into clusters. In each cluster, a cluster head with the best reporting channel condition forwards the local information to the FC.

Censoring method is a different user selection scheme, which mainly aims at reducing overhead [32]. In this method, based on two threshold values, only SUs with sufficient informative data are allowed to send their observations or decisions to the FC. In [33], the authors show that the censoring method reduces the required bandwidth of the control channel. The energy efficiency capability of censoring method, which is a vital factor in battery powered cognitive sensor networks, is demonstrated in [34]. Moreover, The works [35] and more recently [36], adopt the MAJORITY fusion rule based on the censoring method.

The aforementioned works, basically used single threshold cooperation methods at the FC to decide about PU activity. Such methods can't carefully create a balance between the two detection error probabilities, false alarm and missed detection, especially when the dynamic range of PU signal is high or the PU signal characteristics are unknown to the FC, which is often the case in CR networks [37]. For example, in the case of K out of N rule, the single threshold K, determines the error probabilities. When a very weak PU signal has to be detected, the number of local decisions in favor of its presence, may fall below the specific K and thus, the FC wrongly declares its absence (missed detection). By using a smaller K the probability of missed detection decreases, but also at the same time the probability of false alarm increases. If the CR network has enough information about the PU signal characteristics, a smaller threshold can be selected for a PU with a lower tolerable signal level, in order to reduces the missed detection probability and as a result, reduces the interference to PU. For a PU with high interference tolerance, a larger threshold is suitable, since it decreases the false alarm probability and lets the CR network to communicate with higher throughput. However, with the lack of sufficient knowledge about the PU, the performance of such methods may be degraded.

Unlike the previous works, we propose in our method to take advantage of using two thresholds for data combining at the FC. When the test statistics exceeds the upper threshold, the presence of PU is declared as the final decision and when it is less than the lower threshold, the absence of PU is declared. In the case of falling the test statistics between two thresholds, the sensing result is considered invalid and another sensing process will be carried out. So the proposed RDC method has a non periodic cooperative spectrum sensing strategy. The conventional periodic sensing method can be regarded as a special case of the proposed method, when all the test statistics are reliable or both thresholds are the same at the FC.

The proposed method is different from censoring method, although they both use two thresholds for detection. The censoring mechanism is applied at each SU locally and only informative local sensing data are sent to the FC. Therefore, the final decision is always made at the FC with the participation of a subset of SUs. In contrast, the RDC method basically is not a user selection mechanism. In this method all the local sensing data are sent to the FC and participate in cooperative sensing. The final decision may be made at the FC or not, depending on the test statistics and thresholds values.

Throughout this paper we refer to EGC and counting rule fusion schemes as the conventional sensing methods, in contrast to the RDC method. We adjust the thresholds and sensing time to maximize throughput conditioned on the PUs being protected and show that the RDC method not only increases the network throughput, but also is an energy efficient method in comparison with the conventional sensing methods.

The reminder of this paper is organized as follows. In Sect. 2 the system model for both soft and hard fusion schemes is presented. Section 3 formulates the network throughput and energy consumption. The performance analysis of the proposed method is given in Sect. 4. Section 5 deals with the simulation results followed by conclusion in Sect. 6.

2 System Model

We assume that the CR network is composed of M SUs and a FC. Each SU with a built in energy detector, estimates the average energy of PU signal during sensing. In soft fusion scheme, this estimated value is sent usually without further processing to the FC, unlike hard fusion in which one bit local decision, regarding the existence of PU is sent. Based on the received information from all SUs, either a final decision is made by FC or another sensing process is performed. The received signal at each SU can be represented by the following binary hypothesis test problem:

$$x_i[n] = \begin{cases} z_i[n] & H_0 \\ s_i[n] + z_i[n] & H_1 \end{cases}, \quad i = 1, 2, \ldots, M, \quad n = 1, 2, \ldots, N. \quad (1)$$

where N is the sample size which is equal to the product of sensing time τ and sampling frequency f_s. Hypothesis H_0 indicates inactivity of PU and H_1 is a hypothesis which indicates PU activity. $x_i[n]$ is the received signal sample by ith SU at sample time $n \cdot s_i[n]$ is the transmitted signal of PU and $z_i[n]$ is the additive noise, which we model both as i.i.d Circularly Symmetric Complex Gaussian (CSCG) random variables with zero means and variances $\sigma_{s,i}^2$ and $\sigma_{z,i}^2$ respectively.

In cooperative spectrum sensing, any frame duration generally consists of sensing, reporting and transmission phases, each one cause delay in the system. Sensing time, reporting delay, asynchronous SUs and asynchronous reporting are mentioned as the cooperative sensing delay overhead [6]. Reporting delay is the time needed for local sensing results to be

Fig. 1 Schematic illustration of RDC method
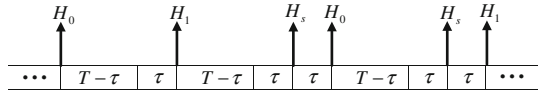
sent to the FC. Asynchronous SUs referred to SUs which operate in the sensing phase, asynchronously. Asynchronous reporting occurs when the local sensing results of all SUs, don't received by the FC concurrently. We assume that the system is perfectly synchronized. Thus, a fixed time overhead is added by the reporting phase. Consequently, without loss of generality the reporting delay is assumed to be zero [8].

In conventional cooperation, the sensing phases are occurred regularly with period T, where T is the frame duration. Local sensing results are reported to the FC in which a final decision always is made in favor of H_0 or H_1, regardless of reliability of its received information. Such a method may be associated with misleading results in the detection of PU status which can either reduce the spectrum efficiency or cause interference to PU. We propose the RDC cooperative sensing method which is schematically illustrated in Fig. 1. To enhance the performance of conventional sensing, after gathering all local sensing data, the possible output of FC is in favor of either H_0, H_1 or H_s. We mean by H_s that an additional sensing phase should be implemented in a case where there is doubt about the reliability of data. This additional sensing may occur in successive until a set of reliable data gathered. We would expect an increase in detection accuracy. Furthermore due to energy consumption at each additional sensing, the performance evaluation of RDC method from energy consumption point of view will be considered. In the following we analytically investigate the RDC method and derive the related probabilities for both hard and soft fusion schemes. For simplicity we assume that all SUs have same SNR, γ [26]. In practice, when distance between two SUs is small rather than distance between SU and primary transmitter, for example when the CR and primary networks are located far from each other, all SUs nearly experience identical SNR [9].

2.1 Soft Fusion

The test statistic for local spectrum sensing based on energy detection can be written as:

$$TS_i = \frac{1}{N\sigma_z^2} \sum_{n=1}^{N} \left| x_i^2[n] \right|, \quad i = 1, 2, \ldots, M \tag{2}$$

where $\left| x_i^2[n] \right|$ is the received signal energy. TS_i is a normal random variable which its mean and variance are 1 and $\frac{1}{N}$ under hypothesis H_0, and $(1+\gamma)$ and $\frac{1}{N}(1+\gamma)^2$ under hypothesis H_1, respectively [38]. In the case of soft fusion, each SU forwards TS_i to the FC in order to performs the average of local received data as:

$$TS = \frac{1}{M} \sum_{i=1}^{M} TS_i \tag{3}$$

It can be verified that TS has a normal distribution with mean 1 and variance $\frac{1}{NM}$ under hypothesis H_0 and mean $(1+\gamma)$ and variance $\frac{1}{NM}(1+\gamma)^2$ under hypothesis H_1. For soft fusion we compare TS with two thresholds λ_1 and λ_2 where $0 \leq \lambda_1 \leq \lambda_2$. If it locates between the two thresholds, the sensing data is considered as unreliable and another spectrum sensing phase is requested by FC. When it is smaller than λ_1, PU is declared as inactive. Otherwise,

the activity of PU is declared. This process may be repeated until a reliable data received. The final decision D_s, can be formulated as:

$$D_s = \begin{cases} 0 & TS < \lambda_1 \\ additional \ \ sensing & \lambda_1 \leq TS < \lambda_2 \\ 1 & TS \geq \lambda_2 \end{cases} \tag{4}$$

where the bits 0 and 1 represent inactivity and activity of PU, respectively. General false alarm and detection probabilities can be obtained as:

$$Q_{Fs} = \Pr(TS \geq \lambda_2 | H_0) = Q\left((\lambda_2 - 1)\sqrt{M \tau f_s}\right) \tag{5}$$

$$Q_{Ds} = \Pr(TS \geq \lambda_2 | H_1) = Q\left((\lambda_2 - \gamma - 1)\frac{\sqrt{M \tau f_s}}{\gamma + 1}\right) \tag{6}$$

And, general missed detection (Q_{Ms}) and opportunity (Q_{Os}) probabilities become:

$$Q_{Ms} = \Pr(TS < \lambda_1 | H_1) = 1 - Q\left((\lambda_1 - \gamma - 1)\frac{\sqrt{M \tau f_s}}{\gamma + 1}\right) \tag{7}$$

$$Q_{Os} = \Pr(TS < \lambda_1 | H_0) = 1 - Q\left((\lambda_1 - 1)\sqrt{M \tau f_s}\right) \tag{8}$$

Q_{Ms} denotes the probability of not distinguishing activity of a really active PU and Q_{Os} is the probability of detecting a really idle spectrum, which gives the CR network an opportunity to engages in communication. Furthermore, the probabilities of making no decision by the FC or equivalently, probabilities of performing additional spectrum sensing in the absence (δ_{0s}) and presence (δ_{1s}) of PU are:

$$\delta_{0s} = \Pr(\lambda_1 \leq \Lambda < \lambda_2 | H_0) = 1 - Q_{Os} - Q_{Fs} \tag{9}$$

$$\delta_{1s} = \Pr(\lambda_1 \leq \Lambda < \lambda_2 | H_1) = 1 - Q_{Ms} - Q_{Ds} \tag{10}$$

2.2 Hard Fusion

In this fusion scheme, each SU compares its test statistic with a predefined threshold λ to make a binary local decision, based on energy detection. The local false alarm and detection probabilities can be obtained as:

$$P_f(\tau, \lambda) = \Pr(TS_i \geq \lambda | H_0) = Q\left((\lambda - 1)\sqrt{\tau f_s}\right) \tag{11}$$

$$P_d(\tau, \lambda) = \Pr(TS_i \geq \lambda | H_1) = Q\left((\lambda - \gamma - 1)\frac{\sqrt{\tau f_s}}{\gamma + 1}\right) \tag{12}$$

Suppose that $b_i \varepsilon \{0, 1\}$ is the decision of ith SU where 0 and 1 represent the absence and presence of PU, respectively. The FC compares $\Lambda = \sum_{i=1}^{M} b_i$ as the sum of all local decisions, with two integer values k_1 and k_2 where $0 \leq k_1 \leq k_2 \leq M$. We will choose this values based on the sensing performance requirements. The final decision D_h, is concluded at the FC according to the following rule:

$$D_h = \begin{cases} 0 & 0 \leq \Lambda < k_1 \\ additional \ sensing & k_1 \leq \Lambda < k_2 \\ 1 & k_2 \leq \Lambda \leq M \end{cases} \tag{13}$$

If Λ falls between k_1 and k_2, the FC dose not trust its received information and consequently, does not vote decisively in favor of H_0 or H_1. Instead, it gives the CR network a

chance to run another sensing phase until a reliable result is obtained. Based on the proposed rule, general probabilities of false alarm (Q_{Fh}) and detection (Q_{Dh}) can be obtained as:

$$Q_{Fh}(k_2, P_f) = \Pr(\Lambda \geq k_2|H_0) = \sum_{l=k_2}^{M} \binom{M}{l}(P_f)^l(1 - P_f)^{M-l} \tag{14}$$

$$Q_{Dh}(k_2, P_d) = \Pr(\Lambda \geq k_2|H_1) = \sum_{l=k_2}^{M} \binom{M}{l}(P_d)^l(1 - P_d)^{M-l} \tag{15}$$

Also, general missed detection probability (Q_{Mh}) and general opportunity probability (Q_{Oh}) are obtained as follows:

$$Q_{Mh}(k_1, P_d) = \Pr(\Lambda < k_1|H_1) = \sum_{l=0}^{k_1-1} \binom{M}{l}(P_d)^l(1 - P_d)^{M-l} \tag{16}$$

$$Q_{Oh}(k_1, P_f) = \Pr(\Lambda < k_1|H_0) = \sum_{l=0}^{k_1-1} \binom{M}{l}(P_f)^l(1 - P_f)^{M-l} \tag{17}$$

The probabilities of additional sensing under hypothesis H_0 and H_1 can be obtained as:

$$\delta_{0h} = \Pr(k_1 \leq \Lambda < k_2|H_0) = 1 - Q_{Oh} - Q_{Fh} \tag{18}$$
$$\delta_{1h} = \Pr(k_1 \leq \Lambda < k_2|H_1) = 1 - Q_{Mh} - Q_{Dh} \tag{19}$$

3 Throughput and Energy Consumption

By considering Fig. 1, when PU is absent and the FC distinguishes it correctly, the achievable throughput for both hard and soft fusion methods can be represented as:

$$R_0 = \frac{P(H_0)(T - \tau) \cdot Q_O}{T \cdot Q_O + (1 - Q_F - Q_O)\tau + T \cdot Q_F}r_0 = \frac{P(H_0)(T - \tau) \cdot Q_O}{\tau + (T - \tau) \cdot (Q_O + Q_F)}r_0 \tag{20}$$

In the presence of PU, if the FC wrongly declares its absence, the achievable throughput becomes:

$$R_1 = \frac{P(H_1)(T - \tau) \cdot Q_M}{T \cdot Q_M + (1 - Q_M - Q_D)\tau + T \cdot Q_D}r_1 = \frac{P(H_1)(T - \tau) \cdot Q_M}{\tau + (T - \tau) \cdot (Q_M + Q_D)}r_1 \tag{21}$$

where r_0 and r_1 are the network throughputs in the absence and presence of PU, respectively. The average network throughput is:

$$R = R_0 + R_1 \tag{22}$$

Since the CR technology has been designed specially to improve the spectrum efficiency, it is more advantageous when PU inactivity occurs most of the time i.e. $P(H_0) \gg P(H_1)$. On the other hand, r_1 is usually very smaller than r_0 due to PU interference. So, we can neglect the second term of (22) and approximate the average throughput after normalization as:

$$R \approx \frac{(T - \tau) \cdot Q_O}{\tau + (T - \tau) \cdot (Q_O + Q_F)} \tag{23}$$

In addition to throughput enhancement, we are also interested in studying the performance of our method from energy consumption point of view. Based on the proposed method, the

additional sensing phases, each of them with some energy consumption are executed for reliability purpose. Denoting e_0 and e_1 as the network energy consumption in the absence and presence of PU respectively, we have:

$$e_0 = P(H_0) \cdot [e_s + P(H_0 \,|\, H_0) \cdot e_t + P(H_s \,|\, H_0) \cdot e_s] = P(H_0) \cdot [e_s + Q_O \cdot e_t + \delta_0 \cdot e_s] \tag{24}$$

$$e_1 = P(H_1) \cdot [e_s + P(H_0 \,|\, H_1) \cdot e_t + P(H_s \,|\, H_1) \cdot e_s] = P(H_1) \cdot [e_s + Q_M \cdot e_t + \delta_1 \cdot e_s] \tag{25}$$

where e_s and e_t are the values of energy consumption during sensing and transmission phases, respectively. The average network energy consumption is:

$$e = e_0 + e_1 \tag{26}$$

Since $P(H_0) \gg P(H_1)$, we can approximate e as follows:

$$e \approx e_s + Q_O \cdot e_t + \delta_0 \cdot e_s \tag{27}$$

4 Performance Analysis

We want to obtain the optimum values of detection parameters in order to maximize throughput, while keeping PU protected against interference. For soft fusion the problem can be formulated as:

$$\underset{\tau, \lambda_1, \lambda_2}{Max} \quad R_s(\tau, \lambda_1, \lambda_2) = \frac{(T - \tau) \cdot Q_{Os}(\tau, \lambda_1)}{\tau + (T - \tau) \cdot [Q_{Os}(\tau, \lambda_1) + Q_{Fs}(\tau, \lambda_2)]} \tag{P1}$$

Subject to:

$$Q_{Ms}(\tau, \lambda_1) \leq \alpha \tag{28}$$

The missed detection probability is forced to be smaller than a predefined value α to immune PU against interference. To solve the problem, it is concluded from (7) that:

$$\lambda_1 = 1 + \gamma + \frac{1 + \gamma}{\sqrt{M \, \tau f_s}} Q^{-1}(1 - Q_{Ms}) \tag{29}$$

Inserting λ_1 into (8) leads to the following relation between opportunity and missed detection probabilities:

$$Q_{Os} = 1 - Q[(1 + \gamma)Q^{-1}(1 - Q_{Ms}) + \gamma \sqrt{M \, \tau f_s}] \tag{30}$$

Thus, Q_{Os} is an increasing function of Q_{Ms}. Taking the partial derivative of R_s with respect to Q_{Os} gives:

$$\frac{\partial R_s}{\partial Q_{Os}} = \frac{(T - \tau) \cdot [\tau + (T - \tau)Q_{Fs}]}{[\tau + (T - \tau) \cdot (Q_{Os} + Q_{Fs})]^2} \tag{31}$$

It is seen that $\frac{\partial R_s}{\partial Q_{Os}} \geq 0$. Since R_s is an increasing function of Q_{Os}, it is also an increasing function of Q_{Ms}. In the other words, the maximum throughput is attained when $Q_{Ms}(\tau, \lambda_1) =$

α. Thus the optimal lower threshold λ_{1opt}, can be represented in terms of the optimal sensing time τ_{opt} as:

$$\lambda_{1opt} = 1 + \gamma + \frac{1+\gamma}{\sqrt{M \tau_{opt} f_s}} Q^{-1}(1-\alpha) \tag{32}$$

The throughput can be represented as a function of τ and λ_2:

$$R_s(\tau, \lambda_2) = \frac{(T-\tau) \cdot Q_{Os}(\tau)}{\tau + (T-\tau) \cdot [Q_{Os}(\tau) + Q_{Fs}(\tau, \lambda_2)]} \tag{33}$$

It can be seen that the throughput is maximized when $Q_{Fs}(\tau, \lambda_2) = 0$. Therefore, theoretically for any sensing time the optimum value of λ_2 is $\lambda_{2opt} = \infty$. But in practice by considering (5) and using the fact that $Q(x) \approx 0$ for $x \geq 4$, we can find λ_{2opt} as:

$$\lambda_{2opt} = 1 + \frac{4}{\sqrt{M \tau_{opt} f_s}} \tag{34}$$

The problem (P1) can be represented as a simple unconstraint line search problem over sensing time τ:

$$\begin{array}{c} Max \\ \tau \end{array} \quad R_s(\tau) = \frac{(T-\tau) \cdot Q_{Os}(\tau)}{\tau + (T-\tau) \cdot Q_{Os}(\tau)} \tag{P2}$$

For hard fusion, suppose that each SU has already sent its binary decision to the FC, while fulfilled the detection constraint $P_d(\tau, \lambda) \geq \beta$. The proof is straightforward to show that throughput maximization occurs if $P_d(\tau, \lambda) = \beta$. Briefly, since $P_f(\tau, \lambda)$ is an increasing function of $P_d(\tau, \lambda)$ for any τ and λ, by setting $P_d(\tau, \lambda)$ to its minimum possible value, $P_f(\tau, \lambda)$ takes also its minimum value which maximizes $Q_{Oh}(k_1, P_f)$ and minimizes $Q_{Fh}(k_2, P_f)$ for any k_1 and k_2, as indicated by (14) and (17). Therefore, the throughput is maximized because as mentioned before, it is an increasing function of $Q_{Oh}(k_1, P_f)$ and decreasing function of $Q_{Fh}(k_2, P_f)$. From $P_d(\tau, \lambda) = \beta$ we have:

$$\lambda = 1 + \gamma + \frac{1+\gamma}{\sqrt{\tau f_s}} Q^{-1}(\beta) \tag{35}$$

and

$$P_f(\tau) = Q\left(\gamma \sqrt{\tau f_s} + (1+\gamma) Q^{-1}(\beta)\right) \tag{36}$$

General probabilities of missed detection and false alarm can be written as:

$$Q_{Mh}(k_1) = \sum_{l=0}^{k_1-1} \binom{M}{l} \beta^l (1-\beta)^{M-l} \tag{37}$$

$$Q_{Fh}(\tau, k_2) = \sum_{l=k_2}^{M} \binom{M}{l} P_f(\tau)^l (1 - P_f(\tau))^{M-l} \tag{38}$$

The problem is as follows:

$$\begin{array}{c} Max \\ \tau, k_1, k_2 \end{array} \quad R_h(\tau, k_1, k_2) = \frac{(T-\tau) \cdot Q_{Oh}(\tau, k_1)}{\tau + (T-\tau) \cdot [Q_{Oh}(\tau, k_1) + Q_{Fh}(\tau, k_2)]} \tag{P3}$$

Subject to:

$$Q_{Mh}(k_1) \leq \alpha \tag{39}$$

Similar to soft fusion it can be shown that for any sensing time, the throughput maximization is occurred when $Q_{Mh}(k_1) = \alpha$ and $Q_{Fh}(\tau, k_2)$ takes its minimum value. Solving $Q_{Mh}(k_1) = \alpha$ gives:

$$k_{1opt} = \left\lfloor Q_{Mh}^{-1}(\alpha) \right\rfloor \tag{40}$$

where $\lfloor x \rfloor$ denotes the integer part of x. Also $Q_{Fh}(\tau, k_2)$ is minimum when k_2 takes its maximum value i.e. $k_{2opt} = M$. The problem is now simplified as the following:

$$\underset{\tau}{Max}\ R_h(\tau) = \frac{(T - \tau) \cdot Q_{Oh}(\tau)}{\tau + (T - \tau) \cdot [Q_{Oh}(\tau) + Q_{Fh}(\tau)]} \tag{P4}$$

5 Simulation Results

In this section, simulation results are presented to evaluate the performance of the proposed RDC cooperative spectrum sensing method. By adjusting optimal detection parameters, we compare the achievable throughput and corresponding energy consumptions of the proposed method with the conventional sensing for various SNR values. α and β are set to 10^{-4} and 0.9, respectively. The number of SUs is 20, sampling frequency is $2MHz$ and frame duration is 5ms.

CR network should sense very weak PU signals, thus the SNRs in the range from -10 dB to -22 dB are considered in the simulations. Simulations are based on soft fusion, unless otherwise stated. Fig. 2 shows the changes in network throughput as a function of sensing time, for SNR $= -16$ dB. It is seen that the proposed method achieves higher throughputs than conventional sensing at any sensing time. Moreover, it reaches the maximum value at a lower sensing time. The optimal sensing time of the conventional and proposed method, are about 1 and 0.5 ms, respectively.

In CR networks, the sensing time is usually occupies a small portion of the frame duration, to allows the SU have more time for communications. Thus, for fixed power SUs the energy consumption of sensing phase is small rather than the transmission phase. In Fig. 3 the energy consumption of the proposed method is plotted versus sensing time for two normalized sensing phase energy consumptions, $e_s = 0.3$ and $e_s = 0.7$. This quantities have been normalized with respect to the total energy consumption, e. We use $e_s = 0.7$, though it may seems impractical, to evaluate the performance of the proposed method in

Fig. 2 Throughput variations over sensing time (SNR $= -16$ dB)
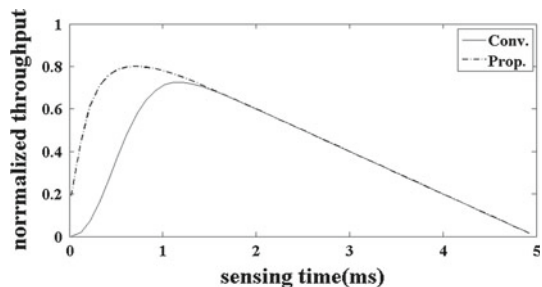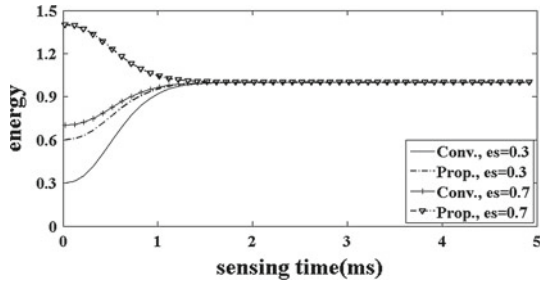
Fig. 3 Energy consumption variations over sensing time (SNR = −16 dB)

poor conditions. As we see, with increasing the energy consumption of sensing phase, the total energy consumption of both methods increases. For $e_s = 0.3$, even though for each specific sensing time, the energy consumption of the RDC method is slightly more than the conventional one, but increasingly at the optimum sensing times, the RDC method consumes less energy. In the case of $e_s = 0.7$, the energy consumption of RDC method grows more rapidly than conventional method. This is reasonable, because in the RDC method the extra sensing phases are carried out. In addition of separate investigation of either throughput or energy consumption, we are interested to know that how much throughput is obtained for a specific energy consumption, at different sensing times. This issue is addressed in Fig. 4, which depicts the ratio of maximum throughput to the corresponding energy consumption. It is observed that the throughput–energy ratio of the RDC method is higher than conventional method even when the sensing energy consumption is high.

As a function of SNR, performance of the proposed method is evaluated for $e_s = 0.2$. Figure 5 shows the maximum throughput and indicates that the maximum throughput of the proposed method, is always higher than the conventional method for all SNR values. The energy consumption is plotted versus SNR in Fig. 6. It demonstrates that the RDC method consumes less energy for a wide ranges of SNRs up to −20 dB. At very low SNRs, like those

Fig. 4 Variations of throughput–energy ratio over sensing time (SNR = −16 dB)
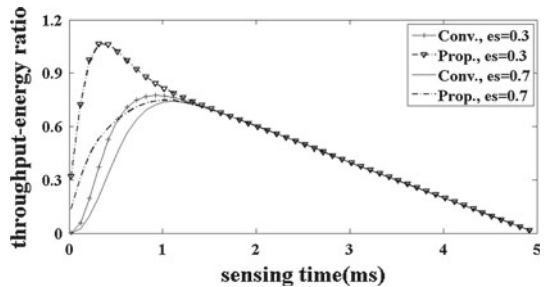
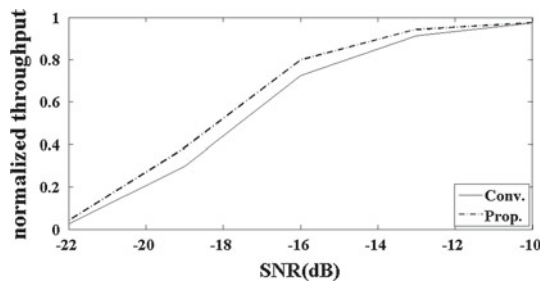**Fig. 5** Max. achievable throughput versus SNR

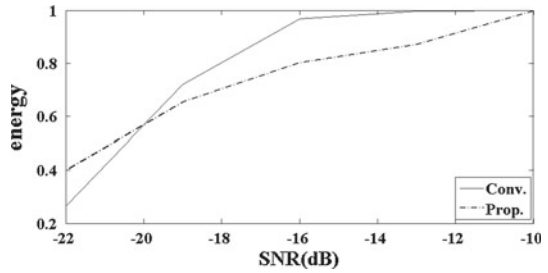**Fig. 6** Energy consumption for optimal spectrum sensing versus SNR

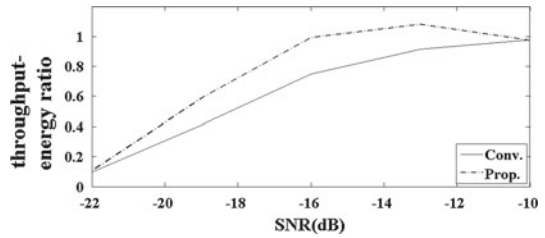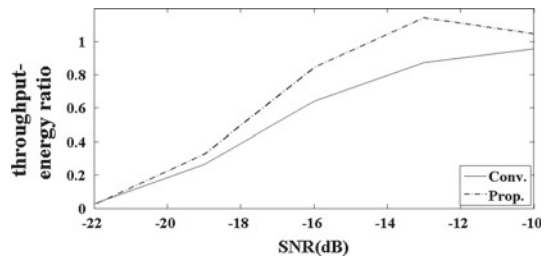**Fig. 7** Ratio of Max. throughput to corresponding energy consumption versus SNR

Fig. 8 Ratio of Max. throughput to corresponding energy consumption versus SNR (hard fusion)

below -20 dB, the energy consumption of RDC method will increase. Because at these SNRs the unreliable situations occur many times and result in much additional sensing executions that increase the energy consumption. In Fig. 7 the maximum achievable throughput per energy consumption is plotted versus SNR. It shows the superiority of the proposed method even at very low SNR values. In the case of hard fusion based RDC method, similar results are obtained, which due to space consideration, we only present the maximum throughput per energy consumption for hard fusion case, as depicted in Fig. 8. It can be seen that the performance of the proposed method is better than conventional one, for both soft and hard fusion schemes.

6 Conclusion

In this paper the RDC method for cooperative spectrum sensing in CR networks has been addressed. When the collected data at the FC is located between the upper and lower thresholds, it is regarded as the unreliable data and no final decision is made. In turn, an extra sensing phase is performed. Sensing time, upper and lower thresholds have been optimized for both soft and hard fusion schemes to maximize the network throughput with sufficient protection of PUs against interference. The performance of the proposed method has been

evaluated by simulations. The results show that it achieves not only higher throughput rather than conventional method at all SNRs, but also consumes less energy for a wide range of SNRs. In term of throughput per energy consumption, the performance of the RDC method is always better than conventional sensing regardless of what type of hard or soft fusion scheme, applied at the FC.

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Author Biographies

Masoud Moradkhani received his B.Sc. degree in electrical engineering from K. N. Toosi University, Tehran, Iran in 2000 and M.Sc. degree in electrical engineering from Iran University of Science and Technology (IUST), Tehran, Iran in 2003. He is currently working toward the Ph.D. degree at the Department of Electrical Engineering, Science and Research Branch, Islamic Azad University, Tehran, Iran. His research interests include radio resource management, wireless sensor networks and cognitive radio networks.

Paeiz Azmi was born in Tehran, Iran, on April 17, 1974. He received the B.Sc., M.Sc., and Ph.D. degrees in electrical engineering from Sharif University of Technology (SUT), Tehran-Iran, in 1996, 1998, and 2002, respectively. Since September 2002, he has been with the Electrical and Computer Engineering Department of Tarbiat Modares University, Tehran, Iran, where he became an associate professor on January 2006 and he is a full professor now. He is a senior member of IEEE. From 1999 to 2001 he was with the Advanced Communication Science Research Laboratory, Iran Telecommunication Research Center (ITRC), Tehran, Iran. From 2002 to 2005, he was with the Signal Processing Research Group at ITRC.

Mohammad Ali Pourmina received his B.Sc. and M.Sc. degrees in electrical engineering (telecommunication) from Islamic Azad University, Central Branch, Tehran, Iran, in 1989 and 1991 respectively. He received his Ph.D. degree at Islamic Azad University, Science and Research Branch, Tehran, Iran, in 1996. He joined Islamic Azad University, Science and research Branch, Tehran, Iran in 1996. He has been a member of Iran Telecommunication Research Center since 1992. He has performed research in the areas of packet radio networks and digital signal processing systems since 1991. His current research interests include spread-spectrum systems, cellular mobile communications, indoor wireless communications and cognitive radio networks.