An Enhanced SLC Scheme for Cooperative Spectrum Sensing System in Cognitive Radio

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Abstract- The hidden-nodes and noise uncertainty have a negative impact on the spectrum sensing results in cognitive radio. Accordingly, cooperative spectrum sensing is proposed to effectively increase detection reliability by dealing with different soft and hard patterns in the fusion center. In the present work, we analyzed various soft and hard fusion rules. Improved Square Law Combining (SLC) rules are proposed to provide better detection performance than the conventional scheme. To validate the introduced rule, MATLAB simulations were conducted revealing the out-performance of the proposed schemes over the conventional one even in a critical wireless environment with a low signal-to-noise ratio. The proposed approach is then more advantageous because it minimizes the trade-off between detection performance and computational complexity.

Keywords- Cognitive radio, cooperative spectrum sensing, SLC, soft fusion rule

I. Introduction

MITOLA [1] is the first one to conceive the notion of Cognitive Radio (CR) face to the spectrum scarcity problem, highlighted in research by the Federal Communications Commission (FCC) [2]. Currently, spectrum bands are the vertebral column of wireless networks. In Cognitive Radio Networks (CRNs), Spectrum Sensing (SS) is a crucial process of a cognitive radio system [3]. By definition, SS is the amount of radio frequency energy on the spectrum and for which several techniques have emerged. Energy Detection (ED) is an example of techniques that are part of the literature [4, 5]. In case the transmission signals of the Primary User (PU) or the licensed user are known, the spectrum detection is done through a matched filter. It is known to be the best approach to detect licensed users [6]. Moreover, cyclostationarity feature detection is a technique for recognizing PU transmissions by taking advantage of the cyclostationarity properties of the received signals [7].

When the PU signal is unknown, the ED is the most commonly employed detector. This detector calculates the received energy in the desired band and compares it to a threshold based on the estimated noise power level and the required false alarm probability. Due to its implementation simplicity and low computing complexity, ED is extensively utilized. Proper threshold regulation in ED requires information about the noise power, which is a disadvantage. This is especially important in low Signal-to-Noise Ratio (SNR) settings, where a lack of awareness regarding the noise level can result in significant performance losses. Furthermore, the ED is unable to differentiate between interference and signal. The challenging task in ED-based sensing consists in minimizing the SNR wall with some detection probability while remaining resilient to noise power uncertainty [8]. The energy detection is the adopted technique in this paper for the spectrum sensing.

Cooperative Spectrum Sensing (CSS) is one proposed solution in literature. It deals with individual spectrum sensing issues caused by shadowing, fading and noise uncertainty. Miss detection as well as false alarm could be significantly reduced thanks to the cooperative sensing. Furthermore, collaboration can tackle a hidden node problem and reduce sensing time [9, 10]. In literature, the CSS has been widely studied [11, 12, 13]. Indeed, [11] and [14] provide a comprehensive assessment of much of the previous research in this field, highlighting the major gains and overheads of CSS.

Sharing information across cognitive radios and fusing data from diverse measures is a difficult problem in CSS. Mainly, there are two models of cooperation: distributed [15] and centralized [16]. Each cognitive device can make soft or hard judgments [17]. In terms of the risk of missing an opportunity, the reported results in [17, 18] suggest that soft data combining surpasses hard decision combination. However, when the number of collaborating users is big, hard decisions turn out to have the same efficiency as soft decisions [19].

In the case of soft data fusion, these algorithms are processed in the FC such as Square Law Combining (SLC) [4], Maximum Ratio Combining (MRC) [20], Selection Combining (SC) [21], Square Law Selection (SLS) [4], and linear rules [17] to integrate the samples. Similarly, the hard decisions combination performs methods like the AND-rule [22], the OR-rule[23] and the MAJORITY-rule [24]. Quite recently, considerable attention has been paid to apply machine learning methods for cooperative spectrum sensing. Theoretically, they give a better detection performance [25, 26, 27, 28] than conventional schemes. In spite, they must be trained on enormous data sets, they have significant computational, memory, and processing power needs [29]. Current researches on CSS are also focused on security issues [30]. In the other words, researchers are motivated to improve the cooperative detection performance in fusion rules without neglecting the security issues such as Spectrum Sensing Data Falsification (SSDF).

Fig.1 presents the main important gain from cooperative spectrum sensing, which is the improvement in receiver sensitivity threshold as explained in [19]. The reformulated data, once estimated, are merged (using the merging rule). The overall decision is then established and that the module plays a decisive role in the scheme despite the ease of this act. The key contribution of this paper is the introduction of a unique software data scheme for CSS that makes use of the SNR average of all CR users. Next sections of this paper serve its content as follows. The CSS schemes as well as the ED method are detailed in section 2 in order to present our model. Section 3 describes the soft and hard merge schemes used to validate our CSS system. In Section 4, the proposed improved SLC is analyzed in depth. Then, Section 5 provides the results and analysis related to our simulation. A small conclusion is finally provided in section 6.

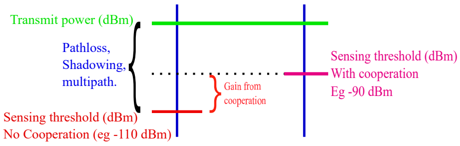

Fig. 1: Improvement in receiver sensitivity threshold in CSS.

II. System model

Fig.2 Illustrates our adopted system model. For our study, we favored the use of a centralized model. We find it to be more realistic than the distributed model where final decision making requires significant detection time. Our CRN has one PU and a single centralized FC to which the N unlicensed users (SU) are reporting their local decisions or their statistic tests regarding PU spectrum activity. At each k^{th} SU, ED based spectrum sensing is performed. Local decision statistic Λ_k was derived by k^{th} SU. Each sensing period consists in collecting L samples ($L = 2u$) which are selected according to the time-bandwidth product u. The secondary user reports a message $\Lambda_k (1 \leq k \leq N)$ to FC through a reporting channel which is assumed, in our paper, an error free reporting channel (ideal).

The overall final decision about the PU spectrum activity status is made on FC. As mentioned above, we apply ED for individual spectrum sensing. We assume that the k^{th} CR threshold is λ_k, which is equal to λ. The PU signal sensing issue could be modeled by a binary hypothesis test with null hypothesis H_0 where the PU signal is absent (white space) and alternative hypothesis H_1 where the PU signal is present. There are two main stages to perform a reliable spectrum sensing.

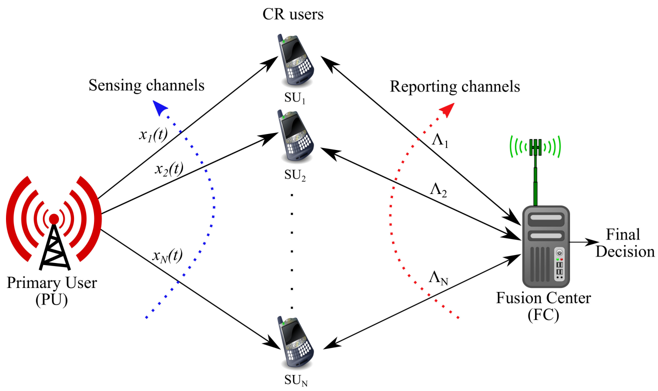

Fig. 2: Centralized cooperative spectrum sensing model.

In the first stage, we apply a local spectrum sensing. In the second one, we perform a cooperative spectrum sensing schemes. The received signal energy spectra $x(t)$ is used by the ED detector and compared to a predefined threshold level λ in estimating the presence or the absence of the PU signal. ED presents a fundamental limits in low SNR environment and can not estimate an exact noise variance σ_w^2. We can consider energy detection as a binary hypothesis testing scheme. As well, we can formulate the received signal at k^{th} SU, $x_k(t)$, by [5]:

$$x_k(t) = \begin{cases} w_k(t) & : H_0 \\ h_k(t)S(t) + w_k(t) & : H_1 \end{cases} \tag{1}$$

Where $S(t)$ is the licensed user (PU) signal with an energy E_s, $w_k(t)$ is the receiver noise at the k^{th} secondary user. The latter is regarded as being an independent identically distributed (i.i.d) random process having zero mean $\mu_w = 0$ and variance σ_w^2 and $h_k(t)$ is a channel gain between PU and k^{th} SU. Due to the limited resources of most CR users (e.g. energy and computing power), this technique is the most used in SS. By taking the average of the frequency intervals of a Fast Fourier Transform (FFT), an energy detector and a spectrum analyzer can be identically constructed. The received energy at the k^{th} SU, following the energy detection method, is provided by [31]:

$$\Lambda_k = E_k = \sum_{i=1}^{L} x_{k,i}^2(t) \tag{2}$$

In our analysis, we studied Additive White Gaussian Noise (AWGN) as sensing channel. As well, the control (reporting) channels are assumed to be ideal (error-free); there is no erroneous error due to the reporting channel. Each SU conducts single sensing separately using L samples of the received signal $x_k(t)$ at the k^{th} secondary user. Once the single spectrum sensing is performed, the results of the individual decision statistics Λ_k (local energies) as given in equation (2) are transmitted to the FC through a common reporting channel, that is assumed to have a large bandwidth to accomplish the assumption of error-free reporting channel.

The test statistic Λ_k for the k^{th} CR can be formulated as central and non-central distributed random variables under H_0 and H_1 respectively, as [5]:

$$\Lambda_k \sim \begin{cases} \chi^2_{2u}, & H_0 \\ \chi^2_{2u}(2\gamma_k), & H_1 \end{cases} \tag{3}$$

Where $\sim$ means "distributed as", γ_k denotes the SNR at the k^{th} SU, and χ^2_{2u}, $\chi^2_{2u}(2\gamma_k)$ are respectively the central and non-central chi-square distributions having, both of them, a same Degree of Freedom (DoF) $2u$ ($u = \frac{L}{2}$), with a non-central parameter $2\gamma_k$. For the AWGN sensing channel, we assume that the noise variance is equal to one ($\sigma_w^2 = 1$). The Probability Density Function (PDF) of Λ_k is provided by [4] as follows:

$$f_{\Lambda_k}(y) = \begin{cases} \frac{1}{2^u.\Gamma(u)}.y^{u-1}.e^{-\frac{y}{2}}, & H_0 \\ \frac{1}{2}.(\frac{y}{2\gamma_k})^{\frac{u-1}{2}}.e^{-\frac{2\gamma_k+y}{2}}.I_{u-1}(\sqrt{2\gamma_k y}), & H_1 \end{cases} \tag{4}$$

Where $\Gamma(a)$ represents the gamma function and $I_i(a)$ denotes the i^{th} order modified Bessel function of the first kind. Detection and false alarm probabilities, at the k^{th} cognitive radio, and for a non-fading Gaussian sensing channel, are described in [4] as follows:

$$P_{f,k} = Pr\{\Lambda_k > \lambda | H_0\} = \frac{\Gamma(u, \frac{\lambda}{2})}{\Gamma(u)} \tag{5}$$

$$P_{d,k} = Pr\{\Lambda_k > \lambda | H_1\} = Q_u(\sqrt{2\gamma_k}, \sqrt{\lambda}) \tag{6}$$

Where $\Gamma(a,x)$ is the upper incomplete gamma function so that $\Gamma(a,x) = \int_x^\infty t^{a-1}e^{-t}dt$, and $Q_u(a,x)$ denotes the generalized Marcum Q-function given by 7

$$Q_u(a,x) = \frac{1}{a^{u-1}}\int_x^\infty t^u e^{-\frac{a^2+t^2}{2}} I_{u-1}(at)dt \tag{7}$$

In Rayleigh fading channels, the false alarm probability does not depend on γ. Consequently, P_f is exactly the same in the Gaussian channel, but the amplitude of gain h_k varies due to the fading. The average detection probability under Rayleigh channel $\bar{P}_{dRay}$ can be formulated as follows [4]:

$$\begin{aligned} \bar{P}_{dRay} &= e^{-\frac{\lambda}{2\sigma_w^2}} \sum_{k=0}^{u-2} \frac{(\frac{\lambda}{2\sigma_w^2})^k}{k!} + \frac{(2\sigma_w^2 + 2\bar{\gamma})^{u-1}}{2\bar{\gamma}} \\ &\times [e^{-\frac{\lambda}{2\sigma_w^2+2\bar{\gamma}}} - e^{-\frac{\lambda}{2\sigma_w^2}} \sum_{k=0}^{u-2} \frac{(\frac{\lambda 2\bar{\gamma}}{2\sigma_w^2(2\sigma_w^2+2\bar{\gamma})})^k}{k!}] \end{aligned} \tag{8}$$

where $\bar{\gamma}$ denotes the sensing channel average SNR under Rayleigh fading. We develop the Gaussian approximations to the precise test statistic distributions, which are valid only for large time-bandwidth products u.

The Central Limit Theorem (CLT) suggests that L samples are i.i.d random variables with finite mean and that, if L is large enough, the variance approximates a normal distribution. Applying CLT, the test statistic distribution, given in equation (2), and for a given sufficient samples number L, can properly be approximated using a normal distribution as follows:

$$\Lambda \sim \mathcal{N}(\sum_{i=1}^{L}[|x(i)|^2], \sum_{i=1}^{L}[|x(i)|^2]). \tag{9}$$

The Λ_k distribution for a large number of L is given by:

$$\Lambda_k \sim \begin{cases} \mathcal{N}(L\sigma_w^2, 2L\sigma_w^4), & H_0 \\ \mathcal{N}(L\sigma_w^2(1+\gamma_k), 2L(1+\gamma_k)^2\sigma_w^4), & H_1 \end{cases} \tag{10}$$

Where $\mathcal{N}(\mu, \sigma_w^2)$ represents a Gaussian distribution with μ as a mean and σ_w^2 as a variance. As a result, the approximated false alarm probability ($P_{f,k,app}$) and the approximated detection probability ($P_{d,k,app}$) for the k^{th} SU are computed as follows [32]:

$$P_{f,k,app} = Q(\frac{\lambda - L\sigma_w^2}{\sigma_w^2\sqrt{2L}}) \tag{11}$$

$$P_{d,k,app} = Q(\frac{\lambda - L\sigma_w^2(1+\gamma_k)}{\sigma_w^2\sqrt{2L(1+\gamma_k)^2}}) \tag{12}$$

From equation 11, the approximated threshold $\lambda_{k,app}$ for k^{th} SU can be expressed as:

$$\lambda_{k,app} = \sigma_w^2(Q^{-1}(P_{f,k,app})\sqrt{2L} + L) \tag{13}$$

We assume that $\lambda_{k,app} = \lambda$ and that $Q(x) = \frac{1}{\sqrt{2\pi}}\int_x^\infty e^{-\frac{t^2}{2}}dt$ is the Gaussian Q-function.

III. Soft and hard fusion schemes in the cooperative system

In the subject of cooperative sensing, sharing data among cognitive radios and combining different statistic tests from various measurements is a challenging process. The shared information can be soft or hard decisions made by each secondary user [33].

CSS depends heavily on combining rules. To approximate the final result, the FC obtains individual data from various CRs and uses particular fusion strategies. As a result, the detection performance depends largely on the fusion rules to be used. In the literature, two kinds of fusion data combination are most used; hard decision combinations and soft data combination rules.

A. Hard rules

In this case, a local decision about the free frequency bands of the PU signals (hole spaces) is made by each SU separately. Then, an overall decision is made based on the one-bit decisions that are reported to the fusion center. Simplicity is the main advantage of this merge rule scheme in which a limited reporting channel bandwidth is sufficient. Making and reporting of binary decisions to the fusion center through the free control channel is followed by the use of three major mixing rules. Take the individual statistics $\Delta_k = 0, 1$ as the hard decision belonging to the k^{th} secondary user. The value "1" indicates the occupation of the PU frequency band while the "0" indicates the absence of licensed user signals, causing the inactivity of the PU frequency band. Collaborative detection probability Q_d as well as cooperative false alarm probability Q_f are respectively formulated in 15 and eq16. The spectrum availability decision is made in each SU by reporting only one bit that is provided by

Δ_k. This is done by making a comparison between the test statistic Λ_k and the predefined threshold λ.

$$\Delta_k = \begin{cases} 1, & \Lambda_k > \lambda \\ 0, & otherwise. \end{cases} \tag{14}$$

$$Q_d = Pr\left\{\Delta = 1|H_1\right\} \tag{15}$$

$$Q_f = Pr\left\{\Delta = 1|H_0\right\} \tag{16}$$

Where Δ represents the fusion center's final judgment, which will be communicated back to SUs. There are three hard decision combining schemes used in CSS as follows:

A..1 OR-rule

In the case where a signal is detected by at least one SU, the PU frequency band transmission/occupation is decided through the OR rule, which uses the binary cooperative hypothesis test in the following way:

$$\begin{cases} H_1 : \sum_{k=1}^{N} \Delta_k \geq 1 \\ H_0 : otherwise \end{cases} \tag{17}$$

Collaborative detection probability $Q_{d,OR}$ as well as collaborative false alarm probability $Q_{f,OR}$, in the OR rule case, are respectively computed by:

$$Q_{d,OR} = 1 - \prod_{k=1}^{N}(1 - P_{d,k}) \tag{18}$$

$$Q_{f,OR} = 1 - \prod_{i=k}^{N}(1 - P_{f,k}) \tag{19}$$

Where $P_{d,k}$ et $P_{f,k}$ are, respectively, detection and false alarm probabilities for k^{th} SU and N is the number of collaborating SUs.

A..2 AND-rule

In the AND rule scheme, if the cognitive nodes report the presence of a PU signal, this spectrum is then taken into consideration. We can describe the cooperative binary hypothesis test of the AND rule as follows:

$$\begin{cases} H_1 : \sum_{k=1}^{N} \Delta_k = N \\ H_0 : otherwise \end{cases} \tag{20}$$

In the case of the AND-rule, cooperative detection and cooperative false alarm probabilities are described by:

$$Q_{d,AND} = \prod_{k=1}^{N} P_{d,k} \tag{21}$$

$$Q_{f,AND} = \prod_{k=1}^{N} P_{f,k} \tag{22}$$

A..3 MAJORITY-rule

In case of signal detection by, at least, M users (among the N users), with $1 \leq M \leq N$, the MAJORITY-rule or voting combination scheme determines the presence of the PU signals. The cooperative binary hypothesis testing with the MAJORITY-rule is given by:

$$\begin{cases} H_1 : \sum_{k=1}^{N} \Delta_k \geq M \\ H_0 : otherwise \end{cases} \tag{23}$$

Indeed, if $M = \frac{N}{2}$, then the MAJORITY rule can be seen as a subset of the voting rule. This is also the case for the AND and OR rules which are seen as special cases if $M = 1$ and $M = N$. For the MAJORITY rule, we can therefore redefine respectively cooperative identification and false probability as follows:

$$Q_{d,MAJ} = \begin{cases} \sum_{k=\lceil \frac{N}{2} \rceil}^{N} \binom{N}{k} P_{d,k}^{k}(1 - P_{d,k})^{N-k}, N\, is\, odd \\ \sum_{k=\frac{N}{2}}^{N} \binom{N}{k} P_{d,k}^{k}(1 - P_{d,k})^{N-k}, N\, is\, even \end{cases} \tag{24}$$

$$Q_{f,MAJ} = \begin{cases} \sum_{k=\lceil \frac{N}{2} \rceil}^{N} \binom{N}{k} P_{f,k}^{k}(1 - P_{f,k})^{N-k}, N\, is\, odd \\ \sum_{k=\frac{N}{2}}^{N} \binom{N}{k} P_{f,k}^{k}(1 - P_{f,k})^{N-k}, N\, is\, even \end{cases} \tag{25}$$

B. Soft combining rules

The effectiveness of several soft data combining algorithms at fusion center (such as: SC, SLC, SLS, and MRC) is analyzed and discussed in this subsection. In soft data combining rules, secondary users send all single sensing findings Λ_k to the fusion center without making any decisions. Then, the global decision is achieved by combining N statistics at the FC, by applying a convenient fusion rule (such as SC, SLS, SLC, and MRC). Soft data combining performs better than hard data combining. However, it requires a higher reporting channel bandwidth. Hence, it provides more overheads than the hard decision combination.

B..1 Square law selection

The Square Law Selection (SLS) technique works on the idea that the FC chooses the maximum statistic test [4]. Therefore, $\Lambda_{SLS} = max(\Lambda_1, \Lambda_2, ..., \Lambda_N)$. In case of null hypothesis, and assuming that $\{\Lambda_k\}_{k=1}^{N}$ are i.i.d variables, so Q_f for SLS scheme ($Q_{f,SLS}$) can be evaluated using cumulative distribution function (CDF) of Λ_{SLS} given H_0, $F_{\Lambda_{SLS}}(\Lambda|H_0)$, yielding:

$$\begin{aligned} Q_{f,SLS} &= 1 - F_{\Lambda_{SLSSLS}}(\Lambda|H_0) \\ &= 1 - Prob\{max(\Lambda_1, \Lambda_2, ..., \Lambda_N) < \lambda|H_0\} \\ &= 1 - [1 - \Gamma(u, \lambda/2)/\Gamma(u)]^N. \end{aligned} \tag{26}$$

Furthermore, $Q_{d,SLS}$ for SLS over AWGN channels may be derived by conditioning on γ_k (under H_1). $Q_{d,SLS}$ is given in the following equation:

$$Q_{d,SLS} = 1 - \prod_{k=1}^{N}[1 - Q_u(\sqrt{2\gamma_k}, \sqrt{\lambda})] \tag{27}$$

In other words, taking advantage of CLT approximations, $Q_{d,app,SLS}$ and $Q_{f,app,SLS}$ can be expressed as:

$$Q_{d,app,SLS} = 1 - \prod_{k=1}^{N}(1 - Q(\frac{\lambda_{SLS} - L\sigma_w^2(1+\gamma_k)}{\sigma_w^2\sqrt{2L(1+\gamma_k)^2}})) \quad (28)$$

$$Q_{f,app,SLS} = 1 - (1 - Q(\frac{\lambda_{SLS} - L\sigma_w^2}{\sigma_w^2\sqrt{2L}}))^N, \quad (29)$$

For SLS, the detection approximated threshold is described by:

$$\lambda_{SLS} = (Q^{-1}(1 - (1 - Q_{f,app,SLS})^{\frac{1}{N}})(\sigma_w^2\sqrt{2L}) + L\sigma_w^2 \quad (30)$$

B..2 Square law combining

Besides the SLS, the SLC features an energy detection on each diversity branch that executes the square and integrate operation. The test statistics sum L, as presented in Fig.3a, is received by the energy detector. A new decision statistic is produced through the combination of various SLC outputs belonging to N users:

$$\Lambda_{SLC} = \sum_{k=1}^{N}\Lambda_k = \sum_{k=1}^{N}\sum_{i=1}^{L}|x_k(i)|^2 \quad (31)$$

Where Λ_k represents the k^{th} secondary user test statistic while x_k is the received signal through the k^{th} SU. Thus, according to the H_0 hypothesis, the test statistic Λ_{SLC} is following a central chi-square distribution with $2Nu$ DoF, assuming that all N Gaussian channels are i.i.d and that all the CRs are having a similar noise variance.

On the other hand, under the H_1 alternative hypothesis, the test statistic is considered non-central chi-square distribution having a $2Nu$ DoF besides a non-central parameter γ_{slc}.

Where $\gamma_{slc} = \sum_{k=1}^{N}\gamma_k$, and γ_k is the SNR of the k^{th} secondary user. In this approach, the estimated test statistic of each cognitive radio user is reported to the FC where they will be added together. The summation is compared to the predetermined threshold λ decision statistic as in [4]:

$$\Lambda_{SLC} \sim \begin{cases} \chi^2_{2Nu}, & H_0 \\ \chi^2_{2Nu}(2\gamma_{slc}), & H_1 \end{cases} \quad (32)$$

Using the SLC method, and with respect to non-fading Gaussian channels, false alarm and detection cooperative probabilities can respectively be calculated as follows:

$$Q_{f,SLC} = Prob\{\Lambda_{SLC} > \lambda | H_0\} = \frac{\Gamma(Nu, \frac{\lambda}{2})}{\Gamma(Nu)} \quad (33)$$

$$Q_{d,SLC} = Prob\{\Lambda_{SLC} > \lambda | H_1\} = Q_{Nu}(\sqrt{2\gamma_{slc}}, \sqrt{\lambda}) \quad (34)$$

The FC employs the SLC diversity technique to calculate the global test statistic Λ_{SLC}. As the received signal from SU takes a Gaussian distribution, the sum of N Gaussian distributions (all weighted by $\omega_k = 1$, then a $\sum_{k=1}^{N}\omega_k = N$), in the case of a value of L which is large, can always follow a Gaussian distribution when approximating it, i.e.:

$$\Lambda_{SLC,app} \sim \begin{cases} \mathcal{N}(LN\sigma_w^2, 2lN\sigma_w^4), & H_0 \\ \mathcal{N}(LN\sigma_w^2(1+\gamma), 2LN(1+\gamma)^2\sigma_w^4), & H_1 \end{cases} \quad (35)$$

Furthermore, the false alarm cooperative probability $Q_{f,app,SLC}$ as well as the detection cooperative probability $Q_{d,app,SLC}$ can respectively be expressed by:

$$Q_{d,app,SLC} = Q(\frac{\lambda_{SLC} - LN\sigma_w^2(1+\gamma)}{\sigma_w^2\sqrt{2LN(1+\gamma)^2}}) \quad (36)$$

$$Q_{f,app,SLC} = Q(\frac{\lambda_{SLC} - LN\sigma_w^2}{\sigma_w^2\sqrt{2LN}}), \quad (37)$$

Where σ_w^2 denotes the noise variance, γ_k represents the SNR value of the k^{th} SU and λ_{SLC} is the approximated detection threshold for SLC, given as:

$$\lambda_{SLC} = \sigma_w^2(Q^{-1}(Q_{f,app,SLC})\sqrt{2LN} + LN) \quad (38)$$

The final decision is then reached by comparing the global test statistic Λ_{SLC} to the threshold λ_{SLC}.

B..3 Maximal ratio combining

The maximal ratio data fusion rule is a coherent combining approach that requires channel state information (CSI). As a result, the design complexity may increase. Fig.3b outlines that SUs automatically amplify (weighting by w_k) and report the received samples of the PU signals, rather than the energy, to the FC, where data from different cognitive radios are summed in an MRC combiner.

On the other side, each k^{th} SU energy will be weighted by w_k, and the output of the MRC combiner will be measured by an energy detector. Therefore, the FC makes a statistical choice; Λ_{MRC} which may be expressed as central and non-central chi-square distributed random variables as:

$$\Lambda_{MRC} \sim \begin{cases} \chi^2_{2u}, & H_0 \\ \chi^2_{2u}(2\gamma_{mrc}), & H_1 \end{cases} \quad (39)$$

Where $\gamma_{mrc} = \sum_{k=1}^{N} w_k\gamma_k$, and $w_k = \frac{\gamma_k}{\sqrt{\sum_{i=1}^{N}\gamma_i^2}}$. The purpose of MRC scheme is based on computing the γ_{mrc}, and we use the same mathematical developments from equation (3) to equation (6) to get the cooperative probability of detection in 40. Finally, using the MRC system, false alarm and detection cooperative probability, under AWGN channel, is obtained by:

$$Q_{d,MRC} = Q_u(\sqrt{2\gamma_{mrc}}, \sqrt{\lambda}). \quad (40)$$

Referring to false alarm cooperative probability, it is independent of SNR, so $Q_{f,MRC}$ is written:

$$Q_{f,MRC} = \frac{\Gamma(u, \frac{\lambda}{2})}{\Gamma(u)}. \quad (41)$$

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From MRC definition, the final test statistic of MRC can be rewritten as follows:

$$\Lambda_{MRC} = \sum_{k=1}^{N} w_k \Lambda_k \tag{42}$$

As CLT assumptions for large L, Λ_k follows a Gaussian distribution. Therefore, Λ_{MRC} is the weighted Gaussian distributions sum and can always follow a Gaussian distribution in approximation. As result, the approximated cooperative probabilities for both detection and false alarm are:

$$Q_{d,app,MRC} = Q(\frac{\lambda_{MRC} - L\sum_{k=1}^{N}\omega_k(1+\gamma_k)}{\sigma_w^2\sqrt{2L\sum_{k=1}^{N}\omega_k^2(1+\gamma_k)^2}}) \tag{43}$$

$$Q_{f,app,MRC} = Q(\frac{\lambda_{MRC} - L\sum_{k=1}^{N}\omega_k\sigma_w^2}{\sigma_w^2\sqrt{2L\sum_{k=1}^{N}\omega_k^2}}), \tag{44}$$

Where the approximated detection threshold for MRC is given by:

$$\lambda_{MRC} = \sigma_w^2(Q^{-1}(Q_{f,app,SLC})\sqrt{2L\sum_{k=1}^{N}\omega_k^2}) + L\sum_{k=1}^{N}\omega_k \tag{45}$$

B..4 Selection combining

In the selection combining soft fusion rule, as shown in Fig.3b, the FC uses a statistic test Λ_{SC} which has the highest SNR γ_{sc}, where $\gamma_{sc} = max(\gamma_1, \gamma_2, ..., \gamma_N)$ and $\Lambda_{SC} = max(\Lambda_1, \Lambda_2, ..., \Lambda_N)$. Using the selection combining approach, the false alarm cooperative probability as well as detection probability, across a Gaussian channel, may be expessed by:

$$Q_{d,SC} = Q_u(\sqrt{2\gamma_{sc}}, \sqrt{\lambda}) \tag{46}$$

$$Q_{f,SC} = \frac{\Gamma(u, \frac{\lambda}{2})}{\Gamma(u)} \tag{47}$$

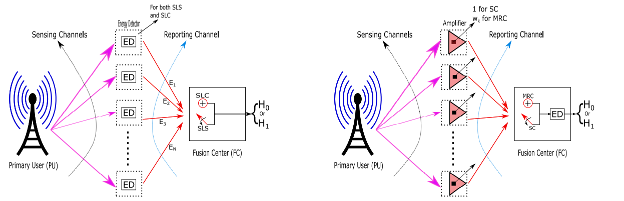
We can clearly see that the approximated values of detection and false alarm cooperative probabilities are respectively provided by:

$$Q_{d,app,SC} = Q(\frac{\lambda_{SC} - L\sigma_w^2(1+\gamma)}{\sigma_w^2\sqrt{2L(1+\gamma)^2}}) \tag{48}$$

$$Q_{f,app,SC} = Q(\frac{\lambda_{SC} - L\sigma_w^2}{\sigma_w^2\sqrt{2L}}) \tag{49}$$

Where the approximated threshold of SC λ_{SC} is given as:

$$\lambda_{SC} = (Q^{-1}(Q_{f,app,SC})\sqrt{2L}\sigma_w^2) + L\sigma_w \tag{50}$$



(a) SLS or SLC fusion rule model. (b) MRC or SC fusion rule model.

Fig. 3: The soft data combining rules structure.

IV. Proposed scheme for SLC

Soft fusion approaches outperform hard fusion methods in terms of detection. However, and contrary to hard fusion [22], transmitting local test statistics to FC in the soft fusion approach requires more control channel bandwidth. This overhead can be forwarded by minimizing the calculation process in the soft fusion technologies. MRC has a great detection performance, but the SLC approach is simple to implement, has a low complexity and do not require channel state information (CSI). Hence, we are motivated to develop SLC schemes to reach the performance of MRC method with minimum computing complexity. Thus, an improved SLC approach is provided in this paper.

The average SNR γ_{avg}, of all secondary users, is computed. In our proposed scheme, users energies (test statistics) with high SNR than the γ_{avg} are collected and aggregated for the final decision. When compared to the traditional SLC, this approach offers a higher detection probability, especially in a low SNR environment and a larger CRs number in the CSS. As a benefit other than increasing detection probability, the number of submitted results to the FC is reduced with no impact on detection performance. Consequently, there can be energy savings. The SNR average is calculated as follows:

$$\gamma_{avg} = \frac{1}{N}\sum_{k=1}^{N}\gamma_k \tag{51}$$

FC will take into account just M energies having SNR higher than average γ_{avg}. Therefore, our algorithm will combine just M test statistics, with M is less than N. The final test statistic of the first enhanced scheme $\Lambda_{ENH1,SLC}$ is defined at the FC. In which, the received local test statistics are combined then compared to the global threshold value $\lambda_{ENH1,SLC}$ in order to detect the spectrum activity of the PU, as in Eq53:

$$\Lambda_{ENH1,SLC} = \sum_{j=1}^{M}\Lambda_j \tag{52}$$

$$\lambda_{ENH1,SLC} = \sigma_w^2(Q^{-1}(Q_{f,Enh1,SLC})\sqrt{2LM} + LM) \tag{53}$$

Their ultimate probabilities are respectively given by:

$$Q_{d,ENH1,SLC} = Q(\frac{\lambda_{SLC} - LM\sigma_w^2(1+\gamma)}{\sigma_w^2\sqrt{2LM(1+\gamma)^2}}) \tag{54}$$

$$Q_{f,ENH1,SLC} = Q(\frac{\lambda_{ENH1,SLC} - LM\sigma_w^2}{\sigma_w^2\sqrt{2LM}}), \quad (55)$$

Our first proposal regarding enhanced SLC scheme is formulated via Algorithm. 1. It aims to perform data soft fusion.

Algorithm 1 First proposed enhanced SLC soft fusion scheme

1: Declare the parameters L,N
2: Determine the value of Λ
3: Compute the average SNR value γ_{avg}
4: Fix the desired value of Q_f
5: Initialize k (k represents the index of a single SU)
6: Conclude the individual test statistics (Λ_k) for k^{th} SU
7: **if** γ_k of k^{th} SU $\geq \gamma_{avg}$ **then**
8: Report Λ_k to FC
9: **else**
10: **end if**
11: Calculate M and $\lambda_{ENH1,SLC}$
12: Calculate final test statistics $\Lambda_{ENH1,SLC}$ Compare the $\Lambda_{ENH1,SLC}$ with the final $\lambda_{ENH1,SLC}$
13: **if** $\Lambda_{ENH1,SLC} \geq \lambda_{ENH1,SLC}$ **then**, set detection true
14: **end if**
15: Estimate the cooperative detection probability and move to step 4

A second improved soft data fusion scheme is similar to first one, but we will weight the M collected test statistics by θ_j, where :

$$\theta_j = \frac{\gamma_j}{\sqrt{\sum_{j=1}^{M}\gamma_j^2}} \quad (56)$$

Similarly, the detection and false alarm cooperative probabilities for the second enhanced SLC scheme can be given as:

$$Q_{d,ENH2,SLC} = Q(\frac{\lambda_{ENH2,SLC} - L\sum_{j=1}^{M}\theta_j(1+\gamma_j)}{\sigma_w^2\sqrt{2L\sum_{j=1}^{M}\theta_j^2(1+\gamma_j)^2}}) \quad (57)$$

$$Q_{f,ENH2,SLC} = Q(\frac{\lambda_{ENH2,SLC} - L\sum_{j=1}^{M}\theta_j\sigma_w^2}{\sigma_w^2\sqrt{2L\sum_{j=1}^{M}\theta_j^2}}), \quad (58)$$

Where the approximated detection threshold for the second enhanced SLC scheme is given as:

$$\lambda_{ENH2,SLC} = \sigma_w^2(Q^{-1}(Q_{f,app,SLC}) \sqrt{2L\sum_{j=1}^{M}\theta_j^2}) + L\sum_{j=1}^{M}\theta_j \quad (59)$$

V. Numerical and simulation results

We present in this section the simulation results as well as the analyzes related to our framework. The receiver operating characteristic curves (ROC) or complementary ROC (CROC) are compared in the different situations provided in the previous sections in order to validate our model. In the first part, we present and discuss our results for different types of soft and hard data combined under a Gaussian channel. In the second part, we present the detection performance of the proposed schemes. It should be noted that each of the following diagrams includes both analysis and simulation results. These results are respectively described through by lines and discrete marks. The primary user signals were modeled as deterministic signals such as BPSK signals, and the noise $w(t)$ is assumed to be AWGN, so $\sigma_w^2 = 1$ and $\mu_w = 0$. In Fig.4, the CROC curves (Q_f versus Q_m) are drawn for different soft and hard data fusion schemes. It is seen from Fig.4 that the individual cooperation suffers both under Gaussian channel and Rayleigh channel when compared to cooperative sensing. It can also be seen that the MRC scheme significantly outperforms all other soft and hard schemes. As mentioned earlier [22], the OR rule outperforms all hard data combinations. In addition, from our findings, the OR rule surpasses SC, and has an identical detection performance with SLS under AWGN channel. One of the great advantages of the SLC method is that it does not require channel state information, and further improves the cooperative detection performance. This fact motivated us to develop the SLC scheme in a critical environment for low SNRs. The exact and the approximate detection probabilities for deterministic and random primary signal models were examined in [34]. It was shown that they converge for low SNR but significantly diverge for high SNR. Another argument to analyze our approaches in case of low SNR [35] is to get our finding more practical in real scenarios [36]. In Fig.5, the detection performance of the two enhanced SLC methods is compared with that of conventional soft fusion methods such as SLC and MRC. Compared to a traditional SLC, the proposed schemes have better detec-

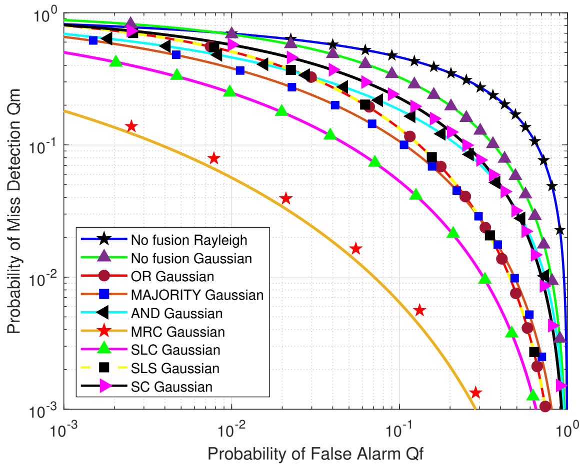


Fig. 4: CROC curves for Hard and Soft fusion rules with $\bar{\gamma} = 0dB$, $N = 3$ and $L = 10$

tion performance. Whereas, for the conventional MRC, the proposed schemes share slightly equal performance with, as shown in the enlarged figure. Analysis and simulation indicate that our results describe for the first time a slightly identical improvement in detection between the proposed method and MRC. Furthermore, they have low computational processing, and power consumption than MRC scheme. The effect of $\bar{\gamma}$ on cooperative detection probability is shown in Fig.6. It is observed that as $\bar{\gamma}$ increases, Q_d increases significantly. It can be noted that MRC scheme is superior over all Soft combining schemes. Clearly the proposed rules have a better performance than SLS, especially the second enhanced method that is competitive to MRC technique.

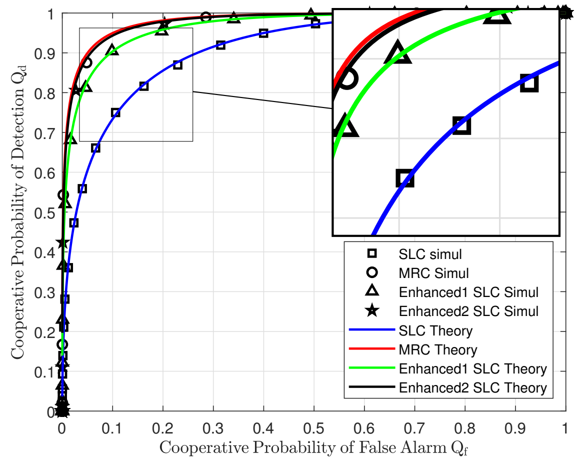


Fig. 5: Comparison of cooperative detection performance of Enhanced SLC with conventional SLC and MRC for $N = 20$, $\bar{\gamma} = -20$ and $L = 1000$.

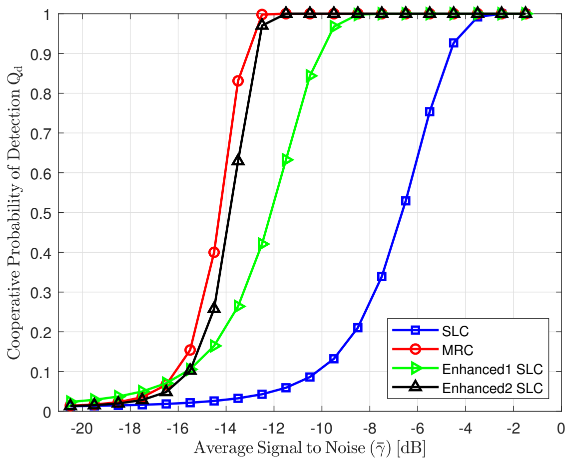


Fig. 6: Detection performance in variation of $\bar{\gamma}$ for $P_f = 0.01$, $N = 20$ and $L = 1000$.

VI. Conclusion

To improve the performance of the SLC method, an enhanced SLC method for soft fusion is proposed and simulated. In fact, the proposed methods have been found to outperform the conventional SLC method and are slightly identical to MRC with less computational complexity. Simulations results reveal that CSS with the OR rule is the best hard combination for high cooperative probability of false alarm. Conversely, for the low probability of false alarm, the MAJORITY rules is the best. SLC and MRC rules have been confirmed to have better detection probabilities than SLS, SC, and all hardware data combinations. The proposed method can be readily used in practice. Therefore, future work will involve the application of the proposed fusion scheme in a realistic scenario using software defined radio platforms, and studying the case of channel fading with erroneous reporting channel.

REFERENCES

[1] J. Mitola and G. Maguire, “Cognitive radio: Making software radios more personal,” IEEE Personal Communications, vol. 6, no. 4, pp. 13–18, Aug./1999.

[2] S. Force, “Spectrum policy task force report,” Federal Communications Commission ET Docket 02, vol. 135, 2002.

[3] A. Ghasemi and E. S. Sousa, “Spectrum sensing in cognitive radio networks: requirements, challenges and design trade-offs,” IEEE Communications magazine, vol. 46, no. 4, pp. 32–39, 2008.

[4] F. F. Digham, M.-S. Alouini, and M. K. Simon, “On the Energy Detection of Unknown Signals Over Fading Channels,” IEEE Transactions on Communications, vol. 55, pp. 21–24, Jan. 2007.

[5] H. Urkowitz, “Energy detection of unknown deterministic signals,” Proceedings of the IEEE, vol. 55, no. 4, pp. 523–531, 1967.

[6] J. Proakis, “Digital communications 4th ed. mcgraw-hill,” New York, 2001.

[7] P. Aparna and M. Jayasheela, “Cyclostationary feature detection in cognitive radio using different modulation schemes,” International Journal of Computer Applications, vol. 47, no. 21, 2012.

[8] K. Captain and M. Joshi, “Snr wall for generalized energy detector in the presence of noise uncertainty and fading,” Physical Communication, vol. 32, pp. 172–184, 2019.

[9] G. Ganesan and Y. Li, “Agility improvement through cooperative diversity in cognitive radio,” in GLOBECOM’05. IEEE Global Telecommunications Conference, 2005., vol. 5, pp. 5–pp, IEEE, 2005.

[10] D. Cabric, A. Tkachenko, and R. W. Brodersen, “Spectrum sensing measurements of pilot, energy, and collaborative detection,” in Milcom 2006-2006 IEEE military communications conference, pp. 1–7, IEEE, 2006.

[11] I. F. Akyildiz, B. F. Lo, and R. Balakrishnan, “Cooperative spectrum sensing in cognitive radio networks: A survey,” Physical Communication, vol. 4, pp. 40–62, Mar. 2011.

[12] J. Ma, G. Zhao, and Y. Li, “Soft combination and detection for cooperative spectrum sensing in cognitive radio networks,” IEEE Transactions on Wireless Communications, vol. 7, no. 11, pp. 4502–4507, 2008.

[13] W. Zhang and K. B. Letaief, “Cooperative spectrum sensing with transmit and relay diversity in cognitive radio networks-[transaction letters],” IEEE Transactions on wireless communications, vol. 7, no. 12, pp. 4761–4766, 2008.

[14] H. Rif`a-Pous, M. J. Blasco, and C. Garrigues, “Review of robust cooperative spectrum sensing techniques for cognitive radio networks,” Wireless Personal Communications, vol. 67, no. 2, pp. 175–198, 2012.

[15] W. Zhang, Z. Wang, Y. Guo, H. Liu, Y. Chen, and J. Mitola III, “Distributed cooperative spectrum sensing based on weighted average consensus,” in 2011 IEEE Global Telecommunications Conference- GLOBECOM 2011, pp. 1–6, IEEE, 2011.

[16] J. Zhuang, Y. Wang, P. Wan, S. Zhang, and Y. Zhang, “Centralized spectrum sensing based on covariance matrix decomposition and particle swarm clustering,” Physical Communication, vol. 46, p. 101322, 2021.

[17] E. Visotsky, S. Kuffner, and R. Peterson, “On collaborative detection of tv transmissions in support of dynamic spectrum sharing,” in First IEEE International Symposium on New Frontiers in Dynamic Spectrum Access Networks, 2005. DySPAN 2005., pp. 338–345, IEEE, 2005.

[18] T. Weiss, “A diversity approach for the detection of idle spectral resources in spectrum pooling systems,” in Proc. of 48th International Scientific Colloquium, Sept. 2003, 2003.

[19] S. Mishra, A. Sahai, and R. Brodersen, “Cooperative Sensing among Cognitive Radios,” in 2006 IEEE International Conference on Communications, (Istanbul), pp. 1658–1663, IEEE, 2006.

[20] H. Guo, W. Jiang, and W. Luo, “Linear soft combination for cooperative spectrum sensing in cognitive radio networks,” IEEE Communications Letters, vol. 21, no. 7, pp. 1573–1576, 2017.

[21] N. Kong and L. B. Milstein, “Average snr of a generalized diversity selection combining scheme,” IEEE Communications Letters, vol. 3, no. 3, pp. 57–59, 1999.

[22] M. S. Hossain, M. I. Abdullah, and M. A. Hossain, “Hard combination data fusion for cooperative spectrum sensing in cognitive radio,” International Journal of Electrical and Computer Engineering, vol. 2, no. 6, p. 811, 2012.

[23] K. Umebayashi, J. J. Lehtom¨aki, and Y. Suzuki, “Study on efficient decision fusion in or-rule based cooperative spectrum sensing,” in 2012 IEEE Wireless Communications and Networking Conference (WCNC), pp. 714–718, IEEE, 2012.

[24] C. Sudhamani, K. A. Reddy, D. S. Hussain, P. P. Kumar, and T. U. Kumar, “Total error rate in cooperative spectrum sensing with and, or and majority fusion rules,” in 2016 International Conference on Communication and Signal Processing (ICCSP), pp. 1822–1825, IEEE, 2016.

[25] R. Sarikhani and F. Keynia, “Cooperative spectrum sensing meets machine learning: Deep reinforcement learning approach,” IEEE Communications Letters, vol. 24, no. 7, pp. 1459–1462, 2020.

[26] D. Cho, K. Minhoe, and L. Woongsup, “Deep cooperative sensing: Cooperative spectrum sensing based on cnn,” IEEE Trans. VT, vol. 68, no. 3, pp. 1–1, 2019.

[27] H. Anandakumar and K. Umamaheswari, “Supervised machine learning techniques in cognitive radio networks during cooperative spectrum handovers,” Cluster Computing, vol. 20, no. 2, pp. 1505–1515, 2017.

[28] K. M. Thilina, K. W. Choi, N. Saquib, and E. Hossain, “Machine learning techniques for cooperative spectrum sensing in cognitive radio networks,” IEEE Journal on selected areas in communications, vol. 31, no. 11, pp. 2209–2221, 2013.

[29] E. Garc´ıa-Mart´ın, C. F. Rodrigues, G. Riley, and H. Grahn, “Estimation of energy consumption in machine learning,” Journal of Parallel and Distributed Computing, vol. 134, pp. 75–88, 2019.

[30] F. Salahdine and N. Kaabouch, “Security threats, detection, and countermeasures for physical layer in cognitive radio networks: A survey,” Physical Communication, vol. 39, p. 101001, 2020.

[31] V. I. Kostylev, “Energy detection of a signal with random amplitude,” in 2002 IEEE International Conference on Communications. Conference Proceedings. ICC 2002 (Cat. No. 02CH37333), vol. 3, pp. 1606–1610, IEEE, 2002.

[32] R. Tandra and A. Sahai, “Fundamental limits on detection in low snr under noise uncertainty,” in 2005 International Conference on Wireless Networks, Communications and Mobile Computing, vol. 1, pp. 464–469, IEEE, 2005.

[33] T. Yucek and H. Arslan, “A survey of spectrum sensing algorithms for cognitive radio applications,” IEEE communications surveys & tutorials, vol. 11, no. 1, pp. 116–130, 2009.
[34] R. Umar, A. U. Sheikh, and M. Deriche, “Unveiling the hidden assumptions of energy detector based spectrum sensing for cognitive radios,” IEEE communications surveys & tutorials, vol. 16, no. 2, pp. 713–728, 2013.
[35] S. Atapattu, C. Tellambura, H. Jiang, and N. Rajatheva, “Unified analysis of low-snr energy detection and threshold selection,” IEEE Transactions on vehicular technology, vol. 64, no. 11, pp. 5006– 5019, 2014.
[36] C. R. Stevenson, G. Chouinard, Z. Lei, W. Hu, S. J. Shellhammer, and W. Caldwell, “Ieee 802.22: The first cognitive radio wireless regional area network standard,” IEEE communications magazine, vol. 47, no. 1, pp. 130–138, 2009.