Decision-Making Rules in Cooperative Cognitive Radio Networks: Evaluation and Comparison

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ABSTRACT

Cognitive radio CR is a communication technology developed to solve the problem of spectrum scarcity. Energy detection based on cooperative spectrum sensing represents a solution to enhance the throughput of CR since the information about primary signal presence are collected using many sensing nodes with different channel conditions. Each node reports its own reports to the network centre to make its decision. However, the throughput cannot be maximized unless efficient decision rules are used to combine the collected information and produce right final judgment. In this paper, a centralized cooperative spectrum sensing scheme is used, and basic decision rules are presented. New decision-making rule based on statistical average of the node reports is proposed. Closed form expressions for probability of detection and false alarm probability for the different decision rules are given. Comparison on the throughput performance of each decision rule is studied simulated via a system model and MATLAB programming. Fading channel is assumed for data transmission, while the reporting channels are assumed to be free of errors.

Keywords: Cognitive radio, cooperative spectrum sensing, decision rules, energy detection.

1 Introduction

Emerging wireless devices and applications further accelerates the development of wireless systems. Such an exponential growth of wireless communication also imposes huge demands on radio spectrum. As a natural resource, radio spectrum is scarce and limited. Nowadays, the spectrum is managed by government agencies such as the Federal Communications Commission (FCC), and assigned to licensed users on a long term basis to avoid interference among wireless systems. Although this static allocation approach worked well in the past, it cannot serve the ever increasing demand for wireless communication well because of the problem of spectrum scarcity. Recent studies reveal that the allocated spectrum is underutilized. Some parts of spectrum remain largely underutilized; some parts are sparingly utilized, while the remaining parts of the spectrum are heavily occupied.

It is recognized that this kind of static allocation police has resulted in poor spectrum utilization. Furthermore, spectrum underutilization by licensed users exacerbates spectrum scarcity. The main reason of spectrum underutilization is that licensed users typically do not fully utilize their allocated bandwidths for most of the time, while unlicensed users are being starved for spectrum availability. To deal with this dilemma, cognitive radio is a paradigm created in an attempt to enhance spectrum utilization, by allowing unlicensed users to coexist with licensed users and make use of the spectrum holes. The spectrum holes are defined as the spectrum bands owned by licensed users, which are unused at a particular time and specific geographic location. Cognitive radio is the key enabling technology that enables next generation communication networks, also known as Dynamic Spectrum Access (DSA) networks, to utilize the spectrum more efficiently in an opportunistic fashion without interfering with the primary users. It is also defined as a radio that can change its transmitter parameters according to the interactions with the environment in which it operates. It differs from conventional radio devices in that a cognitive radio can equip users with cognitive capability and reconfigurability.

Cognitive capability defines the ability to sense and gather information from the surrounding environment, such as information about transmission frequency, bandwidth, power, modulation, etc. With this capability, cognitive users (CU) can identify the best available spectrum. Reconfigurability is the ability to rapidly adapt the operational parameters according to the sensed information in order to achieve the optimal performance. By utilizing the spectrum in an opportunistic fashion, cognitive radio allows secondary users to sense the portion of the spectrum if available, select the best available channel, co-ordinate spectrum access with other users, and leave the channel when a primary user reclaims the spectrum usage right [1].

Spectrum sensing process is needed to achieve this detection in cognitive radio. CR users must be able to detect the signal of the primary user. Individual spectrum sensing is sometimes difficult since the fundamental characteristics of wireless channels such as multipath fading, shadowing, can degrade the signal. To overcome these issues of individual spectrum sensing, cooperative spectrum sensing is proposed, where CRs send their local sensing information to Fusion Centre (FC) where the final decision can be made [2].

In cooperative spectrum sensing, the cognitive cycle which include sensing operation of each cognitive user, transmits the sensing information to FC and takes a final decision about licensed users signal presence. All these operations should be done as fast as possible and with a high probability of correct decision. The performance measure of these two requirements is the throughput. The throughput of CR is defined as the ratio of the total transmission time to the total frame time after successful final decision is taken. The throughput is normally deteriorated because of the existence of channel noise, fading and because of the use of inefficient fusion rules at FC. Therefore, there is always a need for developing efficient approaches to handle this deterioration. In this paper, most fusion rules will be analyzed and evaluated furthermore, one new fusion rule is proposed.

The remainder of this paper is organized as follow. Section 2 presents the system model. The spectrum sensing analysis is given in Section 3. The cooperative sensing and decision-making rules are covered in Section 4. Section 5 introduces the concept of throughput in CR network. Simulation results are given in Section 6. Finally the paper is concluded in Section 7.

2 System Model

The system model is set up as illustrated in Figure 1. Energy detection technique is adopted to detect whether primary user is transmitting or not. It is assumed that number of cognitive radio users are random uniformly distributed around the area where the primary user is in operating. The sensing procedure is that the CR users locally sense the PU. Then, they collaboratively forward either its decision or observation to the fusion center. An error-free transmission is assumed in reporting channel such that the fusion center receives exactly the same information as sent. The fusion center makes final decision and inform all CR users.

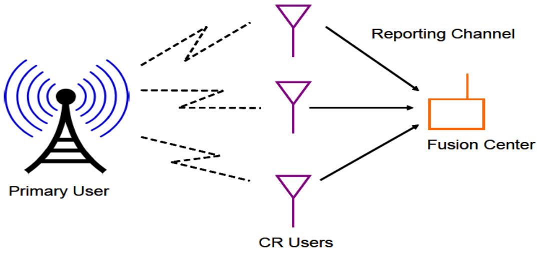

Figure 1: The system model.

3 Spectrum Sensing Analysis

Noncooperative spectrum sensing occurs when only one secondary user performs the primary user detection process. According to this scenario, three different aspects for spectrum schemes are discussed the proceeding subsections. Cooperative spectrum sensing is introduced in the next section.

3.1 Energy Detection

Energy detection has become a widely used technique to sense the primary user signal [3]. A block diagram of a conventional energy detector is illustrated in Figure 2. A band-pass filter (BPF) is first applied, and then its output is squared, integrated, and compared against a threshold to make a decision on the presence of a signal. The energy detection method is attractive because of its implementation simplicity compared to other sensing schemes, as well as fast detection of the primary signals. It has a good resistance against dynamic radio environment where none a prior knowledge about the PUs is available (non-coherent detector). However, the performance of the energy detector is easily affected by channel fading, shadowing, and interferences.

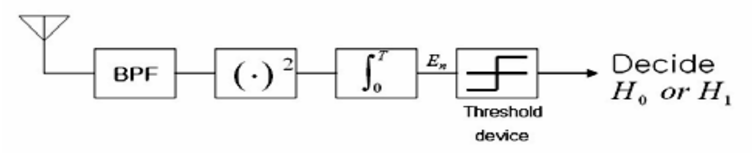

Figure 2: Block diagram of a conventional energy detector.

The signal statistics (the computed energy) are compared to a predetermined threshold. The average total energy detected E, using N_s samples, is defined as

$$E = \frac{1}{N_s}\sum_{i=1}^{N_S} |r(n)|^2 \tag{1}$$

where $r(n)$ is the voltage value received at sample n. If E is more than or equal to γ, this indicates that the spectrum is used (hypothesis H_1) and if E is smaller than γ, this means there is hole in spectrum (hypothesis H_0).

Specifically, the energy of the received signal is collected in a fixed bandwidth W and a time slot duration T and then compared with a pre-designed threshold γ, if $E \geq \gamma$, then the cognitive radio assumes that the primary system is in operation, i.e., H_1. Otherwise, it assumes H_0. The average probability of detection, false alarm, and missing of energy detection (The miss detection occurs when the primary user is in operation but the cognitive radio fails to sense it) over noisy and fading channels can be given by, respectively, [4]:

$$P_D = E[P_r\{H_1|H_1\}]_\eta = e^{-\frac{\gamma}{2}}\sum_{n=0}^{\alpha-2}\frac{1}{n!}\left(\frac{\gamma}{2}\right)^2 + \left(\frac{1+\bar{\eta}}{\bar{\eta}}\right)^{\alpha-1} \times \left(e^{-\frac{\gamma}{2(1+\bar{\eta})}} - e^{-\frac{\gamma}{2}}\sum_{n=0}^{\alpha-2}\frac{1}{n!}\left(\frac{\gamma\,\bar{\eta}}{2(1+\bar{\eta})}\right)^n\right) \tag{2}$$

$$P_{FA} = E[P_r\{H_1|H_0\}] = \frac{\Gamma(m, \frac{\gamma}{2})}{\Gamma(m)} \tag{3}$$

$$P_m = E[P_r\{H_0|H_1\}] = 1 - P_D \tag{4}$$

where $\bar{\eta}$ denotes the average SNR at the cognitive radio. α is a certain margin of protection which is a measure of how much interference above the noise floor the primary user can tolerate (typical value is 5dB). $E[\cdot]_\eta$ represents the expectation over the random variable η (the instantaneous SNR) which is modelled as exponential distributed. $P_r\{\cdot\}$ is the probability of the event. $\Gamma(\cdot)$ is the *gamma function, and* $\Gamma(\cdot,\cdot)$ is the *incomplete gamma function.*

3.2 Matched Filter

The matched filter detection is a linear filter and is used when a secondary user has a prior knowledge of the PU signal properties. This prior information includes carrier frequency, modulation type and pulse shape. This condition makes the matched filter detection impractical. A matched filter maximizes the signal-to-noise ratio (SNR) of the received signal so it is the optimal signal detection. Its performance degrades when there is a reduction of channel knowledge due to rapid changes in the channel state conditions.

A matched-filtering process is equivalent to a correlation scheme; wherein a signal is convolved with a filter whose impulse response is a mirror and time shifted version of the reference signal. The matched filter $h(t)$ convolves the received signal $r(t)$ with a time-revered version of the known signal as;

$$r(t) \otimes h(t) = r(t) \otimes s(T - t - \tau) \quad (5)$$

where T refers to a symbol time duration and τ is a shift in the known signal $s(t)$, and $\otimes$ refers to the convolution operator. The details of this technique can be found in [5,6].

3.3 Cyclostationary Detection

A signal is said to be cyclostationary if its autocorrelation is a periodic function of time with some period. Cyclostationary feature detection exploits the periodicity of the received signal to identify the presence or absence of primary users. The periodicity is commonly embedded in sinusoidal carriers, spreading code and cyclic prefixes of the primary signals. Due to the periodicity, these cyclostationary signals exhibit the features of periodic statistics and spectral correlation. The complex system depicting this method of detection is also presented in [6].

A signal $s(t)$ is said to be Cyclostationary, if its mean and autocorrelation function $E[s(t)], R_s(t, \tau)$ are periodic, i.e., for any integer k:

$$E[s(t)] = E[s(t + kT_0)] \quad \text{and} \quad R_s(t, \tau) = R_s(t + kT_0, \tau)] \quad (6)$$

The details of using cyclostationary analysis as a technique to accomplish signal detection is described in [7].

Compared to energy detection, Cyclostationary feature detection has a better performance when SNR is low. However, it has the same disadvantage as matched filter detection in the sense that it needs prior knowledge of the primary user. Also, it requires a long detection time which makes it less popular than energy detection.

Because energy detection is the most popular and simplest sensing method, it has selected for spectrum sensing in this paper. So, the two disadvantages mentioned above are overcome.

4 Cooperative Sensing and Decision-Making Rules

Cooperation has always benefits. With cooperation, communications can greatly improve the data transmission and reduce the transmission errors. It is defined as the willingness of users in the same network to share information, power and computation with neighbouring nodes and this can lead to savings of overall network resources. In this section, cooperation among cognitive users is considered. This eases to reduce the uncertainty of information recorded by single user detection. The cooperative detection can provide more accurate performance. However, it requires additional operations and overhead traffic to communicate among CR users. As a result, there can be an effect on the performance of resourceconstrained networks. Different decision-making rules to collect and combine this information is analysed and evaluated.

In combining rules based cooperative spectrum sensing, CR users forward their local decision to the fusion center to make a final decision. Assuming that the energy observations at each CR user is independent and identically distributed (i.i.d.). All decisions from the cognitive radio users are then sent to the fusion center, where the global decision is made. The probability of detection and false alarm probability at the fusion center is given by [7]:

$$\mathrm{P}_D = \sum_{i=K}^{N_c} \binom{N_c}{i} (P_{D,i})^k (1 - P_{D,i})^{N_c - i} \tag{7}$$

$$\mathrm{P}_{FA} = \sum_{i=k}^{N_c} \binom{N_c}{i} (P_{FA,i})^k (1 - P_{FA,i})^{N_c - i} \tag{8}$$

where N_c is the number of secondary users sensing the spectrum and $P_{FA,i}$ and $P_{FA,i}$ is the probability of detection and false alarm probability of the i^{th} cognitive user respectively, k is set according to the used rule, and $\binom{\mathrm{Nc}}{k}$ is binomial coefficient.

Here, different decision combining rules are described.

4.1 OR Rule Decision

In this rule, if any one of the local decisions sent to the decision maker is a logical one, the final decision made by the decision maker is one. The OR rule decides that a hole is present if any of the users detect a hole [8, 9], therefore k is set to 1 in Eq. (3.1) and Eq. (3.2). The probability of detection and probability of false alarm of the final decision of this rule are, respectively [10]:

$$\mathrm{P}_{D,OR} = 1 - (1 - P_D)^{N_c} \tag{9}$$

$$\mathrm{P}_{FA,OR} = 1 - (1 - P_{FA,})^{N_c} \tag{10}$$

4.2 AND Rule Decision

In this rule, if all of the local decisions sent to the decision maker are one, the final decision made by the decision maker is one. The fusion center's decision is calculated by logic AND of the received hard decision statistics. The AND rule decides that a hole is present if all users detect a hole [8] therefore k is set to N_c in Eq. (7) and Eq. (8). The probability of detection and probability of false alarm of the final decision of this rule are, respectively:

$$\mathrm{P}_{D,AND} = (P_D)^{N_c} \tag{11}$$

$$\mathrm{P}_{FA,AND} = (P_{FA})^{N_c} \tag{12}$$

4.3 MAJORITY Rule Decision

In this rule, if half or more of the local decisions sent to the decision maker are the final decision made by the decision maker is one, the MAJORITY rule decides that a hole is present if half or more of users detect a hole [9] therefore k is set to $N_c/2$ in Eq. and (7) Eq. (8). The probability of detection and probability of false alarm of the final decision are, respectively:

$$\mathrm{P}_{D,MAJORITY} = \begin{cases} \sum_{i=Nc/2}^{N_c} \binom{N_c}{i} (P_{D,i})^i (1 - P_{D,i})^{N_c - i}, & N_c \ is\ even \\ \sum_{i=ceil(\frac{Nc}{2})}^{N_c} \binom{N_c}{i} (P_{D,i})^i (1 - P_{D,i})^{N_c - i}, & N_c \ is\ odd \end{cases} \tag{13}$$

$$\mathrm{P}_{FA\ MAJORITY} = \begin{cases} \sum_{i=Nc/2}^{N_c} \binom{N_c}{i} (P_{FA,i})^i (1 - P_{FA,i})^{N_c - i}, & N_c \ is\ even \\ \sum_{i=ceil(\frac{Nc}{2})}^{N_c} \binom{N_c}{i} (P_{FA,i})^i (1 - P_{FA,i})^{N_c - i}, & N_c \ is\ odd \end{cases} \tag{14}$$

where $ceil(\frac{Nc}{2})$ rounds the elements of $Nc/2$ to the nearest integers greater than or equal to $Nc/2$.

4.4 Middle Plus One MPO Decision

Middle Plus One MPO is first proposed rule and it is a type of hard decision rules. The mechanism of its operation is as follows: the fusion center makes a final decision of "0" when half plus one or more of the local decisions sent to the fusion center are "0" (indicating the existence of hole) therefore k is set to $(\frac{Nc}{2} + 1)$ in Eq. (7) and Eq. (8) and the fusion center indicates that the hole is present. This rule will increase the throughput since it increases the number of secondary users that give the same decisions which decrease the probability of false alarm. The probability of detection and the probability of false alarm of MPO rule is given in the following equations:

$$\mathrm{P}_{D,MPO} = \begin{cases} \sum_{i=\frac{Nc}{2}+1}^{N_c} \binom{N_c}{i} (P_{D,i})^i (1 - P_{D,i})^{N_c - i}, & N_c \ is\ even \\ \sum_{i=ceil\left(\frac{Nc}{2}\right)+1}^{N_c} \binom{N_c}{i} (P_{D,i})^i (1 - P_{D,i})^{N_c - i}, & N_c \ is\ odd \end{cases} \tag{15}$$

$$\mathrm{P}_{FA,MPO} = \begin{cases} \sum_{i=\frac{Nc}{2}+1}^{N_c} \binom{N_c}{i} (P_{FA,i})^i (1 - P_{FA,i})^{N_c - i}, & N_c \ is\ even \\ \sum_{i=ceil\left(\frac{Nc}{2}\right)+1}^{N_c} \binom{N_c}{i} (P_{FA,i})^i (1 - P_{FA,i})^{N_c - i}, & N_c \ is\ odd \end{cases} \tag{16}$$

4.5 AVERAGE Rule Decision

In this rule, the final decision of H_1 is made only when the average of all CR reports lies above a certain predefined threshold. This threshold represents the long-term observations of the average of probabilities of detection of the primary user presence. Monte Carlo (MC) method, which is a stochastic technique based on the use of random numbers can form the basis of calculating this threshold. The higher the number of Monte Carlo samples, the greater the confidence of this threshold. Therefore k in Eq. (7) and Eq. (8) is set a value where the count of CR users preforming spectrum sensing exceed the predefined threshold. The threshold of the probability of detection and false alarm probability can be expressed as

$$\mathrm{P}_{D,a} = average\big(P_{D,i} \colon \forall\, i = 1 \ldots N_c\big)|_{MC} \quad (17)$$

$$\mathrm{P}_{FA,a} = average\big(P_{FA,i} \colon \forall\, i = 1 \ldots N_c\big)|_{MC} \quad (18)$$

where $average(\cdot)$ is the statistical average function, and MC refers to Monte Carlo algorithm.

Then the value of k will be the minimum value of users those satisfy the following criteria

$$\mathrm{k} = \min \begin{cases} count(P_{D,i} \colon P_{D,i} \geq \quad P_{D,a} \ \forall\, i = 1 \ldots N_c) \\ count(P_{FA,i} \colon P_{FA,i} \geq P_{FA,a} \ \forall\, i = 1 \ldots N_c) \end{cases} \quad (19)$$

where $min(\cdot)$ is the known minimum function, and $count(\cdot)$ is a function that counts its arguments.

Now, this value of k can be plugged in Eq. (7) and Eq. (8) to find the probability of detection and probability of false alarm of the final decision.

$$\mathrm{P}_D = \sum_{i=1}^{k} \binom{k}{i} (P_{D,i})^k (1 - P_{D,i})^{k-i} \quad (20)$$

$$\mathrm{P}_{FA} = \sum_{i=1}^{k} \binom{k}{i} (P_{FA,i})^k (1 - P_{FA,i})^{k-i} \quad (21)$$

5 Throughput of Cognitive Radio

The throughput in cognitive radio is defined as the ratio of the total transmission time to the total frame time after successful final decision is taken [10]. The frame structure in cognitive radios of duration T consists of sensing time τ and data transmission time $(T - \tau)$. The cognitive user senses the spectrum band for a specific time duration τ . Then, in the case of hole presence, the user starts data transmission over remaining frame time duration $(T - \tau)$. The normalized achieved throughput can be expressed as [11]

$$\mathrm{R} = \frac{(T-\tau)}{T}(1 - P_{FA}) \quad (22)$$

5.1 Throughput Improvement in Cognitive Radio

According to Eq. (22) and what previously discussed, by controlling some parameters, the throughput of cognitive radio can be improved. Some of these parameters act directly and others indirectly to the throughput improvement. For example, for sensing time τ parameter, a higher sensing time results in precise spectrum sensing, and avoiding interference with the licensed user. However, on the other hand, an increase in sensing time results a decrease in transmission time, leading to low throughput, and shorter sensing time degrades the sensing process, so the optimal sensing time can maximize the SU's throughput.

Frame duration T is very important parameter, for a given sensing time, the larger frame duration, the longer the data transmission time $(T - \tau)$ and maximum throughput value. Also, the longer the frame duration, the more chances that the PU becomes active, thus more interference between PU and SU, which degrades the throughput. Thus, there exists an optimum frame duration for which interference is minimum and throughput of the CR is maximum.

Number of secondary user performing sensing N_c is also a sensitive parameter to throughput. Using more cooperative SUs can enhance spectrum decision making which leads to increase the throughput.

Last but not least, throughput is affected by the adopted fusion rules make the global decisions. However, using appropriate fusion rule in cooperative spectrum sensing causes improvement in cognitive radio throughput.

6 Simulation Results

In this section, the simulation of four decision rules to enhance throughput in CR are presented. The traditional decision rules: OR rule, MAJORITY rule and Middle Plus One (MPO) rule are simulated. Then the proposed decision rule named as AVERAGE rule is also simulated. For the sake of brevity, AND rule is omitted in this study because it gives the worst performance compared to the other decision rules.

These rules are evaluated for the purpose of comparing the throughput with each other. The scenario consists of sensing stage (local decision), transmission stage (reporting) and decision stage (global decision).

A centralized cooperative spectrum sensing scheme is used, where a number of secondary users sensing for the primary user. The primary user data are generated randomly and QPSK modulated. The sensing stage is performed using the energy detection method, in which each secondary user computes the energy of the sensed spectrum. This requires to transform the primary signal to frequency domain. The sensing process is performed in AWGN channel. After that either hard or soft decision schemes are used. An error free transmission is assumed at the reporting channel where the throughput is calculated. In the simulation, the sampling frequency is chosen to be 6 MHz and there are two bits per symbol. The total frame length is 0.1 sec. Number of cooperative users is varied from 1 to 10 users.

In Figure 3, the probability of detection versus the number of cooperative users is plotted. It shows that the probability of detection increases with the increase of the number of users, for all schemes. This is because that when there are number of devices (or users) are involved in the cooperative communication model, there is a high probability of correct decision making expected. When there is a high density of cooperative mobile users, then there would be high probability to make a correct decision. It can also be observed from Figure 3 that the probability of detection of 'OR Rule' better than the rest of the schemes. For instance, in the case of 7 users, the probability of detection of 'OR Rule' and the probability of detection of 'MPO Rule' is 98%, the probability of detection of 'MAJORITY Rule' is 86% however, AVERAGE Rule is only 80%. It is important to note that the performance of all the schemes matches when there are high number of mobile users performing spectrum sensing. In summary, for a lower number of users, 'OR Rule' outperforms than rest of the schemes.

Figure 4 illustrates the probability of false alarm as a function of number of cooperative users. The probability of false alarm has a higher value for a lower number of users. This is because, when lower number of users are present in the network, there is a high probability that the fusion center will make wrong decisions of existing a channel (false alarm). In the case of fewer users, the fusion center does not have enough statistics information to make the correct decision about the presence of the primary user signal.

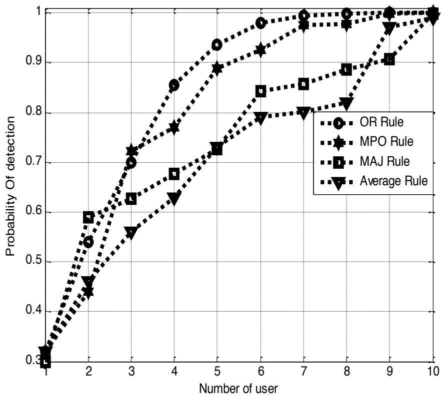

Figure 3: Probability of detection versus number of users.

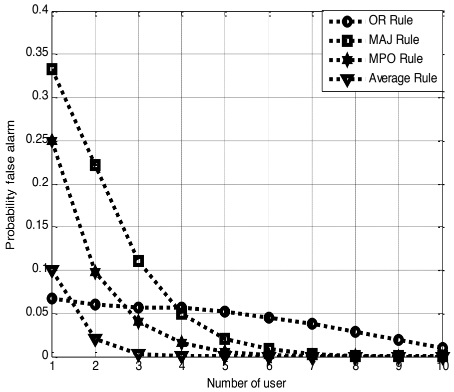

Figure 4: Probability of false alarm versus number of users

Figure 5 compares the performance of all the studied schemes in terms of achieved throughput versus the number of users present in the network. It is obvious that for a higher number of users in the network, there would be higher throughput It can be depicted from Figure 5 that for a higher number of users, throughput is high as well. However, 'AVERAGE Rule' gives better throughput compared to the other traditional schemes. In conclusion, 'AVERAGE Rule' is the best option when throughput maximization is the key requirement of the network.

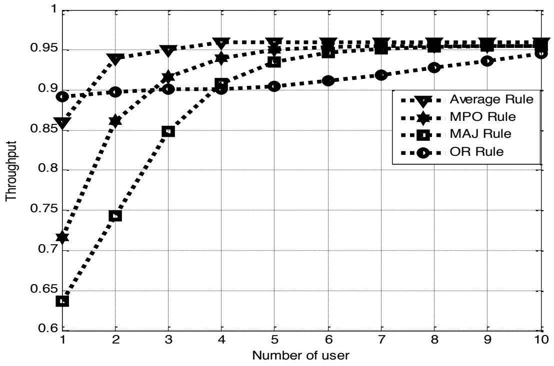

Figure 5: Throughput versus number of users.

7 Conclusions

Static spectrum assignment policy causes low spectrum utilization while the demand for spectrum continues to increase. To solve this issue, Cognitive Radio has been introduced. In order to implement dynamic spectrum access, techniques including spectrum sensing, spectrum analysis and spectrum decision must be adapted. This paper focuses on investigating spectrum sensing techniques by applying energy detection in collaboration sense. Group of user independently perform local spectrum sensing and then report a decision to FC. The FC then makes a final decision. Different decision fusion rules are studied and analyzed. A new rule is also proposed which based on taking the statistical average of all sensing information measured by the individual cooperative users. Monte Carlo algorithm is used to simulate the statistical average for the similar channel environment. This value is used as a threshold value to compare with the measured results.

The comparison between all these rules is done by evaluating the performance of each rule and its response to the detection probability and false alarm. Channel throughput is adopted as a key performance for each rule. The performance of the different all the studied schemes in terms of achieved throughput versus the number of users present in the network are presented. It is observed that more number of users in the network, higher throughput is achieved. However, the ‘AVERAGE Rule’ gives better throughput compared to the other traditional schemes. In conclusion, ‘AVERAGE Rule’ offers the best option when throughput maximization is the key requirement of the network.

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