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Bayesian Detection Based Cooperative Spectrum Sensing For CRN”

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Abstract: Spectrum sensing is the basis of cognitive radio technology. Cooperative spectrum sensing has been shown to increase the reliability of spectrum sensing. To reduce sensing overhead and total energy consumption, it is recommended that the users with good performance should be selected to increase the sensing reliability. However, which of the cognitive users have the best detection performance is not known a priori. In this paper, a selective cooperative sensing strategy and a user selection method based on B value are proposed so as to increase the sensing reliability and reduce sensing overhead.

A Bayesian detector structure that maximizes detection probability and achieves a higher overall spectrum utilization is proposed, considering a BPSK modulated primary signal. The Bayesian detector is optimum detector for signals in low SNR region. It reduces to energy detector in this condition.

Simulations are used to evaluate and compare the B value method with other methods. Simulation results show that B value selection has the same sensing performance with signal-to-noise ratio(SNR) selection. B value selection obviously outperforms the simple counting selection in the presence of noise uncertainty. In general, the SNRs of all cognitive users are not known a priori and there must be certain noise uncertainty, in this sense, B selection is a simple, feasible and effective selection method.

Keywords: Cognitive radio, detection probability, energy detection, relay selection, spectrum sensing

I. INTRODUCTION

With the rapid development of communication technology and industries, spectrum resource is becoming increasingly scarce. Recently, cognitive radio (CR)technology is considered to be an effective method to solve the lack of spectrum resources. The main idea is to allow cognitive users (non-authorized users) to share spectrum resources without causing any harmful interference to those primary users (authorized users).Spectrum sensing is one of the key technologies. According to the rule of IEEE 802.22 WLAN, the cognitive users system should be far away from the primary user system to ensure that the primary users (PUs) are kept away from interference produced by CR transmitter. In that case, CR node will sense the primary user signal with low signal-to-noise ratio (SNR). In addition, in a fading environment, the channel uncertainty due to the deep fading and shadow challenges the spectrum sensing. To combat multi path and shadow effect of spectrum sensing, cooperative spectrum sensing has been shown to increase the reliability of sensing. However, a large number of cooperating CRs typically lead to more energy consumption of the system. During cooperative spectrum sensing, each CR implements local spectrum sensing independently, then sends the result to Fusion Center (FC) and waits for the final system judgment. While waiting for the judgment, all CRs cannot send and receive their own data, which reduces the average system throughput. In addition, the fusion principle which is widely used by fusion center is not optimized, when the users with poor performance participate in cooperative sensing, they actually degrade the system sensing performance.

This paper presents a new method for selecting cooperating CRs. During the selecting period, every CR calculates each B value of the received signal and passes it to the fusion center. Fusion center selects the cooperating CRs based on their β values. The main contributions of this paper can be described as follows:

We propose a selective cooperative sensing strategy in which a selecting slot is designed before the sensing slot. Only the users with good performance are selected to cooperate sensing so as to increase the sensing reliability and reduce sensing overhead.

II. SYSTEM MODEL

The system model used in this paper is based on the IEEE 802.22 WRAN deployment scenario. A centralized CR network (CRN) is illustrated in Fig.1, which consists of M CRs and a fusion center (FC). For primary user (PU)network, we assume that it consist of a primary transmitter denoted as base station (BS) and several receivers, e.g., a TV radio station and many TV radio receivers. The FC is far away from the primary user BS. All CRs are independently and randomly distributed in a circle centered at the FC with radius RS. The received power of the CR i is

$$P_i = \frac{P_{pu}}{d_i^{\alpha}}\mu \qquad (2.1)$$

Where P_{pu} is the PU's signal power, i d is the actual distance from the CR i to the PU, α is the path loss exponent factor and μ is a scalar.

In this CRN, CR needs to detect the activities of PU before its transmissions. If PU is detected, CR will defer its transmissions and then try again in the next transmission phase, otherwise, CR is allowed to send its messages. However, if PU is undetected when it is actually present, CR may affect the operations of PU. To improve the detection performance of CR and well protect primary transmissions, the cooperative CRs should assist PU to monitor the spectrum.

It assumes that all CRs operate in a fixed time division multiple access (TDMA) manner. In 802.22 WRAN, each medium access control (MAC) frame consists of two consecutive durations called sensing slot and data transmission slot, as depicted in Fig. 2 (a).

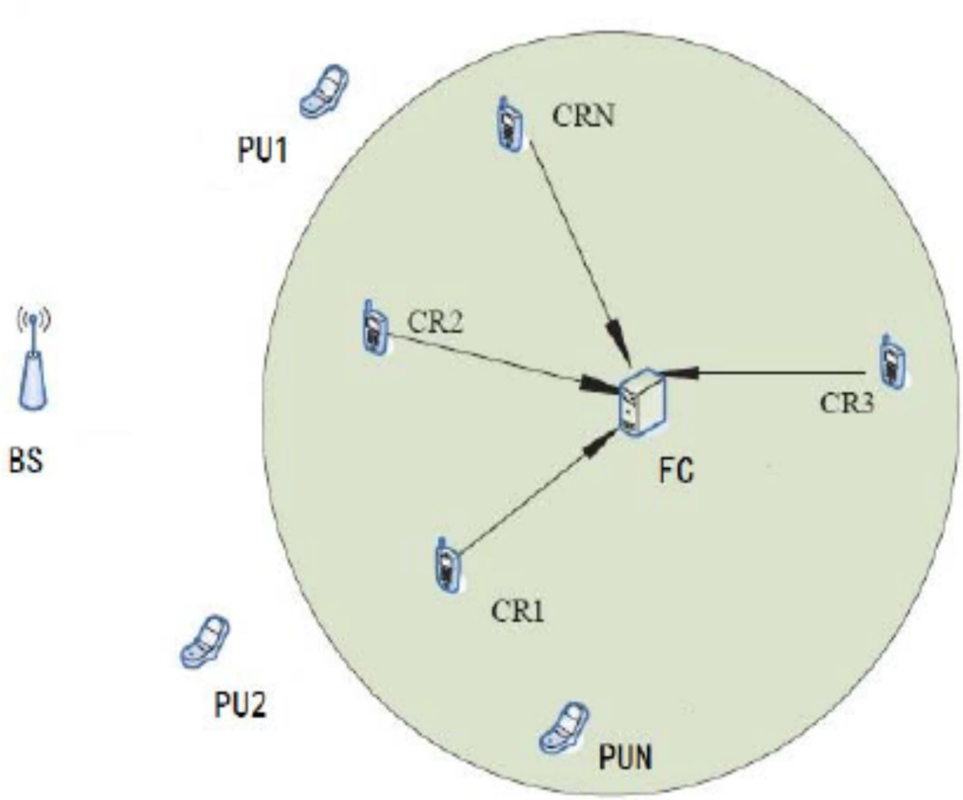

Fig.1. Simulation scenario in CR networks

In traditional strategy, all CRs independently detect PU's states in the sensing slot at the beginning of each MAC frame and then each cooperative CR reports its local 1-bit hard decision to the FC.

We further propose a frame structure of selective cooperative detection as depicted in Fig.2 (b). A selecting slot is designed before the sensing slot.

In selecting slot every CRs calculates the specific parameter of the received signal and transfer the parameter to the FC. At the end of the selecting slot, basing on the all parameters, the FC selects the best CRs to cooperate sensing based on the proposed selection methods.

At the start of each cognitive radio selection round, i.e., at the very start of selecting period, the FC assigns an identity number to each cognitive radio. The FC grants a contention free channel to individual cognitive radios by polling them (using their identity numbers) for transmitting their parameters. At the end of the selecting period, only the cognitive radios with the best detection performance are selected.

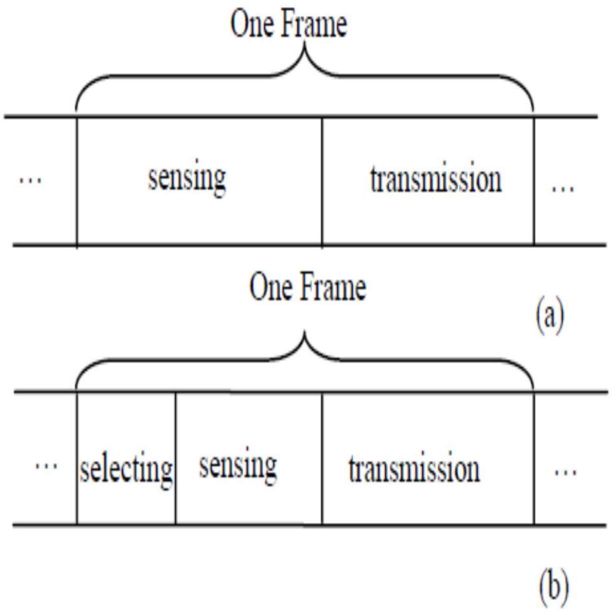

Fig.2. (a) Frame structure of traditional cooperative detection; (b) Frame structure of selective cooperative detection.

At this juncture, the accounting SU determination can be accomplished in both the unique strategies.
RSR: One SU is arbitrarily picked from the recognition set to inform its conclusion in reporting time slot whereas remaining cooperative SUs stay quite.
BSR: The most excellent reporting SU, which has the maximum signal to interference plus noise ratio (SINR) at S, is looked over to inform its decision in reporting time slot. In the meantime, other accommodating SUs keep quiet.
Mobility of CRs can cause changes to the probability of detection. Slow mobility can be taken into account by periodically performing the CR selection process.
n sensing slot, all selected CRs independently detect PU’s state and then each cooperative CR reports its local1-bit hard decision to the FC. We use the method given in to transmit and receive the local decisions. Specifically, each cooperative CR encodes its local decision by a cyclic redundancy code (CRC) and then sends the CRC-encoded indicator signal to FC where CRC checking is performed. Finally, only the successfully decoded outcomes are used for fusion. Typically, after FC makes a global decision, it should broadcast a message containing PU’s state information to notify its neighboring CRs. Like many existing works, it is assumed that the final decision notification can be correctly received by cooperative CRs, where the details of final decision declaring is out of scope of this paper and thus not discussed.

III. METHODOLOGY

Consider an outline of the non-helpful ED technique. The signal from P got at I ($I \in \{S, R_i \,|i = 1, \ldots, N\}$) in a specific detecting stage is communicated as

$$y_I = \theta\sqrt{E}_P h_{PI} x_P + n_I \qquad (3.1)$$

where $h_{PI\ is}$ the fading coefficient of the frequency band of P to I with the variance, σ_{PI}^2.
θ indicates the condition of P, where $\theta = 1$ infers that P is progressive, and$\theta = 0$ exhibits that P is dormant. As per the energy recognition method, the signal received at y_I is initially pre-isolated by a flawless BPF with uneven transmission limit W and after that squared and incorporated over a particular time period T_0 . Finally, the essentialness test estimation Y_I is produced as the yield of the integrator and evaluated against λ, the power threshold, which satisfies a practical false-alert likelihood. For feasibility, the threshold used by individual SUs is considered to be the same. If $Y_I \geq \lambda$, then Ith user declares P's presence or else, Ith user asserts P's nonappearance. The process is depicted in following flowchart in Fig 3.1.
Let H_0 ($\theta = 0$) and H_1 ($\theta = 1$) indicate two customary speculations utilized as a part of spectrum detecting. By description, false caution implies that P is distinguished under H_0 , and recognition shows that P is recognized under H_1. Furthermore, miss location implies that P is undetected under H_1.

A. Energy Detector

In case of energy detection method , the levels of received signal are compared with a threshold to recognize the presence or absence of the primary signal.The probability of false-alert and probability of detection of the energy detector for auxiliary user, I, are specified as in equation 3.2

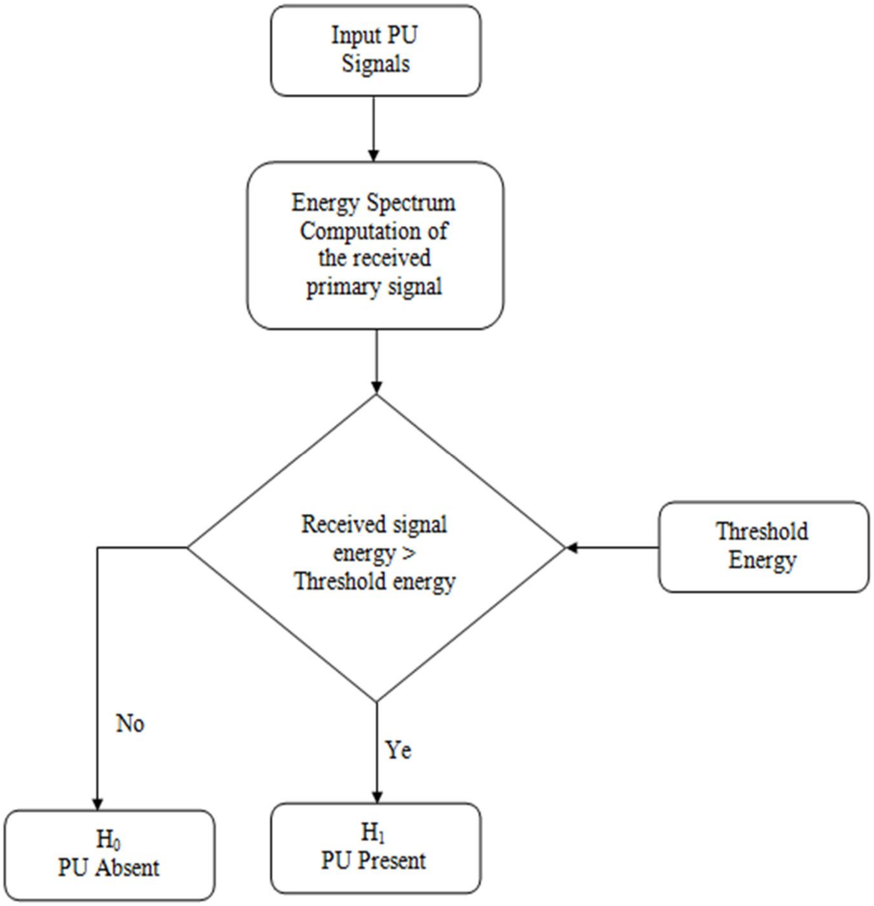

Fig 3.1: Flowchart of Detection of Primary User

$$P_{fI} = \Pr\{Y_I \geq \lambda | H_0\}$$

$$= \frac{\Gamma\left(u, \frac{\lambda}{2}\right)}{\Gamma\ (u)} = \varphi_{fa}(u, \lambda) \qquad (3.2)$$

$$P_{dI} = \Pr\{Y_I \geq \lambda | H_1\}$$

$$= \varphi_{d_{ED}}(U, \lambda, \bar{\gamma}_I) \qquad (3.3)$$

Where $\bar{\gamma}_I = 2\gamma_P u \sigma_{PI}^2$ is the SNR at the SU node received from transmitting PU node and $u = T_0 W$ is BW (Time–Bandwidth Product) of the ED.

B. Bayesian Detector

In case of Bayesian detector, the probability of false alarm at each SU node can be written as,

$$P_F = \frac{\Gamma\left(\frac{N}{2}, \frac{N\gamma + ln\delta}{2\gamma}\right)}{\Gamma\left(\frac{N}{2}\right)} \qquad (3.4)$$

Where N is the total number of signal samples considered for sensing time and Γ(·, ·) is the incomplete gamma function and the P_d can be expressed as:

$$P_D = Q_{\frac{N}{2}}\left(\sqrt{2N\gamma}, \sqrt{\frac{N\gamma + ln\delta}{\gamma}}\right) \qquad (3.5)$$

here QN/2(·, ·) is the general Marcum Q-function which can be obtained with a arithmetical approach to the problem. However the above calculation method is still not completely feasible, an alternative approach is been given to compute PD and PF based on Central Limiting Theorem. According to CLT, addition of signal power's (say $x^2(n)$) can be assumed to have Gaussian distribution if N is adequately large number . As a result,

$$P_D = Q\left(ln\delta - \frac{2N\gamma^2}{\gamma\sqrt{2N(1+4\gamma)}}\right) \qquad (3.6)$$

$$P_{d_{BD}} = \varphi_{d_{BD}}(u, \lambda, \gamma)$$

Where δ=λ and N=u

$$P_F = Q\left(\frac{ln\delta}{\gamma\sqrt{2N}}\right)$$

$$P_{f_{BD}} = \varphi_{f_{BD}}(u, \lambda)$$

C. Random Selection Reporting Strategy (RSR)

The detecting period of the planned methodologies is redesigned, where the node recognition time of fusion center and R_i is

$$\tau_1 = \eta\beta T = \eta\beta(N+1)\tau$$

D. Best Selection Reporting Strategy (BSR)

As said in pervious parts, BSR chooses the best cooperating secondary user from the recognition set to report in t_2', which is not the same as RSR. Here, the supportive secondary user, which can identify P's nearness and cause the most noteworthy received SINR at fusion center, is seen as the best. As a result, the best reporting SU determination paradigm is written as

$$R_{best} = \underbrace{max}_{R_k \in \Omega}\left(\frac{\gamma_{Ri}|h_{RiS}|^2}{\theta\gamma_p|h_{PS}|^2+1}\right) = \underbrace{max}_{R_k \in \Omega}\left(\gamma_{Ri}|h_{Ri}|^2\right)$$

Where Ω indicates the recognition set.

IV. NUMERICAL AND SIMULATION RESULTS

Few analytical and simulation outcomes are presented in this chapter that evaluate the performances of the proposed methodologies with energy detector in higher SNR region and energy and Bayesian detector in lower SNR region and then compare these results with the conventional method.

A. Overall Detection Probability

In Fig. 3, we plot the overall detection probability versus the overall false-alarm probability α_0, where one can easily observe that BSR always outperforms other strategies due to the selection of the best reporting SU. When the reporting channel is weak, the transmit power of reporting SUs is a dominant factor to affect the performance of cooperative detection. As a consequence, RSR achieves higher overall detection probability than the traditional case under σ^2_{RiS}= 0.1 since, in RSR, less interference is induced to PUs and then more power is allowed for the reporting SU. However, when the reporting channel is strong, reporting-SU diversity becomes a dominant factor to affect the cooperative detection performance. Therefore, the traditional strategy outperforms RSR under σ^2_{RiS}= 1 due to the fact that the selected reporting channel may experience deep fading in RSR.

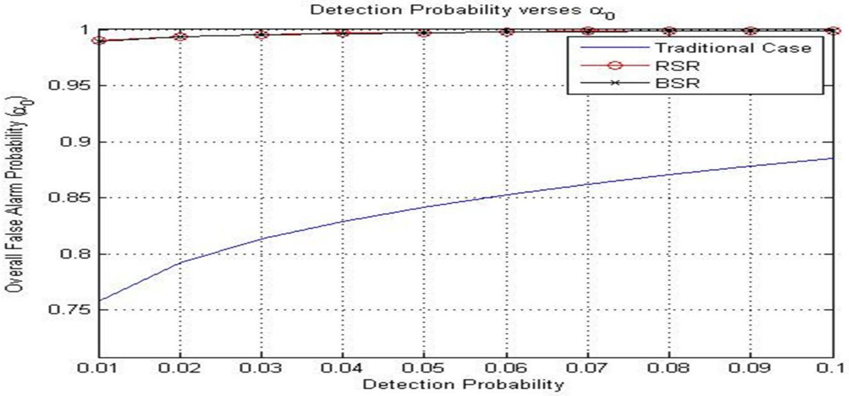

Fig.3. Overall detection probability versus α_0 for the traditional and proposed strategies with the PU transmit SNR γ_P= 6 dB, primary data rate V_P=0.2 bits/s/Hz, PU QoS requirement Thr = 0.04, the number of cooperativeSUs N = 5, the time–bandwidth product of energy detector μ_0 = 3, thetime–bandwidth product of t_i $B_0\tau$ = 10, β = 1/2, η = 1/3, σ^2_{PS}= σ^2_{PRi}=0.6, σ^2_{RiP0}= 0.1, and σ^2_{PP0}= 1.

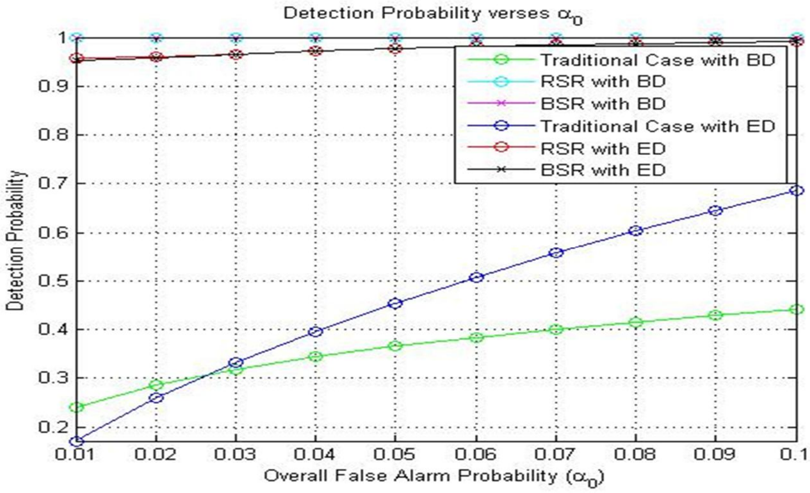

Fig.4 False alarm probability verses detection probability with α_0=0.001, γ_P= -6 dB, V_P=0.2 bits/s/Hz, Thr=0.04, μ_0=10, $B_0\tau$ =10, η=1/3, σ^2_{PS}=σ^2_{PRi}=0.6, σ^2_{RiP0}=0.1, and σ^2_{PP0}=σ^2_{RiS}=1.

Second, we show that BD detector with BSR strategy has higher detection probability compared to any other method.

Impact of β and η on the overall miss detection probability in Fig. 5 and 6, where the overall miss detection probability will decrease as β increases in the proposed strategies due to an increase in the local detection time and reporting time. In low β regions, the overall miss detection probability in the proposed strategies is higher than that in the traditional case, which is because both the local detection time and reporting time allocated to the proposed strategies are very small. As previously shown, there exists performance loss in overall miss detection probability for RSR compared with the traditional case due to the random selection of the reporting SU. Moreover, as expected, the overall miss detection probability can be reduced by improving the number of cooperative SUs in both traditional and proposed strategies.

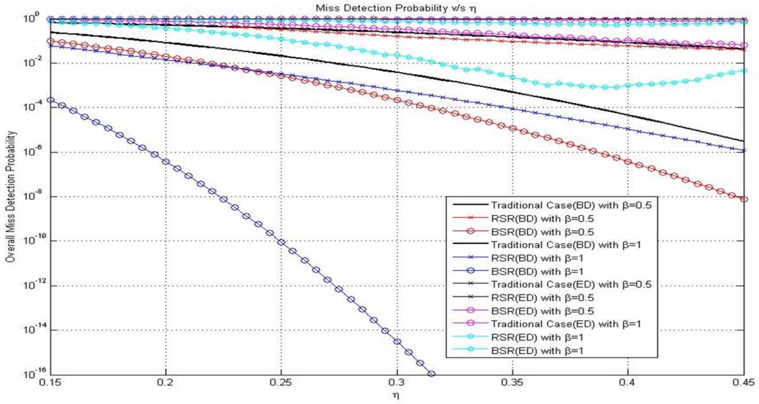

Fig.5. Overall miss detection probability versus η for the proposed strategies with α_0=0.001, N =5, γ_P=-6 dB, V_P=0.2 bits/s/Hz, Thr=0.04, μ_0=40,$B_0\tau$ =5, σ^2_{PS}=σ^2_{PRi}=0.2, σ^2_{RiP0}=σ^2_{RiS}=0.1, and σ^2_{PP0}= 1.

Third, Fig. 5 shows the impact of η on overall miss detection probability in the proposed strategies. In Fig. 5, we know that, for a given β, minimized overall miss detection probability can be achieved by adjusting η to an optimal value. Clearly, improving η leads to an increase in local detection time, which will decrease individual miss detection probability. However, at the same time, the reporting time will be reduced in this case, which causes degradation in reporting performance. Hence, there exists a tradeoff between the performances of local detection and decision reporting for the proposed strategies.

B. Detection Time

First, Fig. 6 shows the ADT versus $\alpha_0$plot for the proposed strategies under different settings. As shown in Fig. 6, the proposed strategies can significantly reduce the ADT as compared with the traditional case. From Section III-D, we know that the ADT in the proposed strategies is mainly determined by the sensing time allocation and the local detection probability of S. Thus, the ADTs of RSR and BSR are nearly identical to each other for given β and η. One can also observe that the ADT in the proposed strategies will decrease as γ_P grows or the quality of the channel from P to S goes high due to an increase in local detection probability of S in these situations.

Then, Figs. 7 and 8 show the impacts of β and η on the ADTs of the proposed strategies, respectively. In Fig. 7, we know that the ADT will increase as β or N increases in the proposed strategies since more sensing time is allocated in these cases according to given β and η.

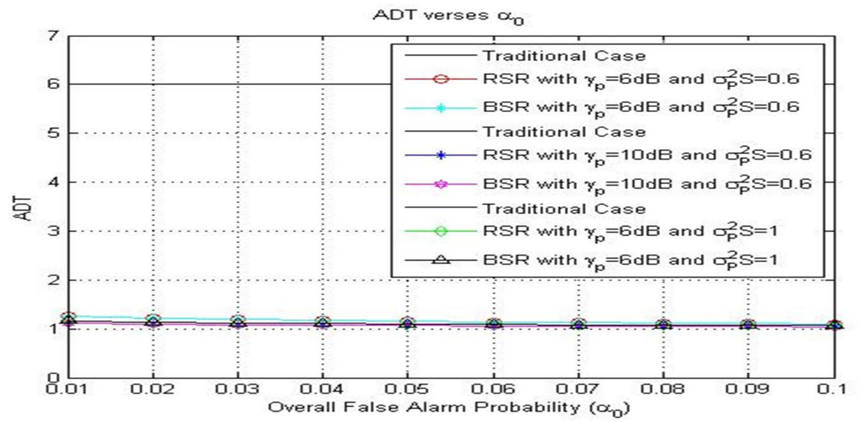

Fig.6. ADT versus false alarmprobability for the proposed strategies with N =5, V_P=0.2 bits/s/Hz, Thr=0.04, μ_0=3, $B_0\tau$ =10, β=1/2, η=1/3, $\sigma^2{}_{PRi}$=0.6,$\sigma^2{}_{RiP0}$=0.1, and $\sigma^2{}_{PP0}$=$\sigma^2{}_{RiS}$=1.

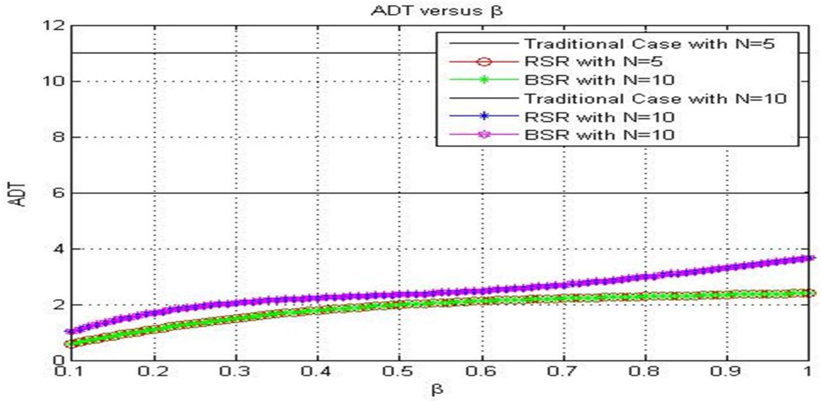

Fig.7. ADT versus β for the proposed strategies with α_0=0.001, γ_P=6 dB,V_P=0.2 bits/s/Hz, Thr=0.04, μ_0=10, $B_0\tau$ =10, η=1/3, $\sigma^2{}_{PS}$=$\sigma^2{}_{PRi}$=0.6, $\sigma^2{}_{RiP0}$=0.1, and $\sigma^2{}_{PP0}$=$\sigma^2{}_{RiS}$=1.

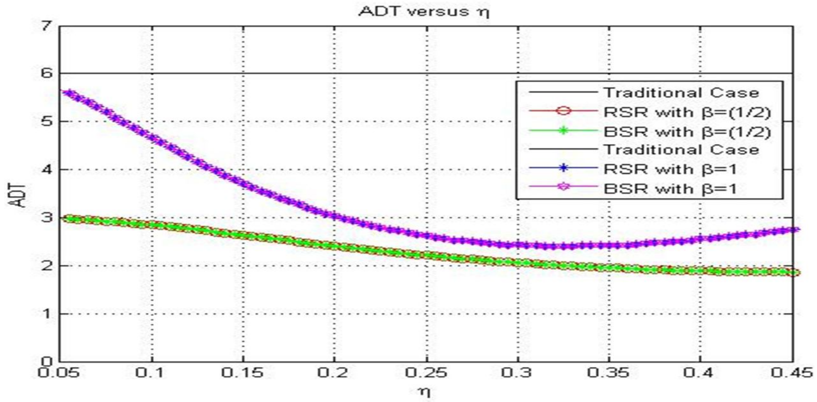

Fig.8. ADT versus η for the proposed strategies with α_0=0.001, N =5, γ_P=6 dB, V_P=0.2 bits/s/Hz, Thr=0.04, μ_0=10, $B_0\tau$ =10, $\sigma^2{}_{PS}$=$\sigma^2{}_{PRi}$=0.6, $\sigma^2{}_{RiP0}$=0.1, and $\sigma^2{}_{PP0}$=$\sigma^2{}_{RiS}$=1.

V. CONCLUSION

In the proposed work, two proficient selective reporting-based cooperating spectrum detecting techniques known as RSR and BSR are proposed along with sub-optimal Bayesian Detector structure for detection in lower SNR regions, to lessen the general detecting overhead. Furthermore, to lessen the obstruction to PUs in CRNs, two disseminated reporting SU choice strategies were produced. Taking into account the reporting frequency band errors due to the multipath attenuations and the impedance from PUs, expressions for Pf and Pd over Rayleigh blurring channels for conventional, RSR & BSR methodologies, individually were derived using energy detector as the preliminary detection method and then comparing the same with Bayesian detection.

The general detecting overhead for the conventional and proposed techniques were formed and likewise analyzed the differences among them. The affect of degradation on PUs affected by decision reporting by the SUs, which demonstrates that such obstruction can be constrained to fulfill a given PU QoS necessity is examined and demonstrated that the planned procedures cause a smaller amount of impedance to PUs than the typical case. At long last, mathematical and simulated results put forward that the implemented procedures accomplish better discovery probability and lower detecting overhead than the conventional case. Besides, BSR accomplishes more prominent overall detection likelihood than that of RSR, with higher usage intricacy. The outcomes can be effectively stretched out by utilizing other local detection strategies.

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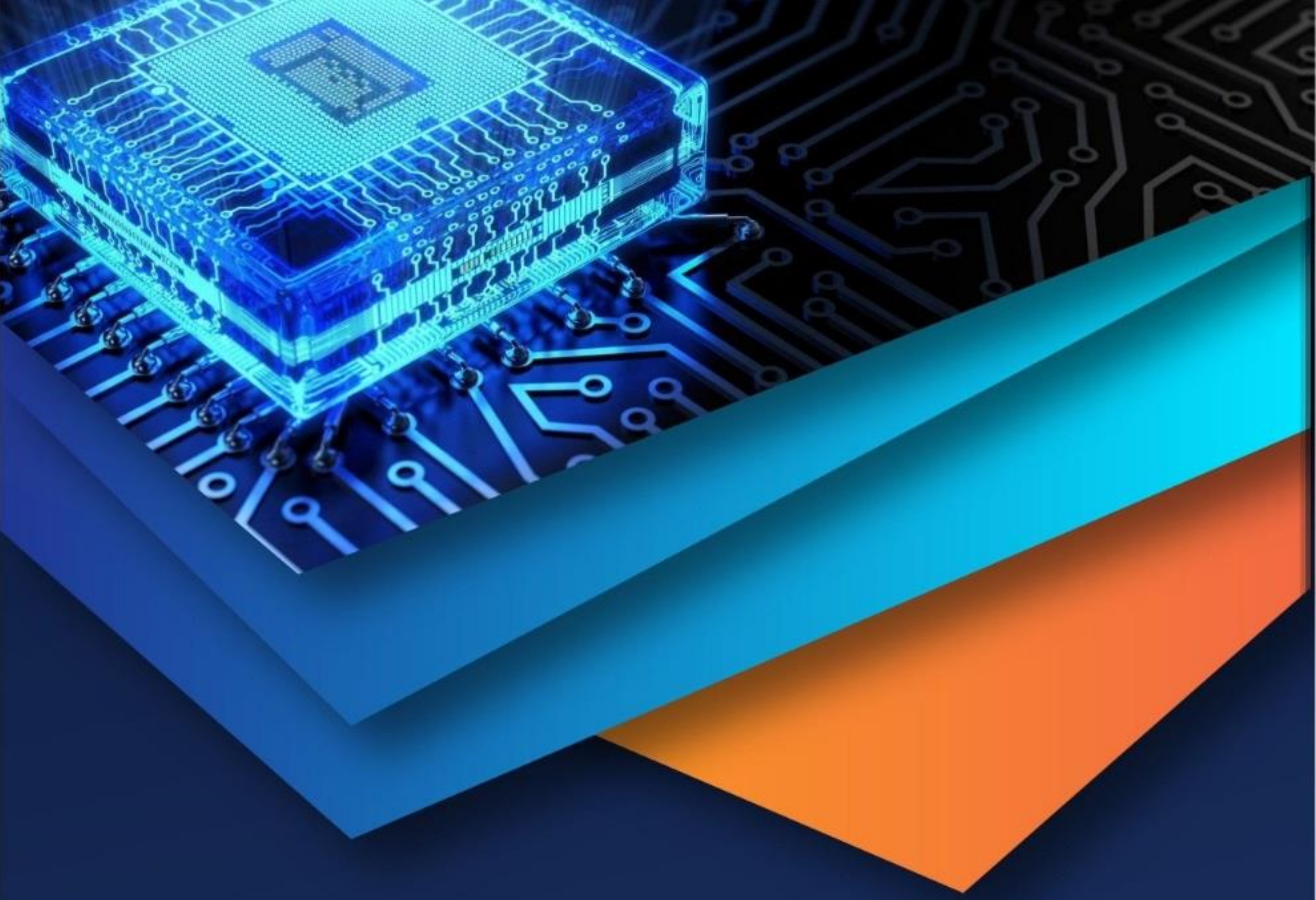

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