**Improved sensing detector for wireless regional area networks**

Jyotshana Kanti and Geetam Singh Tomar

**Abstract:** In wireless communication, noise and fading affect the radio signals. Multiple antennas one of the solutions to nullify these affects. In this paper, authors proposed an improved sensing detector for wireless regional area networks. The presented scheme uses two detectors concept, detectors imply multiple antennas, follows selection combination to select best signals. The proposed model not only improves the detection performance but also decreases the sensing time. Out of the two detectors the first one is energy detector with single adaptive threshold and second one is energy detector with two adaptive thresholds. The thresholds are adaptive as they are dependent on noise variance ($\sigma^2$), and the value of this noise variance changes according to the noise signal. Both the detectors work simultaneously and their output is then fed to a decision devise which takes the decision using OR rule. In the proposed scheme more than one antenna has been used and is compared with existing sensing techniques. Results show that the proposed an improved sensing detector technique while number of antennas ($N_r$) = 2, improves the detection performance by 24.6, 53.4, 37.9, and 49.6%, as compared to existing schemes (i.e. EDT-ASS-2015 scheme, ED and cyclo-2010, adaptive SS-2012, and conventional-ED) scheme at −12 dB SNR respectively. Meanwhile, proposed technique also decreases sensing time in the order of 47.0, 49.0, and 53.2 ms as...
compared to existing schemes (EDT-ASS-2015, Adaptive SS-2012, and ED and Cyclo-2010) scheme at −20 dB SNR respectively. Further, in cooperative SS the local decisions from each cognitive radio are transferred to a fusion center which makes the final decision and shares the decision to every cognitive radio. It is also found that the proposed detection technique with CSS when number of CR users \((k) = 10\), and \(N_r = 2\), achieves spectrum detection performance in the order of 0.9 for SNR value of as low as −20 dB.

Subjects: Computer Engineering; Information & Communication Technology (ICT); Communication Technology

Keywords: cognitive radio networks; single adaptive threshold; two adaptive thresholds; two detectors; cooperative spectrum sensing; spectrum sensing

1. Introduction
In present scenario, day-by-day technology is growing, and cognitive radio network (5-G technology) is one of the examples of this. In cognitive radio network (CRN), spectrum sensing plays an important role. There are various techniques have been proposed by researchers to sense licensed signal. Such as in Maleki, Pandharipande and Leus (2010), authors have proposed two-stage spectrum sensing technique (ED and cyclo-2010) to improve detection performance. This technique carried two detectors, first stage consisted energy detector and second stage consisted cyclostationary detector to give better sensing performance, however it was computationally more complex and required longer sensing time. Then, in Ejaz, Hasan, and Kim (2012), authors have proposed adaptive spectrum sensing scheme (adaptive SS-2012). In this scheme, out of two stages only one of the detection stage performed at a time, which was based on the estimated SNR. Presence of cyclostationary detector in Ejaz et al. (2012) made system implementation more complicated. Furthermore, in Sobron, Diniz, Martins, and Velez (2015), authors presented energy detection technique for adaptive spectrum sensing (EDT-ASS-2015). Here, authors focused on cost-function that depended upon a single parameter which, by itself, contained the aggregate information about the presence or absence of primary users.

In this paper, we optimize detection performance using multiple antennas with two detectors, two detectors ED_SAT and ED_TAT perform sensing operation simultaneously. Thresholds are adaptive that’s why chances of occurring sensing failure problem is negligible (Liu, Hu, & Wang, 2012). The output results of detectors go to decision device (DD) who takes final decision using OR-rule, if the output of DD is 1 shows frequency band is busy \((H_1)\), otherwise free \((H_0)\). The main difference between this paper and others (Ejaz et al., 2012; Maleki et al., 2010; Sobron et al., 2015) are that none of these techniques focused on spectrum sensing failure (Liu et al., 2012), and fading problem. Adaptive threshold scheme reduces sensing failure problem while multiple antennas mitigate fading problem.

We further cooperative spectrum sensing scheme with an improved sensing detector (ISD). Here, all the CRs perform local observation by using ISD technique. The local decision will be made and reported to the fusion center (FC) in the form of binary bit i.e. 0 or 1. The FC will make a final decision using hard decision rule. In the proposed model we have used hard decision rule because it has better detection performance when the number of cooperating CR users is large (Akyildiz, Lo, & Balakrishnan, 2011), and provides slightly better performance at low probability of false alarm \((P_f)\) (Teguig, Scheers, & Le Nir, 2008).

The novelty of this paper that proposed model is using multiple antennas to mitigate fading problem, and detectors are using adaptive thresholds to mitigate sensing failure problem. Final decision makes by DD, simulation results show that the proposed model enhances detection performance at \(P_f = 0.1\), performs well at low SNRs, and reduces sensing time as well.
The rest of the paper is organized as follows: Section 2 presents system description. Section 3 describes proposed system model. Section 4 shows the numerical results and analysis. Finally, Section 5 concludes the paper.

2. System description

There is a mathematical expression to detect the PU signal by using following hypothesis for received signal (Bagwari & Singh, 2012):

\[
 r(n) = \begin{cases} 
 w(n), & H_0 \\
 x(n)h + w(n), & H_1 
\end{cases} \quad (1)
\]

In Equation (1), \( r(n) \) is signal received by each CR user, \( x(n) \) is the PU licensed signal, \( w(n) \) is AWGN (additive white gaussian noise) with zero mean i.e. \( w(n) \sim \mathcal{N}(0, \sigma^2) \), \( \sigma^2 \) is noise variance, \( h \) is the gain of Rayleigh fading channel. \( H_0 \) is the null hypothesis, shows the absence of PU and \( H_1 \) is the alternative hypothesis, shows that PU is present.

3. Proposed system model

3.1. An improved sensing detector

Figure 1 illustrates the proposed system model of an ISD. There are \( N_r \) number of antennas are implemented at each CR users. \( N \) is number of samples transmitted by PU. In Figure 1, Maximal-ratio combining (MRC) scheme is not considered since it has spectrum sensing overhead due to channel estimation. Moreover, a combining scheme based on the sum of the decision statistics of all antennas in the CR is not analytically tractable. Therefore, we assume that each CR contains a selection combiner (SC) that outputs the maximum value out of \( N \) decision statistics calculated for different diversity branches as \( x = \max(x_1, x_2, x_3, ..., x_{N_r}) \). The output of the SC is applied to upper stream and lower stream. In Figure 1, upper stream carries ED with single adaptive threshold, this detector is similar as conventional-ED, except adaptive threshold that’s why detector is an advance version of conventional-ED. ED with single adaptive threshold calculates energy \( X \) of received signal (Bagwari & Singh, 2012) and compares with adaptive threshold \( \lambda_1 \), then generates output \( L_1 \) and passes to decision device (DD) in the form of binary bits. If the calculated energy \( X \) is greater and equal to adaptive threshold \( \lambda_1 \), then the output of detector \( L_1 \) is bit 1 else bit 0. Similarly, the lower stream...
carries ED with two adaptive thresholds (ED_TAT), this detector is different from the upper stream detector because it has two adaptive thresholds. Two adaptive thresholds concept is fruitful to reduce sensing failure problem (Liu et al., 2012). Now, ED_TAT computes the energy, compares with thresholds ($\lambda_2$) and produces output ($L_2$). If computed energy is greater and equal to $\lambda_2$, then the output $L_2$ will be bit 1 else bit 0. The outputs of detectors (ED_SAT and ED_TAT) go to decision device (DD), further, DD adds $L_1$ & $L_2$ using OR-rule operation. According to OR-rule, if the sum of $L_1$ & $L_2$ is greater or equal to 1, shows $H_1$ (channel is busy), else shows $H_0$ (channel is free) as shown in Figure 1.

Suppose, $x_j(k)$ is the received signal at $j$th antenna for $k$th data stream, sensing channel between PU and CR is assumed to be Rayleigh fading channel, $N$ is total number of samples to be sensed by CR and $N_r$ is number of antennas. Hence, the overall output of a SC as follows:

$$SC_{o/p} = \max \sum_{j=1}^{N} \left[ \sum_{k=1}^{N} |x_j(k)|^2 \right]$$  \hspace{1cm} (2)

It is seen from Figure 1 that individual antennas are allocated to cognitive radio. Now we consider that antenna branch which has maximum gain and passes to detectors for further process.

- Probability of detection of an ISD can be defined as:

$$P_D^{ISD} = P_r \times P_{d,ED_SAT} + (1 - P_r) \times P_{d,ED_TAT} + P_r$$  \hspace{1cm} (3)

$$P_D^{ISD} = P_r (1 + P_{d,ED_SAT} - P_{d,ED_TAT}) + P_{d,ED_TAT}$$  \hspace{1cm} (4)

- Total error probability of an ISD can be defined as:

$$P_e^{ISD} = P_{f,ISD} + (1 - P_{d,ISD})$$  \hspace{1cm} (5)

$$P_e^{ISD} = P_r \left( P_{f,ED_SAT} - P_{f,ED_TAT} + P_{f,ED_TAT} \right) + P_{f,ED_TAT} + P_{d,ED_TAT} + 1$$  \hspace{1cm} (6)

where $P_{d,ED_SAT}$ and $P_{d,ED_TAT}$ are the probability of detection throughout of ED_SAT and ED_TAT detector respectively, $P_{f,ED_SAT}$ and $P_{f,ED_TAT}$ are the probability of false alarm of ED_SAT and ED_TAT detector respectively. $P_r$ is the probability factor that a channel would be reported to ED_SAT and therefore, the probability that a channel would be reported to ED_TAT detector will be $(1-P_r)$, $P_r$ depends on SNR of the channels to be sensed i.e. if $P_r < 0.5$ shows channel is very noisy, and $P_r \geq 0.5$ shows channel is less noisy or has a good SNR. Hence, the overall probability of false alarm and probability of detection directly depend on $P_r$ (0 ≤ $P_r$ ≤ 1).

3.1.1. Energy detector with single adaptive threshold (ED_SAT)

Energy detector plays an important role in CRN in order to detect PU signal due to its simplicity and easy to implement (Urkowitz, 1967). Figure 2 shows the internal architecture of ED with single adaptive threshold (ED_SAT). Here, input PU licensed signal received by square law device, which shows detected signal energy ($X$) and compared with single adaptive threshold ($\lambda_1$) to make an output decision to determine whether the PU is present or absent.

![Figure 2. Energy detector with single adaptive threshold (ED_SAT).](image-url)
3.1.1.1. Expression of single adaptive threshold. The mathematical expression of single adaptive threshold ($\lambda_1$) can be defined as (Tandra & Sahai, 2008):

$$\lambda_1 = \left[ N \times N_r \times \sigma_m^2 \left\{ Q^{-1} \left( P_f \right) \times \sqrt{\frac{2}{N \times N_r} + 1} \right\} \times \frac{\left( \frac{\sigma_x}{\sigma_m^2} \right)}{\left( \frac{\sigma_x}{\sigma_m^2} \right)} \right]$$

(7)

where, $N$ is number of samples, $N_r$ is number of antennas, $Q^{-1}()$ denotes inverse-gaussian tail probability $Q$-function, $P_f$ is probability of false alarm, and $\sigma_m^2$ is noise variance. Analyze Equation (7), threshold ($\lambda_1$) is directly proportional to noise variance ($\sigma_m^2$), noise variance depends on noise signal, and noise signal is random in nature and change w.r.t. time, due to this noise variance ($\sigma_m^2$) varies, and then threshold ($\lambda_1$) also change. Threshold is adaptive in nature, therefore, at every time instant its value changes.

Consider Figure 2, decision device-I of ED_SAT is given by:

$$DD - I = \begin{cases} \text{if } \lambda_1 \leq X, & \text{bit 1} \\ \text{if } X < \lambda_1, & \text{bit 0} \end{cases}$$

(8)

3.1.1.1.1. Probability of detection for ED_SAT detector. The final expression for probability of detection can be written as (Sobron et al., 2015):

$$P_{ED_SAT}^d = Q \left[ \sqrt{\frac{N \times N_r}{2}} \times \left( \frac{\lambda'}{N \times N_r} - 1 \right) \right]$$

(9)

In Equation (9), $N$ is number of samples, $Q()$ denotes Gaussian tail probability $Q$-function, and $\lambda'$ is defined as $\lambda' = \frac{\lambda_1}{\left( \frac{\sigma_x}{\sigma_m^2} \right)}$, where, $\lambda_1$ is single adaptive threshold, $\sigma_x^2$ is PU signal variance, and $\sigma_m^2$ is noise variance.

3.1.1.1.2. Probability of false alarm for ED_SAT detector. The final mathematical expression of probability of false alarm can be derived as (Sobron et al., 2015):

$$P_{ED_SAT}^f = Q \left[ \sqrt{\frac{N \times N_r}{2}} \times \left( \frac{\lambda''}{N \times N_r} - 1 \right) \right]$$

(10)

In Equation (10), $N$ is number of samples, and $\lambda''$ is defined as:

$$\lambda'' = \frac{\lambda_1}{\left( \frac{\sigma_x}{\sigma_m^2} \right)}$$

3.1.1.1.3. Total error probability for ED_SAT detector. The total error rate is the sum of the probability of false alarm ($P_f$) and the probability of missed detection alarm ($P_m$). Hence, the total error probability rate as follows (Bagwari, Kanti, Tomar, & Samarah, 2015):

$$P_{e}^{ED_SAT} = (P_{m}^{ED_SAT}) + P_{f}^{ED_SAT}$$

(11)

where $(1 - P_f)$ shows the probability of missed detection ($P_m$), then:

$$P_{e}^{ED_SAT} = Q \left[ \sqrt{\frac{N \times N_r}{2}} \times \left( \frac{\lambda''}{N \times N_r} - 1 \right) \right] + \left(1 - Q \left[ \sqrt{\frac{N \times N_r}{2}} \times \left( \frac{\lambda'}{N \times N_r} - 1 \right) \right] \right)$$

(12)
3.1.2. Energy detector with two adaptive thresholds (ED_TAT)

This is a simple kind of a circuit of ED except threshold. In this model we used two adaptive thresholds.

Figure 3 depicts internal model of ED_TAT in which firstly square law device (SLD) receives the sensed PU signal and computes signal energy \( Y \). Further SLD, there are two parts, in upper part if detected energy values \( Y \) are greater than or equal to \( \lambda_{22} \), it generates bit 1, or less than \( \lambda_{21} \) generates bit 0.

But, if detected energy values \( Y \) fall between \( \lambda_{21} \) and \( \lambda_{22} \) then it consider lower part as follow:

\[
Y_1 = \begin{cases} 
  \text{represent bit 0} & \text{if } Y < \lambda_{21}, \\
  \text{represent bit 1} & \text{if } \lambda_{22} \leq Y 
\end{cases}
\]

(13)

But, if detected energy values \( Y \) fall between \( \lambda_{21} \) and \( \lambda_{22} \) then it consider lower part as follow:

\[
\begin{align*}
Y_1 & = \begin{cases} 
  \text{represent bit 01} & \text{if } \lambda_{21} \leq Y < \lambda_{22}, \\
  \text{represent bit 10} & \text{if } \lambda_{2} \leq Y < \lambda_{22}
\end{cases} \\
Y_2 & = \{1, 2\}, \quad \lambda_{21} \leq Y < \lambda_{22}
\end{align*}
\]

(14)

(15)

\[ Z = (Y_1 + Y_2) \]

(16)

Finally, using Equations (13), (15) and (16) the local decision (DD-II) of ED_TAT is expressed as:

\[
DD-II = \begin{cases} 
  \text{bit 1}, & \lambda_{2} \leq Z \\
  \text{bit 0}, & Z < \lambda_{2}
\end{cases}
\]

(17)

Equation (17), equating the resultant value \( Z \) to threshold \( \lambda_z \) to maintain overall system probability of false alarm \( P_f \) 0.1. If \( Z \) is greater than or equal to \( \lambda_z \) then signal is present otherwise absent.

3.1.2.1. Two adaptive threshold scheme for spectrum sensing. In CRN, this is very difficult situation for detector to detect correct signal when noise and PU signal overlap to each other as shown in Bagwari and Tomar (2013a). To overcome this problem two adaptive thresholds are the fruitful solution. The area comes under thresholds \( \lambda_{21} \) and \( \lambda_{22} \) known as confused region (Bagwari & Tomar, 2013a). \( \lambda_{21} \) is known as upper bound and \( \lambda_{22} \) is known as lower bound.

In Bagwari and Tomar (2013a), if the energy of received signal lies beyond \( \lambda_{21} \) or \( \lambda_{22} \), detector generates bit 0 or bit 1 respectively, whereas, between \( \lambda_{21} \) and \( \lambda_{22} \), we divided the confused region into equal quantization level. We further, converted these levels into decimals. Now, correlating (Bagwari & Tomar, 2013a) with Figure 3, if \( X \) lies beyond \( \lambda_{21} \) or \( \lambda_{22} \), upper part of Figure 3 (ED_TAT) shows \( Y_1 \).
\[ Y_1 = \begin{cases} \text{bit } 0, & Y \leq \lambda_{21} \\ \text{bit } 1, & \lambda_{22} < Y \end{cases} \]  

(18)

But if energy lies between \( \lambda_{21} \) and \( \lambda_{22} \), then lower part of Figure 3 (ED_TAT) shows \( Y_2 \).

\[ Y_2 = \begin{cases} 1, & \lambda_{21} \leq Y < \lambda_2 \\ 2, & \lambda_2 \leq Y < \lambda_{22} \end{cases} \]  

(19)

Hence, final expression can be written as:

\[ Z = \begin{cases} \text{if } Y < \lambda_{21} \text{ or } \lambda_{22} < Y, & \text{show } Y_1 \\ \text{if } \lambda_{21} \leq Y < \lambda_{22}, & \text{show } Y_2 \end{cases} \]  

(20)

3.1.2.2. Expression of two adaptive threshold. In the proposed double threshold decision, the value of maximum noise variance shows the value of upper threshold \( \lambda_{22} \) and the value of minimum noise variance shows the value of lower threshold \( \lambda_{21} \). Hence, the mathematical expression of two adaptive threshold \( (\lambda_{21} \text{ and } \lambda_{22}) \) can be defined as:

\[ \lambda_{22} = \left( N \times N_r \times \rho \times \sigma_w^2 \right) \times \left( Q^{-1}(\overline{P}_f) \times \sqrt{2 \times \rho \over N \times N_r} + 1 \right) \]  

(21)

\[ \lambda_{21} = \left( N \times N_r \times \rho \times \sigma_w^2 \right) \times \left( Q^{-1}(\overline{P}_f) \times \sqrt{2 \times \rho \over N \times N_r} + 1 \right) \]  

(22)

Earlier, we have discussed that threshold is adaptive if it depends on noise variance, in above Equations (21) and (22) thresholds \( (\lambda_{22} \text{ and } \lambda_{21}) \) depend on noise variance \( \sigma_w^2 \). \( Q^{-1}(\cdot) \) denotes the inverse Gaussian tail probability \( Q \)-function. Assuming that the noise uncertainty in the wireless network environment is defined as \( [1/\rho \sigma_w^2, \rho \sigma_w^2] \), where \( \rho \) is a constant parameter that computes the size of the uncertainty and \( \rho > 1 \).

3.1.2.2.1. Probability of detection for ED_TAT detector. Suppose that \( r_i \) is the normalized version of received sample \( r(n) \), the cumulative distribution function (CDF) of the ED_TAT, can be calculated as:

\[ f_{Z}(z) = Pr \left( |r_i| \leq \sqrt{z^2} \right) \]  

(23)

In Equation (23), \( \alpha \) is an arbitrary constant, has value two. The zero-mean primary signal \( r(n) \) with average power \( \sigma_h^2 \) is independent of the circularly symmetric complex Gaussian noise \( w(n) \) with variance \( \sigma_w^2 \) and \( h_i \) denotes the Rayleigh faded channel that is independent of \( w(n) \). Hence, \( |h_i| \) is Rayleigh distributed with variance \( \sigma_h^2/2 \). Thus, the Probability distribution function (PDF) of the ED_TAT detector for \( H_j \) (where \( j = 0, 1 \)) is given as:

\[ f_{Z_i|H_j}(z) = \frac{2 \times z^2}{(z + \alpha)} \times f_{r_i|h_i}(z^2) \]  

(24)

where \( f_{r_i|h_i}(z) \) is exponentially distributed as follows:

\[ f_{r_i|h_i}(z) = \left[ (1 + S)^{-1} \right] \times \exp \left[ -z \times (1 + S)^{-1} \right], \quad z \geq 0 \]  

(25)

Note that \( S = (\sigma_h^2 \times \sigma_w^2) / \sigma_h^2 \) is the average signal-to-noise ratio (SNR) of the sensing channel. Finally, by using Equations (24) and (25) we have:

\[ f_{Z_i|H_j}(z) = \frac{2 \times z^2 \times (1 + S)^{-1}}{(z + \alpha)} \times \exp \left[ -z^2 \times (1 + S)^{-1} \right], \quad z \geq 0 \]  

(26)
Now, the probability of detection for ED_TAT can be obtained as:

\[ P_{d}^{ED\_TAT} = \int_{-\infty}^{\infty} f_{Z|H_1}(z)dz \] (27)

\[ P_{d}^{ED\_TAT} = \int_{-\infty}^{\infty} \left[ \frac{2 \times z^{(i)}}{(z \times a) \times (1 + S)} \right] \times \exp \left[ -\frac{z^{(i)}}{(1 + S)} \right] dz \] (28)

\[ P_{d}^{ED\_TAT} = \exp \left[ -\frac{\left( \lambda^{\frac{1}{2}} \right)^2}{(1 + S)} \right] \] (29)

3.1.2.2.2. Probability of false alarm for ED_TAT detector. Considering Equation (24), \( f_{H_0|H_0} \) is exponentially distributed as follows:

\[ f_{H_0|H_0}(z) = \exp\{-z\}, \quad z \geq 0 \] (30)

Finally, by using Equations (24) and (30) we have:

\[ f_{Z|H_0}(z) = \frac{2 \times z^{(i)}}{(z \times a)} \times \exp\left( z^{(i)} \right), \quad z \geq 0 \] (31)

Now, the probability of false alarm for ED_TAT will be calculated as:

\[ P_{f}^{ED\_TAT} = \int_{-\infty}^{\infty} f_{Z|H_0}(z)dz \] (32)

\[ P_{f}^{ED\_TAT} = \int_{-\infty}^{\infty} \left[ \frac{2 \times z^{(i)}}{(z \times a)} \right] \times \exp\left( z^{(i)} \right) dz \] (33)

\[ P_{f}^{ED\_TAT} = \exp \left[ -\left\{ \left( \lambda^{\frac{1}{2}} \right)^2 \right\} \right] \] (34)

3.1.2.2.3. Total error probability for ED_TAT detector. The total error rate is the sum of the probability of false alarm (\( P_f \)) and the probability of miss-detection alarm (\( P_m \)):

\[ P_e^{ED\_TAT} = P_f^{ED\_TAT} + (1 - P_d^{ED\_TAT}) \] (35)

Using Equations (29), (34), and (35) we get:

\[ P_e^{ED\_TAT} = 1 + \exp \left[ -\left\{ \left( \lambda^{\frac{1}{2}} \right)^2 \right\} \right] - \exp \left[ -\frac{\left( \lambda^{\frac{1}{2}} \right)^2}{(1 + S)} \right] \] (36)

where \((1 - P_d^{ED\_TAT})\) shows the probability of missed detection alarm (\( P_m^{ED\_TAT} \)).

3.1.3. Decision device
This device takes final decision whether PU frequency band is free or not, using OR-rule. The mathematical expression is given as:
Figure 1 illustrates the working operation of ISD technique. In the given Figure 1, CR receiver sense received signal and perform the respective sensing operations using ED_SAT and ED_TAT detectors, and further makes final decision via decision device (DD) that PU band is available or not.

### 3.2. Cooperative spectrum sensing with proposed an ISD

CSS technique is used to mitigate shadowing and fading in order to improve sensing performance of both local sensing performance and global sensing performance in a CRN (Bagwari & Tomar, 2013b, 2014; Do & Mark, 2012; Ling-Ling, Jian-Guo, & Cheng-kai, 2011). Here all CRs are using an ISD spectrum sensing scheme to sense PU signal. Once all CRs have taken the local decision individually, they send their local decisions in the form of binary bit i.e. 0 or 1 to the FC over error free orthogonal channels to take final decision. In Figure 4, let there are \(k\) numbers of CRs, all of them transmit local decision \(O_i\) to a common single FC.

Finally, FC combines the binary bit decisions of all CRs where each CR have proposed scheme i.e. an ISDs, and makes global decision to show presence or absence of PU signal as follows

\[
D = \sum_{i=1}^{k} O_i
\]  \hspace{1cm} (38)

\[
O_i = \begin{cases} 1, & L_1 + L_2 \geq 1 \\ 0, & L_1 + L_2 < 1 \end{cases}
\]  \hspace{1cm} (39)

In Equation (38), \(D\) is the sum of the all local decisions \(O_i\) from the CRs. The FC considers a hard decision rule to decide whether PU signal is present or not. The hard decision rule states that a signal is present only and only if any of the CRs sense a signal. As per the hard decision rule if \(O\) is greater or equal to 1, then signal is detected and if \(O\) is smaller than 1, then signal is not detected. The mathematical expression can be written as:

\[
FD = \begin{cases} 0, & \sum_{i=1}^{k} O_i < 1 \\ 1, & \sum_{i=1}^{k} O_i \geq 1 \end{cases}
\]  \hspace{1cm} (40)

**Figure 4.** CSS technique with proposed an improved sensing detector.
Finally, Equation (41) shows the global or final decision of FC. Now, the performance of overall proposed system can be analyzed via $P_{D}$. Hence, using hard decision rule in CSS, the probability of detection ($P_{D}$) of the FC can be expressed as follows:

$$P_{D} = P_{1} \left\{ \sum_{j=1}^{k} O_{j} \geq 1 | H_{1} \right\}$$ \hspace{1cm} (42)

$$P_{D} = 1 - \prod_{j=1}^{k} \left( 1 - P_{d_{j}} \right)$$ \hspace{1cm} (43)

In Equation (43), $P_{d_{j}}$ is the probability of detection of individual CR users, can be calculated using Equation (3).

4. Numerical results and analysis

In our simulations we first evaluate the systems using QPSK modulation scheme and Rayleigh channel. In this section, the proposed ISD scheme is compared with conventional energy detection, energy detection technique for adaptive spectrum sensing-2015 (EDT-ASS-2015) (Sobron et al., 2015), Adaptive spectrum sensing-2012 (Ejaz et al., 2012), ED and cyclostationary-2010 (Maleki et al., 2010), and hierarchical with quantization-2012 detection (Liu et al., 2012). The parameters used for simulation are given in Table 1.

In the following simulation given in Figure 5, we employ an ISD technique for 1,000 numbers of samples, we set the threshold for the system to achieve false alarm probability 0.1. In the simulation environment the value of $\lambda_{1}$, $\lambda_{2}$, $\lambda_{21}$, and $\lambda_{22}$ varies at every iteration. But in this case we have chosen $\lambda_{1} = 1.25$, $\lambda_{21} = 0.9$, $\lambda_{22} = 1.2$ and $\lambda_{2} = 1.014$ as trade-off value.

In simulation environment, there is detection performance comparison between proposed an ISD scheme, EDT-ASS-2015 scheme, ED and cyclo-2010, adaptive SS-2012, and conventional-ED scheme. It can be seen from Figure 5 that when the number of antennas increases, probability of detection also increases. Proposed ISD scheme with number of antennas ($N_{r}$) = 3 outperforms $N_{r} = 1$, 2, EDT-ASS-2015 scheme, ED and cyclo-2010, adaptive SS-2012, and conventional-ED scheme by 9.0, 4.5, 29.1, 57.9, 42.4, and 54.1% at −12 dB SNR in terms of probability of detection respectively under constraint at probability of false alarm ($P_{f}$) = 0.1.

| Table 1. Parameter values for simulation |
|-----------------------------------------|
| Parameter                              | Value                   |
| Signal type                            | QPSK                    |
| Channel                                | Rayleigh                |
| Number of samples ($N$)                | 1,000                   |
| Number of antennas ($N_{r}$)           | 3 & 2                   |
| Threshold ($\lambda_{1}$)              | 1.25                    |
| Threshold ($\lambda_{2}$)              | 1.014                   |
| Threshold ($\lambda_{21}$)             | 0.9                     |
| Threshold ($\lambda_{22}$)             | 1.2                     |
| Range of signal to noise ratio         | −20 dB to 0 dB          |
| Probability of false alarm for each detection scheme | 0.1                |
| Software                               | MATLAB R2012a           |
IEEE 802.22 states that if the value of $P_f$ is set at 0.1, the minimum acceptable value required for detection probability is 0.9. It shows that proposed ISD scheme detects PU signal at approximately -12.5 dB SNR.

The spectrum sensing time defines the total time taken by cognitive radio users to detect licensed frequency band. Sensing time can be computed as:

$$T_{ISD} = T_{SC} + T_{ED\_SAT} + T_{ED\_TAT} + T_{DD}$$  \hspace{1cm} (44)$$

Where, $T_{ISD}$ is total time taken by proposed sensing technique for SS. $T_{SC}$, $T_{ED\_SAT}$ and $T_{ED\_TAT}$ are the selection combiner (SC), ED\_SAT and ED\_TAT detectors SS time respectively. Therefore, the SC sensing time can be calculated as:

$$T_{SC} = C \times S_{SC}$$  \hspace{1cm} (45)$$

$C$ is total number of sensed channels by secondary users, and $S_{SC}$ is the average detection time for each channel calculated as:

$$S_{SC} = \frac{1}{2} \times \left(\frac{M_{SC}}{B}\right)$$  \hspace{1cm} (46)$$

$M_{SC}$ is the number of samples during the observation interval, $B$ is the channel bandwidth. Now, the ED\_SAT sensing time can be calculated as:

$$S_1 = \frac{1}{2} \times \left(\frac{M_{ED\_SAT}}{B}\right)$$  \hspace{1cm} (47)$$

$S_1$ is the mean sensing time for each channel, in which $M_{ED\_SAT}$ is the number of samples during the observation interval, $B$ is the channel bandwidth, $C$ is number of sensed channels and probability factor $P_r$ that a channel would be reported to the ED\_SAT. Hence, the detection time of the energy detection is:

$$T_{ED\_SAT} = C \times P_r \times S_1$$  \hspace{1cm} (48)$$

Similarly, the ED\_TAT detector sensing time can be calculated as:

$$S_2 = \frac{1}{2} \times \left(\frac{M_{ED\_TAT}}{B}\right)$$  \hspace{1cm} (49)$$
$S_2$ is the mean sensing time for each channel, in which $M_{ED_TAT}$ is the number of samples during the observation interval. $(1 - P_r)$ is the probability factor that a channel would be reported to the ED_TAT detector. Hence, the detection time of ED_TAT detector is:

$$T_{ED_TAT} = C \times (1 - P_r) \times S_2 \quad (50)$$

The decision device (DD) sensing time can be calculated as:

$$T_{DD} = C \times S_0 \quad (51)$$

$C$ is total number of sensed channels by secondary users, and $S_0$ is the average detection time for each channel calculated as:

$$S_0 = \frac{1}{2} \times \left( \frac{M_0}{B} \right) \quad (52)$$

In Equation (52), $M_0$ indicates the total numbers of samples during the observation interval, and channel bandwidth denoted by $C$.

Thus, the overall spectrum sensing time is calculated by substituting Equations (45), (48), (50), and (51) in Equation (44) as:

$$T_{ISD} = C \times S_{SC} + C \times P_r \times S_1 + C \times (1 - P_r) \times S_2 + C \times S_0 \quad (53)$$

$$T_{ISD} = C \times [S_{SC} + P_r \times S_1 + (1 - P_r) \times S_2 + S_0] \quad (54)$$

Figure 6 shows the graph of spectrum sensing time versus SNR. The proposed scheme at $N_r = 2$ requires lesser sensing time than the existing schemes. It is observed that there is an inverse relation between SS time and SNR. As SNR increases, sensing time decreases. We have used Equation (54) for potting the graph between sensing time and SNR. The value of parameters used in Equation (54) is defined in Table 1.

Now, at −20 dB SNR, proposed scheme at $N_r = 2$ requires approximately 46.7 ms while presently existing schemes (EDT-ASS-2015, Adaptive SS-2012, ED and Cyclo-2010) require around 47.0, 49.0, and 53.2 ms sensing time respectively. The SS time is directly related to the numbers of samples received by the CR user. The more sensing time is devoted to detecting, the less sensing time is available for transmissions and hence degrading the CR throughput. This is known as the sensing efficiency problem (Lee & Akyildiz, 2008) or the sensing-throughput tradeoff (Liang, Zeng, Peh, & Hoang, 2008) in SS.
Figure 7 shows the graph of probability of detection ($P_d$) versus SNR between proposed CSS with ISD scheme, CSS-EDT-ASS-2015, and Hierarchical with Quantization-2012 scheme. In CSS we consider only three CR users. Simulation results show that Cooperative SS with ISD outperforms EDT-ASS-2015, and Hierarchical with quantization-2012. CSS with ISD improves detection performance around 12.5 and 19.1% as compared to EDT-ASS-2015 and Hierarchical with quantization-2012 at $-12$ dB SNR respectively. CSS with ISD achieves 0.9 detection probability at $-12.5$ dB with $N_r = 2$, while EDT-ASS-2015 and Hierarchical with quantization-2012 detection scheme achieves the same detection probability at $-11$ and $-10.5$ dB respectively.

In Figure 8, we have plotted the probability of detection ($P_d$) versus SNR plots for different number of cooperative CR users $k = 3, 4, 5, 6, 7, 8, 9, 10$, $P_f = 0.1$, $N_r = 2$, and $N = 1,000$. It can be concluded from Figure 8 that the value of probability of detection increases with increase in the value of SNR for different number of CRs. The probability of detection is maximum for $k = 10$, it's implies that for $N = 1,000$, $N_r = 2$, and $P_f = 0.1$, only ten CR users are required for deciding the presence of the PU by using the ISD spectrum sensing scheme. When $k = 10$, $P_f = 0.1$ and SNR = $-20$ dB approximately, the proposed SS model can achieve probability of detection value 0.9, which is the SS requirement of IEEE 802.22 (Cordeiro, Challapali, Birru, & Shankar, 2005).
5. Conclusion
In this paper, an ISD for WRANs has been proposed. This scheme enhances detection performance, reduces bit error rate as well as sensing time. Numerical results show that proposed ISD scheme while \( N_r = 2 \) outperforms other existing schemes (i.e. EDT-ASS-2015 scheme, ED and cyclo-2010, adaptive SS-2012, and conventional-ED scheme), by 24.6, 53.4, 37.9, and 49.6% at −12 dB SNR respectively. It is also shown that the proposed scheme has lesser sensing time than EDT-ASS-2015, Adaptive SS-2012, and ED and Cyclo-2010 scheme in the order of 47.0, 49.0, and 53.2 ms at −20 dB SNR respectively. ISD has also been implemented with CSS scheme, it further shows that when \( k = 10, N_r = 2, \) and \( P_r = 0.1 \), proposed detector is able to detect PU licensed signal at −20 dB SNR. Finally, results conclude that the proposed scheme exhibits better performances than existing schemes.

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