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Throughput maximization for multimedia communication with cooperative cognitive radio using adaptively controlled sensing time

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Abstract
In the last years, most researches proved that spectrum holes are not efficiently utilized in wireless communications. Cognitive radio (CR) is an efficient solution to face inefficient utilization of spectrum resources. The key technique, which enables CR to provide efficient utilization of spectrum resources is called spectrum sensing. Spectrum sensing enables a secondary user (SU) to track the activity of the primary user (PU) and the availability of spectrum holes that can be used without any disturbance to the PU. Fixed sensing time schemes give inefficient throughput performance with varying received signal-to-noise ratios (*SNR*s). So, in this paper, an adaptive sensing time optimization scheme in cooperative CR based on energy detection is investigated with different fusion rules. The proposed scheme adapts the sensing time based on the value of received SNR to maximize the achieved throughput with an acceptable probability of false alarm. The performance of the proposed scheme is investigated with AND, OR, and Marjory fusion rules and compared to those of fixed sensing time schemes. Simulation results show that the proposed scheme significantly enhances the achieved throughput, and reduces the probability of false alarm compared to those of the fixed sensing time schemes. In addition, the proposed scheme provides better performance as the number of SUs increases with the marjory fusion rule.

Keywords Cognitive radio · Spectrum sensing · Energy detection · Cooperative communication

1 Introduction

In the last few years, there was a decay of using wired communications and a growth of using wireless communications. However, there is a restriction of this growth, because spectrum resources are limited all over the world. Each country government regulates the use of

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frequency bands by a national organization such as the Federal Communication Commission (FCC) in USA. The FCC allocates frequencies to systems within geographical area, and other systems are prohibited from using these bands. Figure 1 shows the FCC frequency allocation. From this chart, we notice that the spectrum is very crowded with nearly all usable bands licensed to governments and other organizations for special services. Due to FCC study of spectrum band utilization, it is clear that 15% to 85% of the band below 3GHz are not utilized efficiently, which indicates that there is a need to improve spectrum utilization. The best technology to overcome inefficient use of spectrum resources is CR [14, 19].

CR is defined as a network that can adapt its communication parameters according to communication environment to get efficient use of network resources. CR has the ability to sense radio environment, identify the spectrum that is unused by the PU to change its parameters to enable an SU to use it without making any interference to the PU. CR networks enable the SU to detect the presence or absence of licensed users to use free spectrum holes. CR enables the SU to use the PU spectrum holes and switch to any other available spectrum holes without any interference with the PUs [2, 4, 5, 26]. CR has four functional blocks: spectrum sensing, spectrum sharing, spectrum management, and spectrum mobility. Spectrum sharing is used to distribute access to the free-license spectrum between SUs. Spectrum management enables the choice of the best free spectrum holes, and the determination of the spectrum holes periods for use by SUs, and the spectrum mobility is responsible for the best transition between spectrum holes, when the PU is detected [18, 21].

Spectrum sensing plays an important rule in spectrum access in CR by enabling unlicensed users to use the unutilized spectrum by the PU without any harmful effects on this PU [2, 5]. Spectrum sensing is considered as the main functional block of CR network, because it enables the network to estimate system and transmission media parameters such as communication frequencies and any other parameters related to the transmission media to prevent any interference to the PU. The SU should have the capability of spectrum sensing to check if the spectrum is used by the PU, and the capability of changing the radio parameters to use the

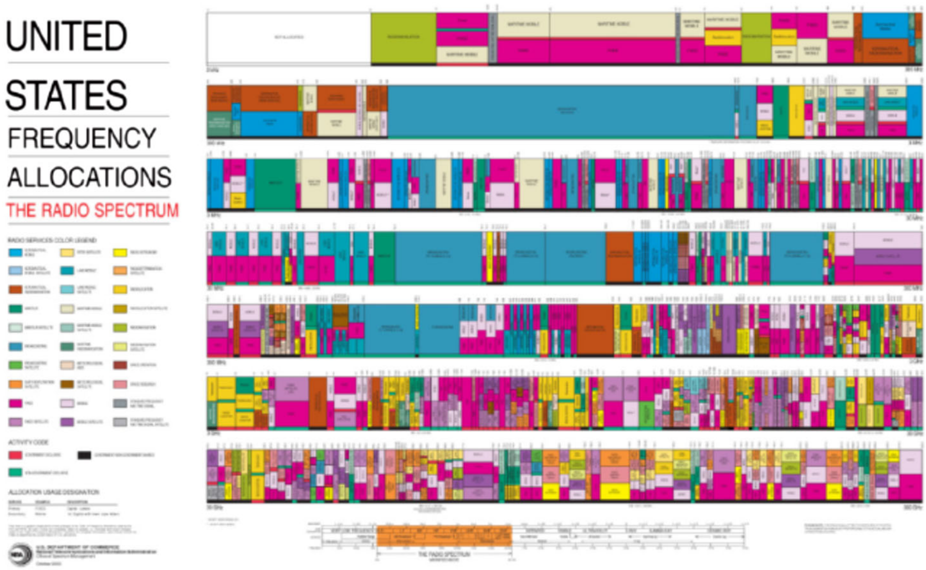

Fig. 1 FCC spectrum allocation chart

unused spectrum [4, 26]. Spectrum sensing can also be used in several wireless applications such as wireless sensor networks (WSNs). A WSN may contain a cognitive transceiver, which enables catching the available free hole to use it for communication [10–12].

There are several spectrum sensing methods such as waveform, matched filter, cyclo-stationary and energy detection methods. The matched filter is considered to be the best detector if the transmitted signal of the PU is known. The basic idea of the matched filter is to compare between an unknown signals with saved templates according to a pilot template, preamble, or spreading code to decide the presence or absence of the PU. So, the matched filter has advantages over other detectors as it takes a small sensing time and achieves a certain probability of false alarm and probability of detection. The cyclo-stationary detector detects unique features and signatures of the PU such as the mean and auto-correlation. So, the cyclo-stationary detector is able to detect the PU form noise, because it has a small auto-correlation and a weak spectral density [6]. There is a large problem facing local spectrum sensing called the hidden user. The hidden user appears in the system with multi-path fading and shadowing media. Cooperative spectrum sensing overcomes the hidden-user problem and enhances the performance of spectrum sensing in fading and shadowing environments in terms of the probability of miss-detection and the probability of false alarm [1, 3, 9].

Cooperative spectrum sensing can greatly increase the detection probability and minimize both miss-detection probability and false alarm probability. In cooperative spectrum sensing, more than one user cooperate to sense the spectrum and share their information about the PU with a common center called the fusion center. This fusion center combines the decisions of all users to obtain a final decision according to a fusion rule such as K-OUT-OF-M fusion rule, AND fusion rule, OR fusion rule, or MAJORITY fusion rule [1, 24, 25]. So, cooperative spectrum sensing is an efficient solution for the problems facing CR networks with the detection of the PU in the cases of multi-path fading, hidden nodes, and shadowing media, and it provides a good protection of the PU from any interference [3, 9].

In cooperative spectrum sensing, the SU throughput and the efficient spectrum sensing are two contradictions. Good protection of the PU requires a large sensing time (τ), which minimizes the time of data transmission leading to a restriction on the achieved CR throughput [23, 27]. To overcome the restrictions of cooperative spectrum sensing with fixed a sensing time, the sensing time must be estimated adaptively according to the received SNR. So, in this paper, we propose a scheme, which adaptively computes the optimum sensing time for the SUs based on the received SNR by investigating the achieved throughput for every value over the SNR range of −20 dB to 10 dB with different values of the sensing time (0.1 ms to 2 ms) with a step of 0.1 ms. We evaluate the value of the sensing time that provides the maximum achievable throughput for each value of the SNR by curve fitting to get an empirical equation that enables calculation of the optimal sensing time, which provides the maximum throughput for each value of the SNR.

The rest of this paper is organized as follows. In section 2, the energy detector is described. In addition, cooperative spectrum sensing with different fusion rules is described in Section 3. Section 4 presents the throughput of cooperative CR. Section 5 presents the proposed scenarion for adaptively computed optimal sensing times. Section 6 gives the simulation results and discussion. Section 7 gives a comparison between the fusion rules. Finally, section 8 gives the concluding remarks of the paper.

2 Energy detection

Energy detection is used to identify the absence or presence of a signal in a specific band. It is the simplest and the widely-used spectrum sensing technique. Energy detection does not need any prior knowledge about the PU. It also ignores the structure of the signal. It needs information about the noise power to determine the threshold of detection. Energy detection is not the optimal but the simplest detection technique to be implemented with low computational cost. In energy detection, the PU is detected by comparing the output energy with an energy threshold [1, 9, 21]. So, there are challenges that face the energy detection such as the selection of the detection threshold, the poor performance of detection in the case of low SNR, and the inability to distinguish between the PU and noise [22]. Based on the energy detection concept, both cooperative and non-cooperative spectrum sensing scenarios using K-OUT-OF-M, logical OR, and logical AND are studied in this paper.

The SU has to sense the spectrum to know if the PU is present or absent. If the SU detects that PU is absent, it begins to use the PU spectrum. The received signal at the SU with bandwidth w, sampling frequency f_s, and carrier frequency f_c can be modeled as follows [23, 26]:

$$r(n) = \begin{cases} u(n) & ,H_0 \\ h*s(n) + u(n) & ,H_1 \end{cases} \tag{1}$$

where $s(n)$ represents the transmitted signal from the PU, $r(n)$ represents the received signal at the SU, h represents the complex channel gain, and $u(n)$ represents the Additive White Gaussian Noise (AWGN). Hypotheses H_1, and H_0 represent the presence and absence of the PU, respectively. In channel sensing, we are interested in the probability of false alarm (P_f). A false alarm occurs, when the sensing algorithm detects a PU under hypothesis H_0. The lower the P_f, the higher the ability to use the PU channel. On the other hand, the probability of detection P_d is required to be high. The correct detection takes place, when the sensing algorithm detects the PU under hypothesis H_1 [121].

In this work, we use the energy detector as a channel sensing algorithm. The test statisty of the energy detector is given by:

$$T(y) = \frac{1}{N} \sum_{n=1}^{N} |y(n)|^2 \tag{2}$$

Under H_0, $T(y)$ is a random variable with Chi-square Probability Density Function (PDF) having $2N$ degrees of freedom. With central limit theorem for a large N, the PDF of $T(y)$ can be approximated by a Gaussian distribution with

$$\text{Mean}\,\mu_0 = \sigma_u^2,$$
$$\text{Variance}\,\sigma_0^2 = \frac{1}{N}\left[E|u(n)|^4 - \sigma_u^4\right]$$

If $u(n)$ is circular symmetric complex Gaussian, then

$$E|u(n)|^4 = 2.\sigma_u^4, \text{and hence } \sigma_0^2 = \frac{1}{N}.\sigma_u^4$$

For a chosen threshold ϵ, the probability of false alarm is given by:

$$\begin{aligned} P_f(\epsilon) = P_r(T(y) > \epsilon|H_0) &= \frac{1}{\sqrt{2\pi\sigma_0}} / \int_{\epsilon}^{\infty} e^{-(T(y)-\mu_0)^2/2\sigma_0{}^2} \\ &= Q\left(\left(\frac{\epsilon}{\sigma_u^2} - 1\right)\sqrt{N}\right) \end{aligned} \tag{3}$$

With central limit theorem, the PDF of $T(y)$ under H_1 can be approximated by Gaussian distribution with

$$\begin{aligned} &\text{Mean}: \mu_1 = \left(\sigma_u^2 + \sigma_s^2\right) \\ &\text{Variance}: \sigma_1^2 = \frac{1}{N}\left[E|s(n)|^4 + E|u(n)|^4 - \left(\sigma_u^2 - \sigma_s^2\right)^2\right] \end{aligned}$$

where $s(n)$ and $u(n)$ are both circular symmetric and complex.

Assume that s (n) is a complex PSK modulated signal and $E|s(n)|^4 = \sigma_s^4$. Then,

$$\sigma_1^2 = \frac{1}{N}\sigma_u^4(1+\gamma)$$

where $\gamma = \frac{\sigma_s^2}{\sigma_u^2}$ is the primary user's signal power-to-noise ratio received at the SU. For a chosen threshold ϵ, the probability of detection is given by:

$$P_d(\epsilon\ ) = P_r(T(y) > \epsilon|H_1) = Q\left(\left(\frac{\epsilon}{\sigma_u^2} - \gamma - 1\right)\sqrt{\frac{N}{2\gamma+1}}\right) \tag{4}$$

where $Q(.)$ refers to Q-function, y refers to the received SNR from the PU at the SU, τ refers to the sensing time, σ_u^2 is the noise variance, and ϵ refers to the decision threshold, which can be determined for a known target probability of detection $\left(\overline{P_d}\right)$ form Eq. (3) as follows:

$$\epsilon = \sigma_u^2\left(Q^{-1}\left(\overline{P_d}\right)\sqrt{\frac{2\gamma+1}{N}} + \gamma + 1\right) \tag{5}$$

3 Cooperative spectrum sensing

For multi-path fading or networks with shadowing, it is difficult to detect the presence of the PU by a single user due to the low received SNR from the PU to the SU. As shown from Fig. 2, the received SNR from the PU at SU_1 and SU_2 is affected by trees and buildings. So, the detection of SU_1 and SU_2 is inaccurate. Hence, all users must cooperate to detect the PU in order to minimize the probability of miss detection and the probability of false alarm [1, 26].

Cooptation for detection of the PU presence can be performed with two methods: centralized and decentralized. In centralized schemes, there is a central Base Station (BS) or fusion center. Each SU preforms its local sensing, determines its local decision about the PU, and sends its decision to the central fusion center. The fusion center combines all SUs decisions according to a fusion rule. In decentralized schemes, there is no central fusion center. Each SU

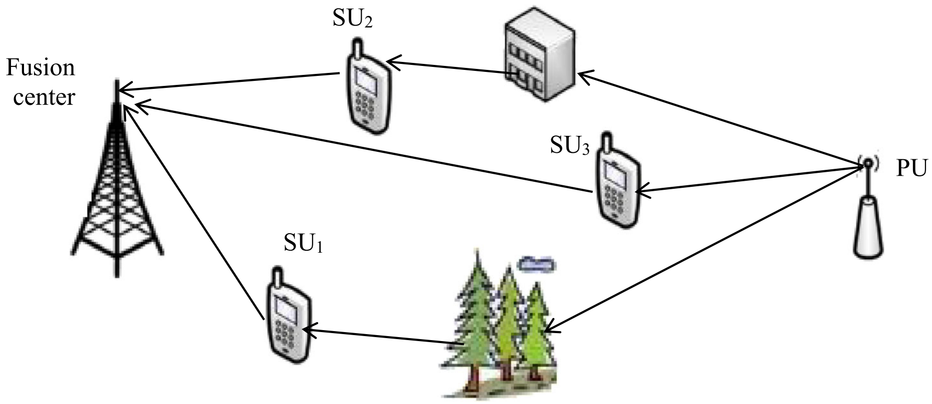

Fig. 2 Cooperative spectrum sensing model

sends its local decision to the neighboring SU. Then, each SU combines the received decisions with its local decision to get the final decision according to the fusion rule. Assuming that the D_i binary local decisions of the SUs ϵ{0,1} refer to the local spectrum sensing of SUs. Specifically, {0} indicates PU absence, and {1} indicates PU presence. In the fusion center, all bits are fused according to the following rule,

$$I = \sum_{i=1}^{M} D_i \begin{cases} < K & for\ H_0 \\ \geq K & for\ H_1 \end{cases} \tag{6}$$

It can be seen that AND rule decides primary user existence if $K = M$, the OR decides primary user existence if $K = 1$ and MAJORITY rule decides primary user existence if $K \geq M/2$ [13, 15].

In centralized and decentralized schemes, cooperation in detection of the PU can be performed as follows [9]:

1- Every SU preforms its local sensing and creates its local decision or measured value depending on the type of the fusion center.
2- Every cooperative SU sends its decision to the fusion center or the other SUs.
3- The fusion center of the SU combines all user decisions depending on the fusion rule.

Centralized and decentralized cooperative network fusion rules are adopted in the literature. The performance of these rules is discussed in the following sub-sections [7, 13, 15]:

3.1 AND rule

In this fusion rule, the fusion center decides that the PU is present if all SUs decide that it is present. Otherwise, the absence of the PU is decided. The AND rule provides a very small false alarm probability, which makes efficient spectrum utilization. On the other hand, it may not provide good protection for the PU form interferences from the SUs. As a result, quality of service for the PU is not sufficient [9]. Performance of cooperative spectrum using AND fusion rule is evaluated by the calculation of the following probabilities:

$$Q_f = \prod_{i=1}^{M} P_{f,i} \tag{7}$$

$$Q_d = \prod_{i=1}^{M} P_{d,i} \tag{8}$$

$$Q_m = 1 - Q_d = 1 - \prod_{i=1}^{M} P_{d,i} \tag{9}$$

where $P_{f,\,i}$ denotes the probability of false alarm of each SU independently and $P_{d,\,i}$ denotes the probability of detection of each cognitive user independently, M denotes the number of cooperative users, Q_f denotes the cooperative probability of false alarm, and Q_d denotes the cooperative probability of detection.

3.2 OR fusion rule

The OR fusion rule, in contrast to the AND fusion rule, gives a positive decision if $K = 1$. It provides very low probability of mis-detection and good protection to the PU. On the other hand, it provides slightly high probability of false alarm, which makes it inefficient in the utilization of the spectrum resources. Performance of cooperative energy detection using OR fusion rule is evaluated by the calculation of the following probabilities as follows:

$$Q_f = 1 - \prod_{i=1}^{M} \left(1 - P_{f,i}\right) \tag{10}$$

$$Q_d = 1 - \prod_{i=1}^{M} \left(1 - P_{d,i}\right) \tag{11}$$

$$Q_m = 1 - Q_d = \prod_{i=1}^{M} \left(1 - P_{d,i}\right) \tag{12}$$

3.3 MAJORITY fusion rule

MAJORITY fusion rule gives a positive decision if $K = M/2$. The fusion center decides that the PU is present if more than $M/2$ SUs decisions belong to H_1. Performance of cooperative energy detection using MAJOURITY fusion rule is evaluated by the calculation of the following probabilities as follows [7, 13, 17]:

$$Q_f = \sum_{i=M/2}^{M} \binom{M}{i} \left(P_{f,i}\right)^i \left(1 - P_{f,i}\right)^{M-i} \tag{13}$$

$$Q_d = \sum_{i=M/2}^{M} \binom{M}{i} \left(P_{d,i}\right)^i \left(1 - P_{d,i}\right)^{M-i} \tag{14}$$

$$Q_m = 1 - Q_d = 1 - \sum_{i=\frac{M}{2}}^{M} \binom{M}{i} \left(P_{d,i}\right)^i \left(1 - P_{d,i}\right)^{M-i} \tag{15}$$

4 Throughput performance of cooperative CR using fixed sensing time

In the previous explanation, probability of detection, probability of false alarm and probability of miss-detection have been considered as the main indicators of detection performance. In this section, we will explain the relation between the sensing time and the achievable throughput of the SU [20]. Transmission frame structure is shown in Fig. 3. It consists of the sensing time denoted by τ and the transmission time denoted by (T- τ).

Study of the achievable CR throughput is explained in two cases: the achievable throughput of the SU when it operates in the absence of the PU ($C_0 = \log_2(1 + SNR_S)$), and the achievable throughput of the SU when it operates in the presence of the PU ($C_1 = \left(1 + \frac{SNR_s}{SNR_P+1}\right)$), where SNR_S is SNR of the SU and SNR_p is the SNR of the PU received at the SU [8, 16]. The average throughput can be evaluated as follows:

- Case 1: when the PU is abscent and no false alarm is generated by the SU.

$$R_0 = \frac{T-\tau}{T}\left(1-Q_f\right)P\left(H_0\right)C_0 \tag{16}$$

- Case 2:- when the PU is present and not detected by the SU

$$R_1 = \frac{T-\tau}{T}\left(1-Q_d\right)P\left(H_1\right)C_1 \tag{17}$$

Total average achievable throughput is,

$$R = R_1 + R_0 \tag{18}$$

It is seen from Eqs. (16) and (17) that the achievable throughput is a function of the sensing time, the probability of detection, the probability of false alarm, and PU activity. Also, we can see from Eq. (16) that maximization of $\boldsymbol{R_0}$ requires minimization of the probability of false alarm. To decrease the probability of false alarm, the sensing time should be increased, which leads to a decrease of R_0. So, we have to find the optimal sensing time, which maximizes the achievable throughput with an acceptable probability of false alarm. Performance of cooperative spectrum sensing using a fixed sensing time is investigated with two values of the sensing time τ = 0.1 ms and τ =2 ms, $P(H_1) = 0.2$, $\overline{Q_d}$ = 0.9, f_s=106 Hz, and number of cooperative users equal to five users as a function of the received SNR at the SU.

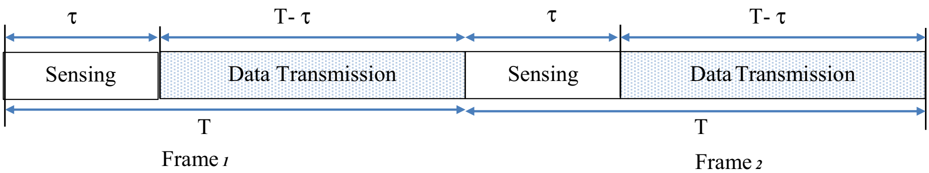

Fig. 3 Frame structure

4.1 Throughput performance using logical AND fusion rule

Figures 4 and 5 present the performance of cooperative spectrum sensing using a fixed sensing time in terms of throughput and probability of false alarm at a long sensing time $\tau = 2$ ms and a short sensing time $\tau = 0.1$ ms. Figure 4 shows that the utilization of a long sensing time in the low SNR range (SNR < −9 dB) provides a high CR throughput. On the other hand, it provides an efficient performance (lower probability of false alarm) as shown in Fig. 5. In this low range of SNR, there is high noise power, which needs a long sensing time to provide a small probability of false alarm and high throughput at the same time. In this low range of SNR, probability of false alarm is considered as the main factor to achieve high throughput.

In the higher *SNR* range (*SNR* > −9 dB), Fig. 4 shows that the utilization of a short sensing time provides higher throughput than that can be achieved by using a long sensing time and provides an accepted level of probability of false alarm as shown in Fig. 5. In this range of *SNR*, the probability of false alarm goes to zero, and the achievable CR throughput mainly depends on the sensing time value.

4.2 Throughput performance using logical OR fusion rule

As shown in Fig. 6, the achievable throughput for $\tau = 0.1$ ms is nearly a constant value of 5.3 bits/s for $SNR \geq -5$ dB due to the very low probability of false alarm, which tends to zero in this range as shown in Fig. 7. For $\tau = 2$ ms, the achievable throughput is significantly lower than that at $\tau = 0.1$ ms, and has a constant value of 3.2 bit/s for $SNR \geq -12$ dB due to the very low probability of false alarm, which tends to zero in this range as shown in Fig. 7.

In addition, it is shown that in the low range of *SNR* ($SNR < -10$ dB), the achievable throughput using a long sensing time ($\tau = 2$ ms) is higher than that can be obtained using a short sensing time ($\tau = 0.1$ ms) due to the low SNR values, which need a long sensing time to minimize the probability of false alarm and to get a high throughput. On the other hand, when $SNR > -10$ dB, the utilization of a short sensing time ($\tau = 0.1$ ms) provides a higher throughput than that can be achieved using a long sensing time ($\tau = 2$ ms), because in this range of SNR, a short sensing time is fair enough to minimize the probability of false alarm, which leads to maximizing the throughput.

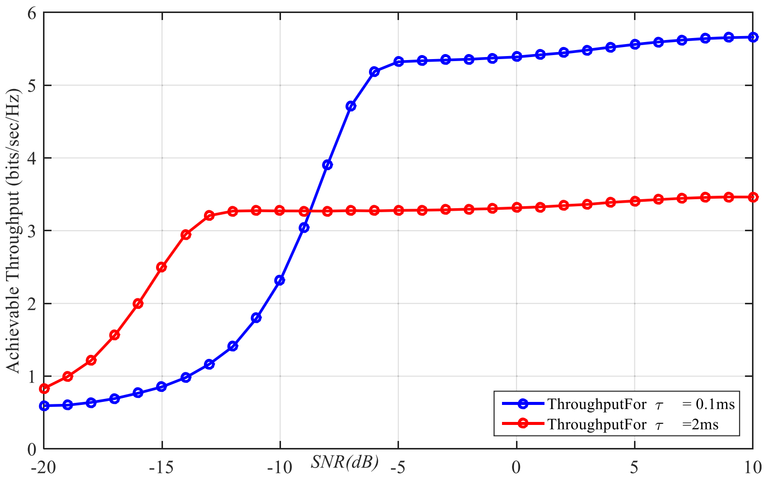

Fig. 4 Achievable throughput versus *SNR* at $\tau = 0.1$ ms and $\tau = 2$ ms for logical AND fusion rule

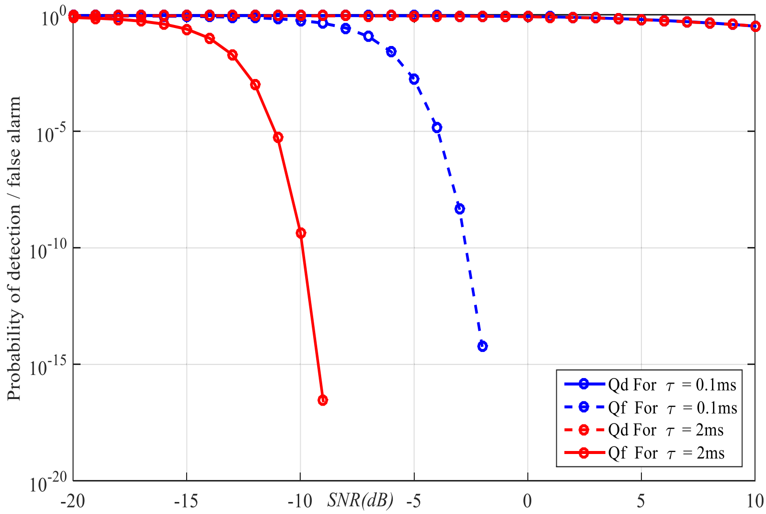

Fig. 5 Probability of detection and probability of false alarm versus *SNR* at τ = 0.1 ms and τ= 2 ms for logical AND fusion rule

From these simulation experiments, we can notice that to get a maximum throughput, we have to use a long sensing time at low levels of *SNR* and a short sensing time at high levels of *SNR*. This proves that the utilization of a fixed sensing time does not provide a maximum throughput for all values of *SNR*.

4.3 Throughput performance using MAJORITY fusion rule

Figure 8 shows that using a long sensing time at low *SNR* ($SNR < -11$) provides a high throughput. On the other hand, it provides a lower probability of false alarm as shown in Fig. 9. In this low range of *SNR*, there is a high noise power, which needs long

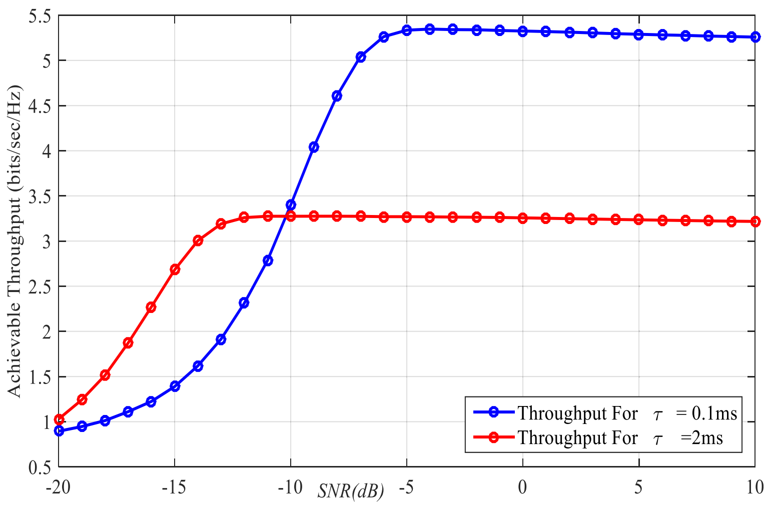

Fig. 6 Achieved throughput as a function of SNR at τ = 0.1 ms and τ = 2 ms for logical OR fusion rule

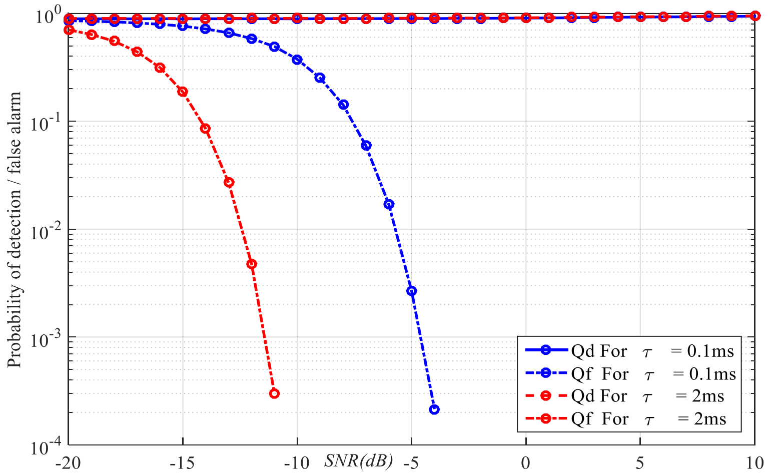

Fig. 7 Probability of detection and probability of false alarm as a function of SNR at τ = 0.1 ms and τ= 2 ms for logical OR fusion rule

sensing time to provide a small probability of false alarm and a high throughput at the same time.

In the higher *SNR* range (*SNR* > -11 dB), Fig. 8 shows that using a short sensing time provides higher throughput than that can be achieved by using a long sensing time and provides an accepted level of probability of false alarm as shown in Fig. 9. In this range of SNR, the probability of false alarm goes to zero, and the achievable throughput mainly depends on the sensing time. So, we can conclude that using a fixed sensing time does not provide efficient performance for all values of *SNR*. At high *SNR* values, the utilization of a short sensing time enhances the throughput performance. So in this paper, a cooperative spectrum sensing scheme is proposed to adaptively control the sensing process according to the value of the *SNR* to maximize the CR throughput using MAJORITY fusion rule.

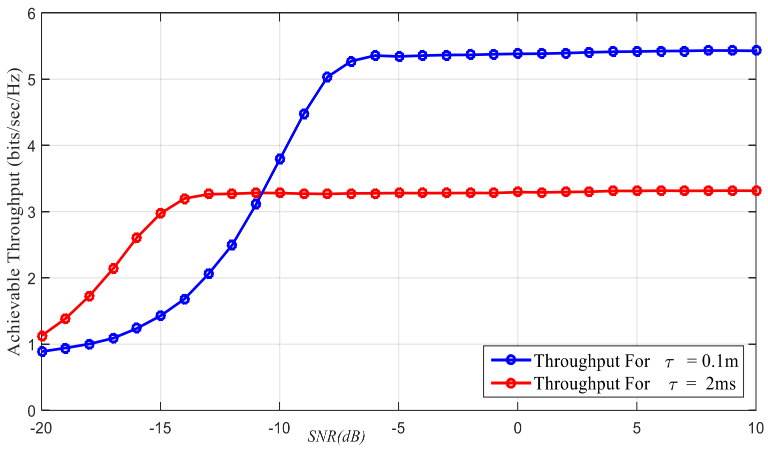

Fig. 8 Achievable throughput versus SNR at τ = 0.1 ms and τ = 2 ms for MAJORITY fusion rule

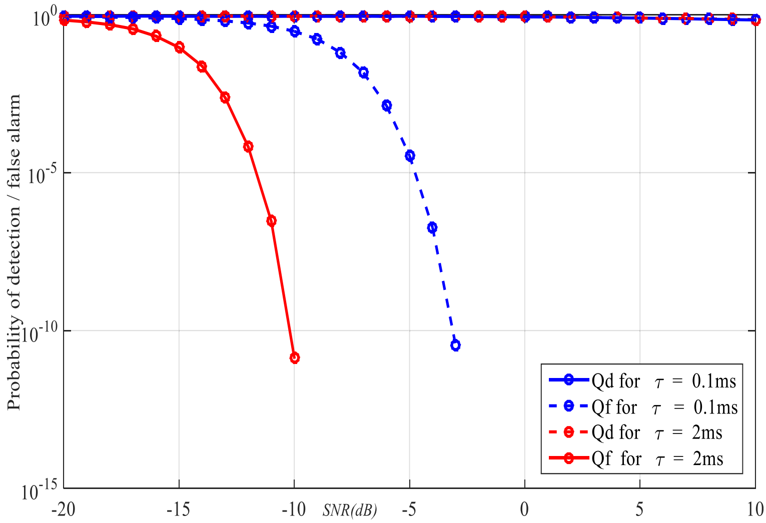

Fig. 9 Probability of detection and probability of false alarm versus SNR at τ = 0.1 ms and τ= 2 ms for MAJORITY fusion rule

Form the simulation of all fusion rules, we conclude that the utilization of a fixed sensing time does not provide an efficient performance for all values of *SNR*, and at high SNR values, the sensing time should be smaller than that used at low *SNR* values to enhance the throughput performance. So in this paper, a cooperative spectrum sensing scheme is proposed to adaptively compute the optimal sensing according to the value of the *SNR* to optimize the CR throughput.

5 The proposed adaptive sensing time scheme for Cooperative CR

The main goal of the proposed adaptive sensing time scheme is to minimize the sensing time to maximize the transmission time, which consequently maximizes the achievable data throughput for cooperative CR with different fusion rules. It is also required to eliminate the problem of inefficient performance due to using a fixed sensing time for all values of SNR, and seek for the acceptable probability of false alarm with the maximum achievable throughput. In the proposed scheme, the sensing time is dynamically adapted according to the received *SNR* at the SU to get the maximum throughput as shown from Fig. 10.

Figure 10 shows that proposed scheme dynamically adapts the sensing time for cooperative spectrum sensing by determining the optimal sensing time according to the received *SNR* at the SU. Each SU estimates its optimal sensing time, which achieves the maximum throughput depending on the received *SNR* form the PU as will be explained in the following sub-sections for each fusion rule. Then, each SU estimates the received signal energy, and compares it with a known threshold to decide if the PU is present or not. Finally, the fusion center collects all SUs decisions and combines them according the used fusion rule using Eq. (6) to take the final decision about the presence or absence of the PU.

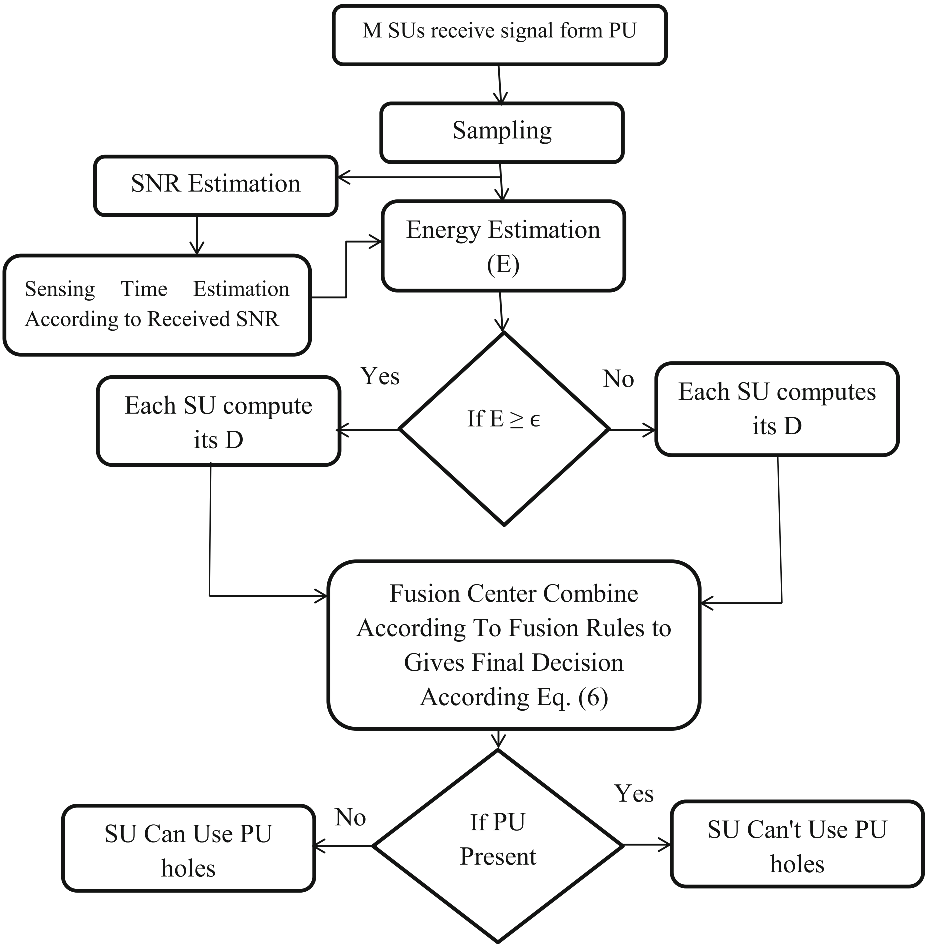

Fig. 10 Flowchart of the proposed sensing time adaptation scheme according to the *SNR* value

To obtain the optimum value of the sensing time (number of samples), which maximizes the achievable throughput and minimizes the probability of false alarm for each *SNR* value, we simulate the achievable throughput versus *SNR* in the range of −20 to 10 dB with a step of 1 dB for a sensing time ranging form $\tau = 0.1$ ms to $\tau = 2$ ms for each fusion rule as will be shown below.

5.1 Adaptive sensing time estimation for AND fusion rule

In Table 1, we investigate the achievable throughput versus *SNR* with a sensing time (τ) ranging from 0.1 ms to 2 ms and step 0.1 ms using AND fusion rule. From the table, we can find the optimum sensing time, which gives the maximum achievable throughput for each value of the *SNR* and plot it versus *SNR* as shown in Fig. 11.

Figure 11 shows a curve for the sensing time versus *SNR*. It provides the maximum throughput for the utilized SNR range. Since the proposed scheme aims to find a relationship

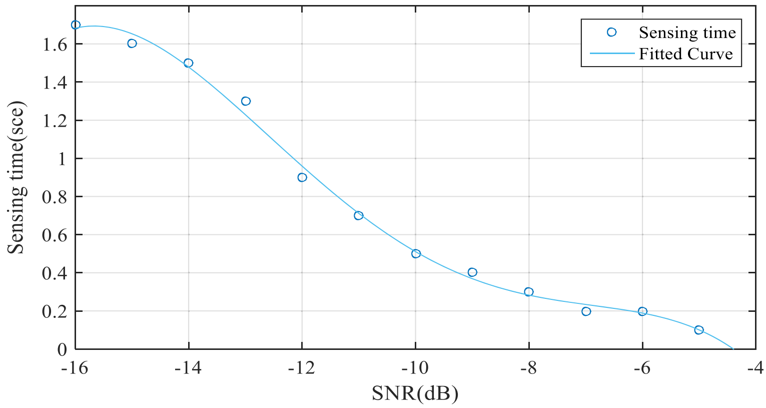

Fig. 11 Sensing time, which achieves the maximum throughput versus *SNR* using AND fusion rule

for the optimum sensing time to maximize the throughput based on SNR, curve fitting will be adopted to find the mathematical relationship between sensing time (τ) and the *SNR* as follows:

$$\tau(x) = \left\{ \begin{array}{ll} 1.7ms & ;x \leq -16 \\ -0.00062x^4 - 0.024x^3 - 0.32x^2 - 1.8x^1 - 3.7 & ;-16 < x < -5 \\ 0.1ms & ;x \geq -5 \end{array} \right\} \tag{19}$$

where $x = SNR$.

Equation (19) demonstrates that the sensing time should be decreased form $\tau =$ 1.7 to 0.1 ms according to the *SNR* value to maximize the throughput and to get an efficient performance with all values of SNR.

Table 1 Achievable throughput for various values of SNR using τ ranging from 0.1 ms to 2 ms for AND fusion rule

	−16 dB	−14 dB	−12 dB	−10 dB	−8 dB	−6 dB	−5 dB
τ = 0.1 ms	0.763	0.977	1.422	2.338	3.909	5.195	5.321
τ = 0.2 ms	0.983	1.388	2.192	3.633	5.011	5.225	5.229
τ = 0.3 ms	1.147	1.679	2.794	4.346	5.091	5.120	5.125
τ = 0.4 ms	1.294	1.969	3.233	4.672	5.009	5.016	5.020
τ = 0.5 ms	1.398	2.183	3.583	4.760	4.897	4.904	4.911
τ = 0.6 ms	1.491	2.408	3.848	4.735	4.797	4.794	4.800
τ = 0.7 ms	1.609	2.574	3.993	4.666	4.685	4.689	4.694
τ = 0.8 ms	1.671	2.715	4.084	4.571	4.574	4.583	4.586
τ = 0.9 ms	1.742	2.839	4.123	4.461	4.466	4.472	4.480
τ = 1 ms	1.804	2.948	4.118	4.361	4.360	4.366	4.370
τ = 1.1 ms	1.839	3.008	4.084	4.249	4.258	4.253	4.261
τ = 1.2 ms	1.896	3.062	4.033	4.143	4.144	4.147	4.150
τ = 1.3 ms	1.923	3.089	3.963	4.034	4.038	4.041	4.041
τ = 1.4 ms	1.958	3.109	3.876	3.926	3.923	3.929	3.935
τ = 1.5 ms	1.981	3.110	3.783	3.813	3.817	3.822	3.822
τ = 1.6 ms	1.995	3.104	3.684	3.707	3.708	3.712	3.716
τ = 1.7 ms	2.011	3.080	3.584	3.599	3.597	3.601	3.606
τ = 1.8 ms	2.004	3.053	3.481	3.492	3.493	3.489	3.498
τ = 1.9 ms	2.003	3.006	3.374	3.380	3.382	3.385	3.386
τ = 2 ms	1.998	2.960	3.268	3.270	3.273	3.272	3.279

5.2 Adaptive sensing time estimation using OR fusion rule

In Table 2, we investigate the achievable throughput versus SNR with a sensing time (τ) ranging from 0.1 ms to 2 ms with a step of 0.1 ms using OR fusion rule. From Table 2, we can find the optimum sensing time, which gives the maximum throughput for each value of *SNR* and plot it versus SNR as presented in Fig. 12.

Curve fitting is applied to the plotted points of Fig. 12 to obtain a mathematical relationship for the optimum sensing time (τ) as a function of *SNR* as follows:

$$\tau(x) = \left\{ \begin{array}{ll} 1.6ms & ; x < -16 \\ -2.9*10^{-5}x^6 - 0.002x^5 - 0.055x^4 - 0.81x^3 & \\ \quad -6.5x^2 - 27*x^1 - 47 & ; -16 < x < -6 \\ 0.1ms & ; x \geq -6 \end{array} \right\} \tag{20}$$

where $x = SNR$.

Form Eq. (20), we can notice that the sensing time should be decreased form $\tau = 1.6$ ms to 0.1 *ms* as the *SNR* increases to maximize the throughput.

5.3 Adaptive sensing time estimation using MAJORITY fusion rule

The achievable throughput versus SNR with a sensing time ranging from 0.1 ms to 2 ms and a step of 0.1 ms using MAJORTY fusion rule is given in Table 3. From table 3, we can find the optimum sensing time which gives the maximum throughput for each value of the *SNR* and plot it as a function of the *SNR* as shown in Fig. 13.

Curve fitting operation is applied to obtain a mathematical relationship for the optimum sensing time (τ), which maximizes the throughput as a function of *SNR* as follows:

Table 2 Achievable throughput for various values of *SNR* using a value of τ ranging from τ =0.1 ms to τ =2 ms with logical OR fusion rule

	−16 dB	−15 dB	−13 dB	−12 dB	−11 dB	−10 dB	−9 dB	−8 dB	−7 dB	−6 dB
τ = 0.1 ms	1.227	1.391	1.927	2.306	2.787	3.392	4.039	4.626	5.045	5.263
τ = 0.2 ms	1.448	1.691	2.475	3.007	3.640	4.274	4.780	5.089	5.215	5.235
τ = 0.3 ms	1.609	1.935	2.877	3.496	4.123	4.635	4.962	5.099	5.128	5.129
τ = 0.4 ms	1.752	2.128	3.181	3.798	4.369	4.766	4.956	5.015	5.023	5.021
τ = 0.5 ms	1.877	2.293	3.402	4.001	4.486	4.780	4.890	4.913	4.913	4.913
τ = 0.6 ms	1.966	2.432	3.567	4.132	4.518	4.731	4.794	4.803	4.804	4.801
τ = 0.7 ms	2.063	2.539	3.679	4.187	4.513	4.654	4.691	4.692	4.693	4.691
τ = 0.8 ms	2.154	2.636	3.748	4.198	4.466	4.564	4.581	4.585	4.585	4.581
τ = 0.9 ms	2.210	2.703	3.788	4.191	4.398	4.466	4.474	4.475	4.474	4.473
τ = 1 ms	2.247	2.749	3.804	4.143	4.318	4.362	4.370	4.366	4.368	4.366
τ = 1.1 ms	2.296	2.791	3.794	4.089	4.225	4.255	4.258	4.258	4.256	4.255
τ = 1.2 ms	2.319	2.828	3.757	4.021	4.124	4.148	4.150	4.146	4.147	4.143
τ = 1.3 ms	2.334	2.828	3.718	3.946	4.024	4.037	4.039	4.041	4.036	4.037
τ = 1.4 ms	2.357	2.846	3.662	3.855	3.920	3.932	3.930	3.929	3.929	3.927
τ = 1.5 ms	2.352	2.836	3.605	3.766	3.813	3.820	3.821	3.821	3.818	3.819
τ = 1.6 ms	2.366	2.820	3.529	3.671	3.708	3.711	3.711	3.712	3.710	3.710
τ = 1.7 ms	2.350	2.792	3.454	3.571	3.600	3.602	3.603	3.603	3.600	3.600
τ = 1.8 ms	2.316	2.754	3.372	3.470	3.492	3.493	3.492	3.493	3.490	3.489
τ = 1.9 ms	2.302	2.724	3.279	3.368	3.383	3.385	3.386	3.382	3.382	3.381
τ = 2 ms	2.269	2.673	3.194	3.261	3.275	3.275	3.275	3.274	3.273	3.271

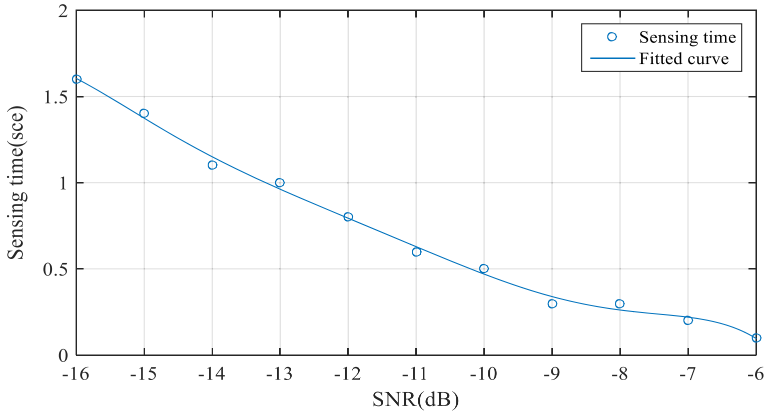

Fig. 12 Sensing time, which achieves the maximum throughput versus *SNR* using OR fusion rule

$$\tau(x) = \begin{cases} 1.6\ ms & x < -16 \\ -0.00066x^3 - 0.0091x^2\ 0.1x - 0.4 & -16 \leq x < -8 \\ 0.1\ ms & x > -8 \end{cases} \tag{21}$$

where $x = SNR$.

Equation (21) demonstrates that the sensing time should be decreased form $\tau = 2$ to 0.1 ms according to *SNR* to maximize throughput for all values of *SNR*.

In the following section, we will investigate the performance of proposed scheme compared to the performance of the fixed sensing time scheme with different fusion rules. In addition, a

Table 3 Achievable throughput for various values of SNR using τ ranging from τ =0.1 ms to 2 ms using MAJORTY fusion rule

	−15 dB	−14 dB	−13 dB	−12 dB	-11 dB	−10 dB	-8 dB
τ = 0.1 ms	1.4247	1.6804	2.0478	2.5227	3.0921	3.8037	5.0109
τ = 0.2 ms	1.8261	2.2244	2.7404	3.4020	4.0915	4.7191	5.2241
τ = 0.3 ms	2.1250	2.6273	3.2400	3.9394	4.5830	4.9670	5.1272
τ = 0.4 ms	2.3770	2.9270	3.6291	4.2635	4.7529	4.9684	5.0258
τ = 0.5 ms	2.5904	3.2132	3.8743	4.4515	4.7854	4.8999	4.9140
τ = 0.6 ms	2.7501	3.3798	4.0312	4.5135	4.7486	4.7958	4.8096
τ = 0.7 ms	2.8905	3.5378	4.1281	4.5143	4.6676	4.6781	4.7022
τ = 0.8 ms	3.0016	3.6172	4.1815	4.4760	4.5804	4.5914	4.5843
τ = 0.9 ms	3.0812	3.6972	4.1697	4.4154	4.4784	4.4668	4.4714
τ = 1 ms	3.1567	3.7202	4.1289	4.3196	4.3576	4.3703	4.3682
τ = 1.1 ms	3.1898	3.7458	4.0923	4.2309	4.2646	4.2632	4.2655
τ = 1.2 ms	3.2169	3.7380	4.0225	4.1404	4.1491	4.1503	4.1529
τ = 1.3 ms	3.2322	3.7009	3.9609	4.0393	4.0365	4.0397	4.0333
τ = 1.4 ms	3.2338	3.6594	3.8677	3.9287	3.9340	3.9278	3.9323
τ = 1.5 ms	3.2153	3.6127	3.7768	3.8232	3.8216	3.8248	3.8230
τ = 1.6 ms	3.1924	3.5252	3.6815	3.7116	3.7047	3.7104	3.7213
τ = 1.7 ms	3.1457	3.4659	3.5724	3.5983	3.6007	3.5980	3.6062
τ = 1.8 ms	3.1040	3.3741	3.4773	3.4979	3.4966	3.4878	3.4969
τ = 1.9 ms	3.0495	3.2919	3.3707	3.3740	3.3851	3.3886	3.3842
τ = 2 ms	2.9844	3.2039	3.2724	3.2696	3.2717	3.2800	3.2736

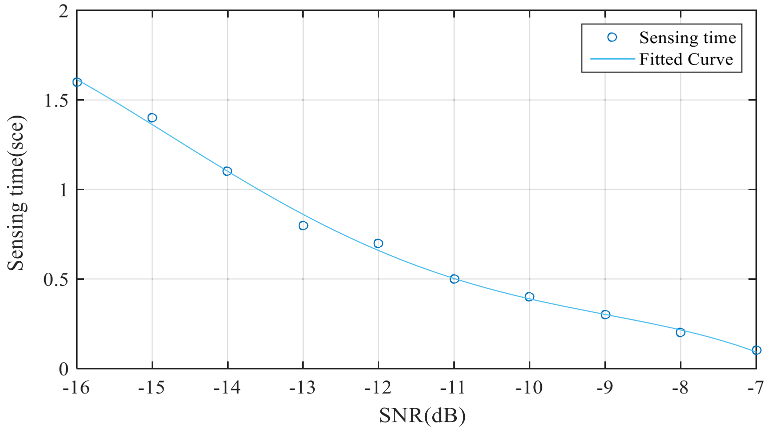

Fig. 13 Sensing time versus SNR using MAJORTY fusion rule

comparative performance evaluation study of the proposed scheme with different fusion rules is presented.

6 Performance evaluation and simulation results

6.1 Performance of the proposed scheme with AND rule

In this section, the performance of the proposed scheme compared to the performance of the fixed sensing time scheme with τ =0.1 ms and τ = 2 ms using AND fusion rule is presented. Figure 14 shows that the proposed scheme achieves significantly higher throughput than that achieved by the fixed sensing time scheme with long sensing time (τ =2 ms), when SNR is greater than −15 dB, because the adaptively computed sensing time with the proposed scheme is significantly lower than 2 ms, when *SNR* is greater than −15 dB. Also, it is shown that the proposed scheme significantly outperforms the fixed sensing time scheme with a small sensing

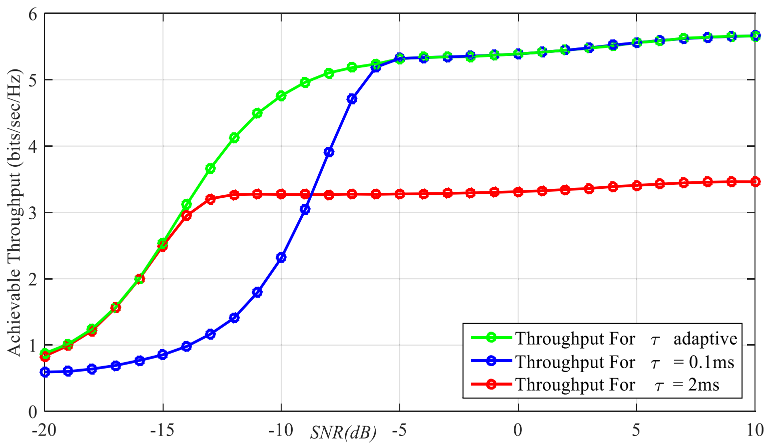

Fig. 14 Achievable throughput versus *SNR* at τ adaptive, τ = 0.1 ms, and τ = 2 ms for AND fusion rule

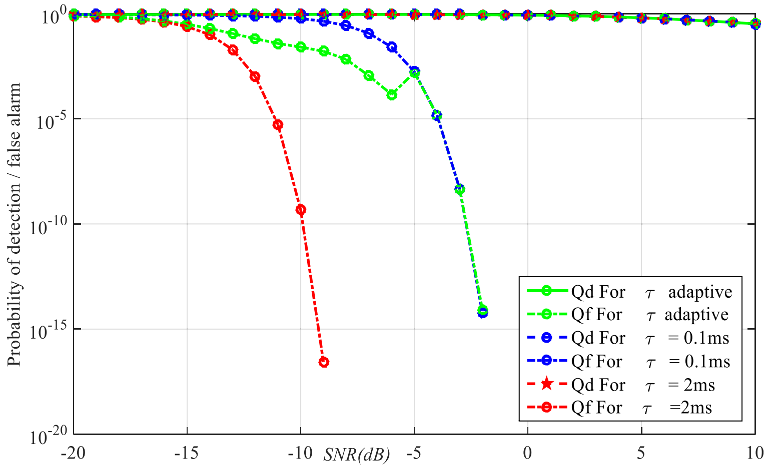

Fig. 15 Probability of detection and probability of false alarm versus *SNR* at τ adaptive, τ = 0.1 ms, and τ= 2 ms for AND fusion rule

time (τ =0.1 ms), when the *SNR* is lower than −5 dB. Both schemes provide the same throughput as *SNR* becomes greater than −5 dB. This is because the proposed scheme provides a lower probability of false alarm than that provided by the fixed sensing time scheme with a small sensing time (τ=0.1 ms), when the *SNR* is lower than −5 dB and both schemes provide the same probability of false alarm, when the *SNR* is greater than −5 dB, as shown in Fig. 15. Also, it is shown that the fixed sensing time scheme with large sensing time (τ=2 ms) provides the lowest probability of false alarm at the expense of the lowest achievable throughput. From these simulation results, we can notice that the proposed adaptively computed sensing time scheme provides the maximum throughput for all values of *SNR* with respect to the fixed sensing time scheme.

Effect of the number of SUs on the performance of the proposed adaptive sensing time scheme is investigated in Fig. 16. It is shown that at low *SNR* values (*SNR* < −10 dB), the

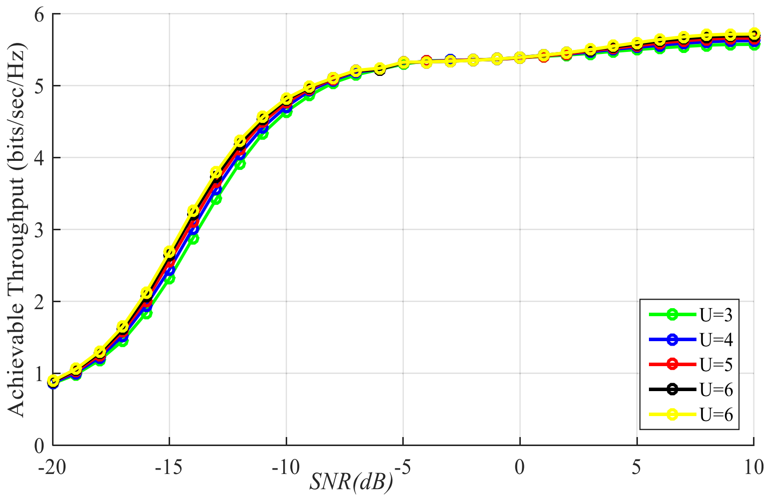

Fig. 16 Achievable throughput versus SNR at τ adaptive for a number of SUs =3, 4,5,6,7 using AND fusion rule

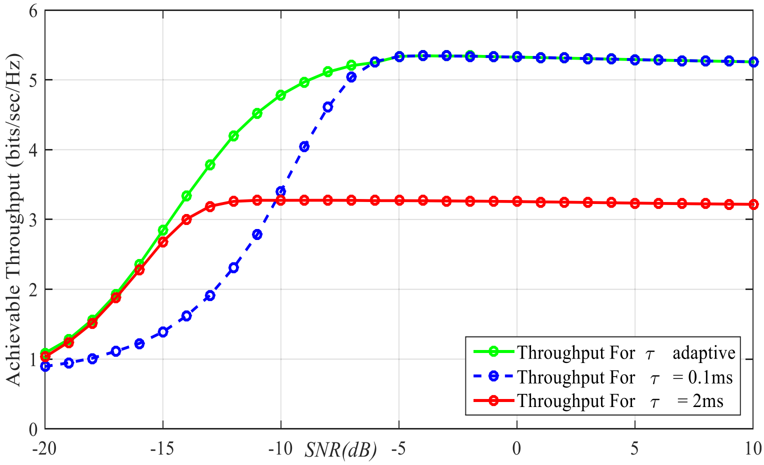

Fig. 17 Achievable throughput versus SNR at τ adaptive, τ = 0.1 ms, and τ = 2 ms for OR fusion rule

achievable throughput slightly increases as the number of SUs increases, while at high *SNR* values ($SNR > -10$ dB), there is no significant increase in the achievable throughput as the number of SUs increases.

6.2 Performance of the proposed scheme with OR fusion rule

In this section, the performance of the proposed adaptive sensing time scheme compared to the performance of the fixed sensing time scheme with τ =0.1 ms and τ =2 ms using OR fusion rule is investigated. As shown from Fig. 17, the achievable throughput by the proposed scheme becomes significantly higher than that of the fixed sensing time scheme with a long sensing time (τ =2 ms) as *SNR* becomes greater than −16 dB. On the other hand, the proposed scheme significantly outperforms the fixed sensing time scheme with a small sensing time (τ =0.1 ms), when *SNR* is lower than −6 dB, and both schemes provide the same throughput as *SNR*

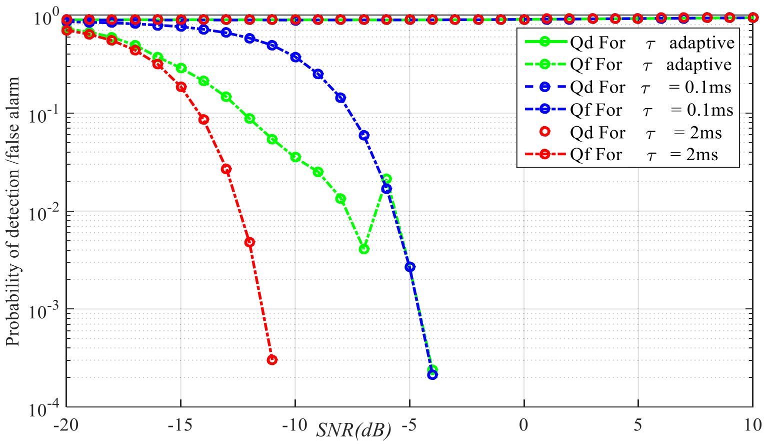

Fig. 18 Probability of detection and probability of false alarm versus SNR at τ adaptive, τ = 0.1 ms and τ = 2 ms forl OR fusion rule

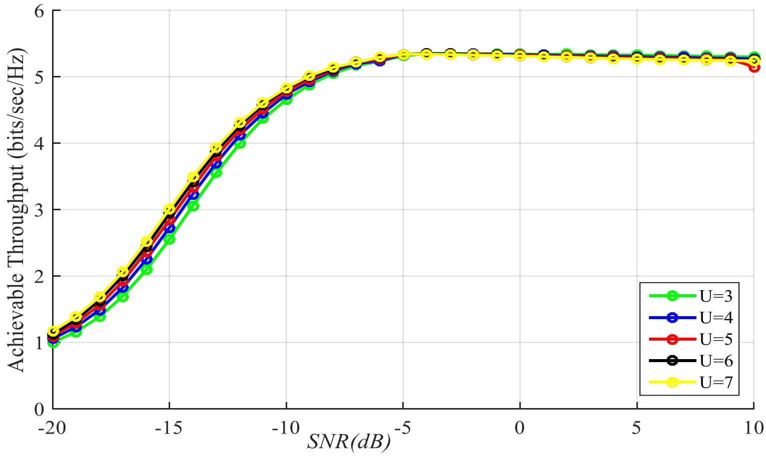

Fig. 19 Achievable throughput versus *SNR* at τ adaptive for number of SUs =3, 4,5,6,7 using OR fusion rule

becomes greater than −6 dB. So, it is obvious that the proposed scheme outperforms the fixed sensing time scheme with a short sensing time (τ =0.1 ms), and with long sensing time (τ =2 ms) as *SNR* ranges from −16 dB to −6 dB. Figure 18 shows that the proposed scheme provides a significantly lower probability of false alarm than that provided by the fixed sensing time scheme with small sensing time (τ =0.1 ms), when the *SNR* is lower than −6 dB and both schemes provide the same throughput as *SNR* becomes greater than −6 dB. On the other hand, the fixed sensing time scheme with long sensing time (τ =2 ms) provides the lowest probability of false alarm at the expense of the lowest achievable throughput.

Effect of the number of SUs on the performance of the proposed adaptive sensing time scheme is investigated in Fig. 19. It is shown that at low *SNR* values ($SNR < -11$ dB), the achievable throughput slightly increases as the number of SUs increases, while at high *SNR* values ($SNR > -11$ dB), there is no significant improvement in the achievable throughput as the number of SUs is increased.

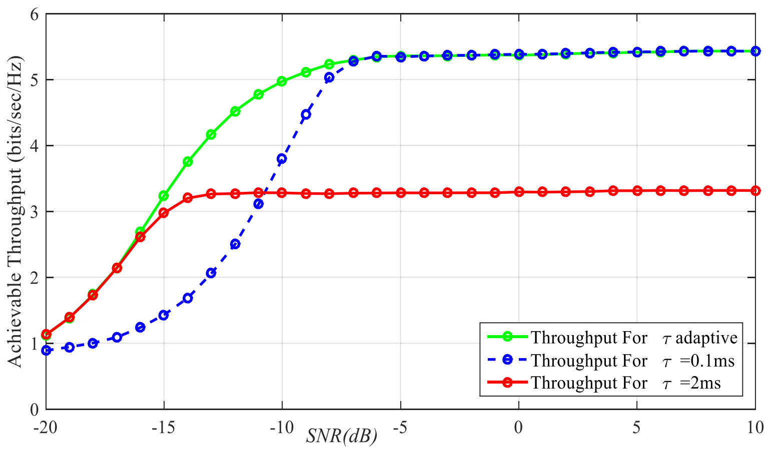

Fig. 20 Achievable throughput versus SNR at τ adaptive, τ = 0.1 ms, and τ = 2 ms for MAJORITY fusion rule

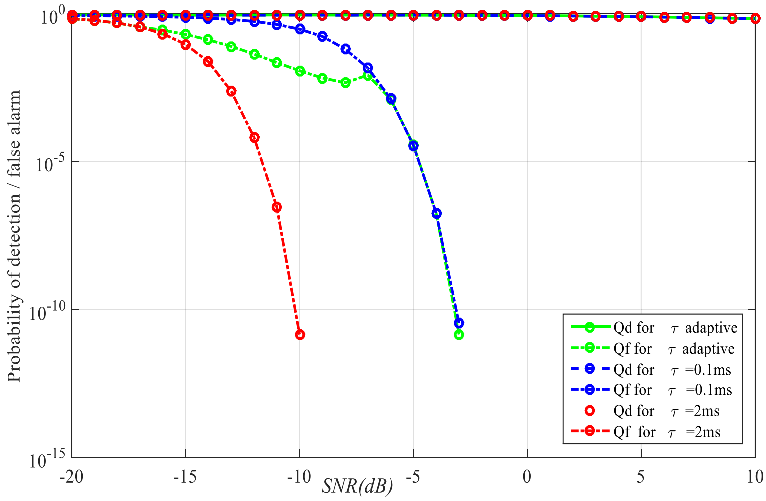

Fig. 21 Probability of detection and probability of false alarm versus *SNR* at τ adaptive, τ = 0.1 ms, and τ = 2 ms for MAJORITY fusion rule

6.3 Performance of the proposed scheme with MAJORITY fusion rule

In this section, the performance of the proposed adaptive sensing time scheme compared to the performance of the fixed sensing time scheme with τ =0.1 ms and τ =2 ms using MAJORITY fusion rule is investigated. Figure 20 shows that proposed scheme significantly outperforms the fixed sensing time scheme, since it achieves significantly higher throughput than that achieved by using a long sensing time (τ = 2 ms), when *SNR* is higher than −16 dB and significantly higher throughput than that achieved by the fixed sensing time scheme using a short sensing time (τ = 0.1 ms) when *SNR* is lower than −8 dB. In addition, the proposed scheme achieves the same throughput as that achieved by the fixed sensing time scheme using τ = 0.1 ms when *SNR* is higher than −8 dB, and provides throughput similar to that

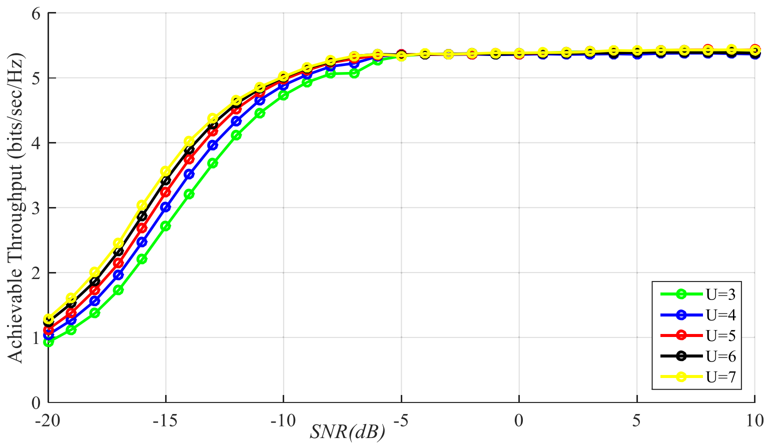

Fig. 22 Achievable throughput versus *SNR* at τ adaptive for numbers of SUs =3, 4,5,6,7 using MAJORITY fusion rule

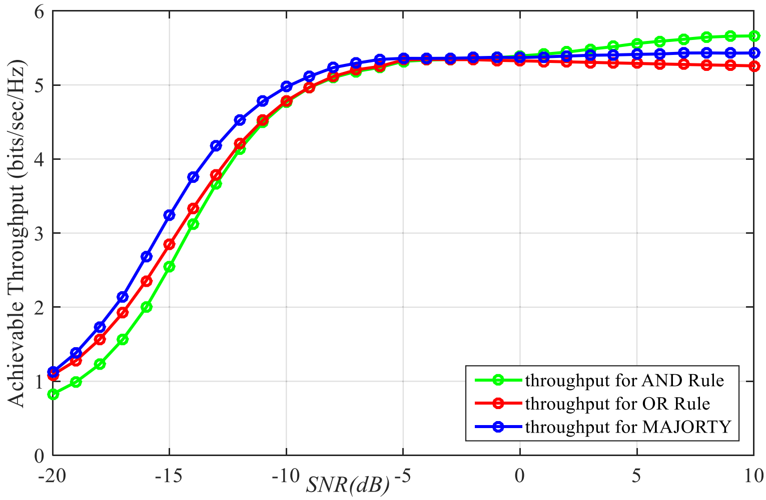

Fig. 23 Achievable throughput versus *SNR* at τ adaptive for AND rule, OR rule and MAJORITY rule

achieved by the fixed sensing time scheme using $\tau = 2$ ms, when SNR is lower than −16 dB. With respect to the probability of false alarm, the proposed scheme provides a lower probability of false alarm than that provided by using a fixed short sensing time ($\tau = 0.1$ ms) when *SNR* is lower than −7 dB as shown in Fig. 21. On the other hand, the fixed sensing time scheme with a long sensing time ($\tau = 2$ ms) provides the lowest probability of false alarm for all values of *SNR* at the expense of the lowest achievable throughput.

The effect of the number of SUs on the performance of the proposed adaptive sensing time scheme is presented in Fig. 22. It is shown that at low *SNR* values (*SNR* < −7 dB), the achievable throughput slightly increases as the number of SUs increases, while at high *SNR*

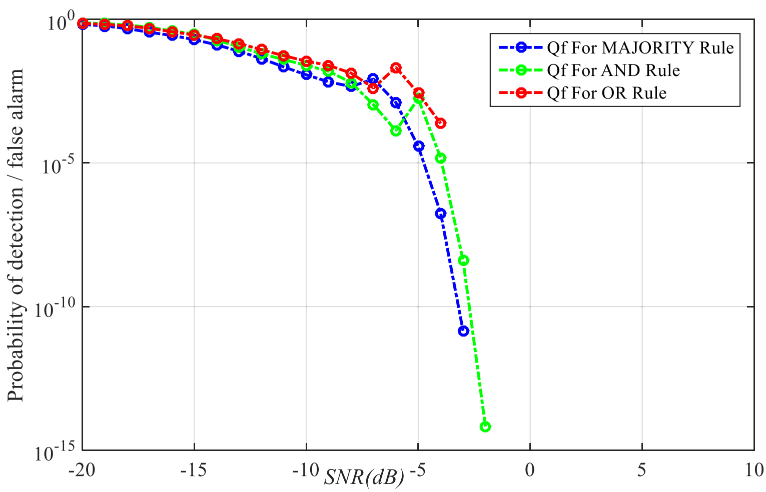

Fig. 24 Probability of detection and probability of false alarm versus *SNR* at τ adaptive for AND rule, OR rule and MAJORITY rule

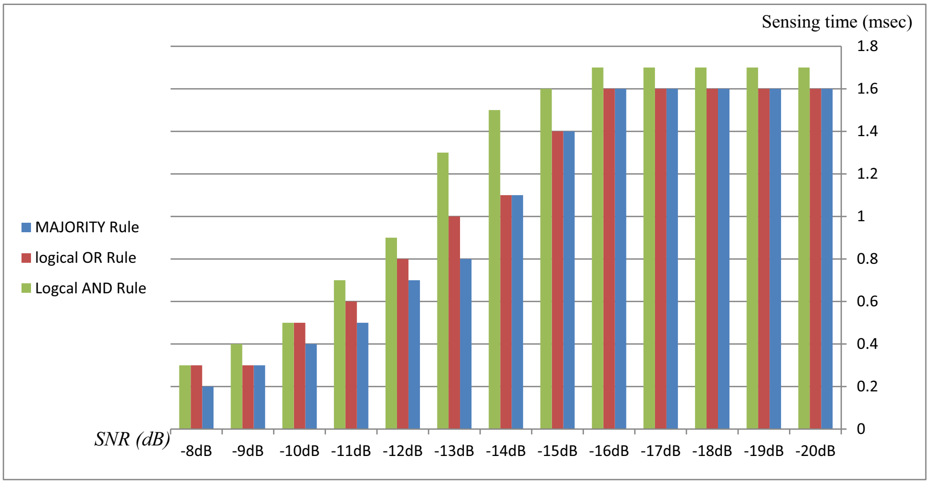

Fig. 25 Sensing time versus *SNR* with τ adaptive for AND rule, OR rule and MAJORITY rule

values (*SNR* > −7 dB), there is no significant improvement in the achievable throughput as the number of SUs is increased.

6.4 Performance comparison of the proposed scheme with different fusion rules

This section introduces a performance comparison of the proposed scheme with different fusion rules (AND, OR and Marjory). As shown form Fig. 23, the proposed scheme achieves the highest throughput using MAJORITY fusion rule and the lowest throughput using AND fusion rule, especially as *SNR* ≤ -5 dB. This is because the MAJORITY fusion rule not only provides the lowest probability of false alarm as shown in Fig. 24, but also requires the shortest

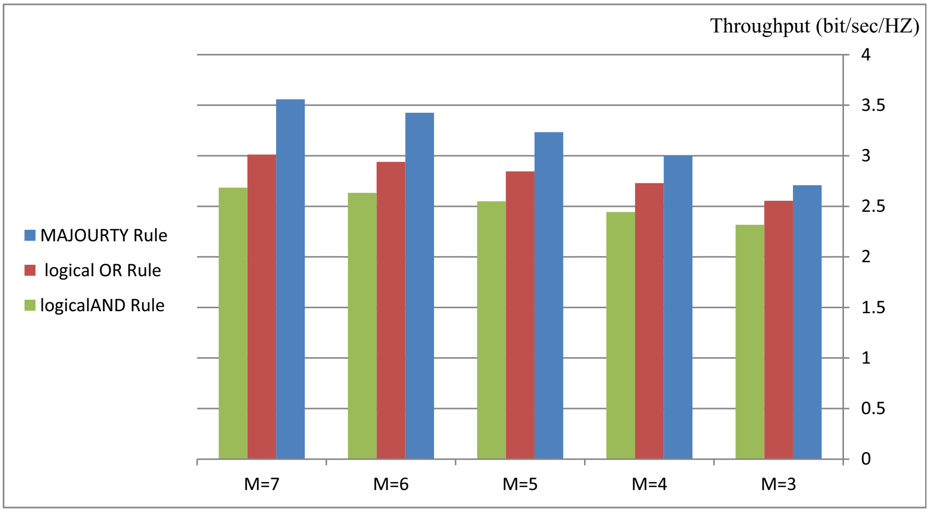

Fig. 26 Achievable throughput for *SNR* −15 dB with numbers of SUs =3, 4, 5, 6 and 7 for AND rule, OR rule and MAJORITY rule

sensing time as shown in Fig. 25. On the other hand, the AND fusion rule provides a slightly lower probability of false alarm than that of the OR fusion rule as shown in Fig. 24, but it provides a lower throughput at $SNR \leq$ -12 dB, because it requires the longest sensing time as shown in Fig. 25. The effect of the number of SUs on the achievable throughput of the proposed adaptive sensing time scheme with different fusion rules at SNR = -15 dB is presented in Fig. 16. It is clear that the MAJORITY fusion rule provides the maximum throughput for all numbers of SUs and the AND fusion rule provides the lowest throughput. In addition, the achievable throughput of the proposed adaptive sensing time scheme with different fusion rules increases as the numbers of SUs is increased Fig. 26.

7 Conclusion

In this paper, a cooperative spectrum sensing optimization scheme for CR using different fusion rules has been proposed. This scheme aims to avoid the inefficient spectrum utilization and throughput of fixed sensing time schemes. So, the proposed scheme adaptively computes the optimally minimized sensing time based on the value of the SNR at the receiver to maximize the throughput at all SNRs. Simulation results showed that proposed scheme significantly outperforms the fixed sensing time scheme in terms of the achievable throughput and the probability of false alarm. In addition, the proposed scheme provides a better performance as the number of SUs increases and with the Marjory fusion rule.

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