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Performance of Spectrum Sensing over Fading Channels and an Energy Efficient Cooperative Spectrum Sensing Scheme for Cognitive Radio

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Abstract: Cognitive Radio (CR) is a radio communications and networking technology that has recently attracted considerable interest from academia as well as industry worldwide. It follows the design philosophy of Dynamic Spectrum Access (DSA) as opposed to a fixed spectrum allocation policy. The enabling technology for CR is spectrum sensing, which is the inference of presence/absence of primary users (PU) in a given spectral band. Spectrum sensing is complicated by the fading effects of wireless channels, which necessitates CRs to collaborate with one another to make sensing results robust. Another aspect that must be considered in practical CR networks is the energy efficiency of the spectrum sensing process, due to the recent emphasis on 'Green Wireless'. This paper first evaluates the performance of spectrum sensing over different fading channels and shows how collaborative sensing improves robustness. Subsequently, the paper considers an improvement to current techniques for energy efficient spectrum sensing by employing techniques from the field of Compressed Sensing (CS).

Keywords: Cognitive Radio, Spectrum Sensing, Energy Detection, Cyclostationary Feature Detection, Energy Efficiency, Compressed Sensing

I. INTRODUCTION

With the emergence of multimedia type applications, the need for higher data rates that must be supported by wireless systems is on the rise. Radio spectrum being a precious resource, the current static spectrum allocation schemes are highly inefficient when it comes to high data rate applications. With most of the spectrum already allocated, it becomes exceedingly difficult to find vacant bands to support new services.

On the other hand, spectral occupancy measurements by the FCC show that most of the licensed bands are not utilized for significant portions of time [1]. Thus, the spectrum scarcity is not due to physical shortage, but due to the inefficient utilization of existing licensed spectrum. As a result, dynamic spectrum allocation schemes are required that can efficiently utilize available spectrum.

Cognitive Radio (CR) is an emerging technique that can solve the spectral congestion problem by means of opportunistic usage of frequency bands that are not in use by licensed users. The definition of CR adopted by the FCC is as follows: "*Cognitive Radio : A radio or system that senses its operational electromagnetic environment and can dynamically and autonomously adjust its radio operating parameters to modify system operation, such as maximize throughput, mitigate interference, facilitate interoperability, access secondary markets*".

The cornerstone of cognitive radio technology is the ability to dynamically gauge the spectral occupancy from power spectral density measurements and exploit the vacant bands for secondary user (SU) transmissions [2]. A primary user (PU) has higher priority or legal access to a particular segment of the spectrum whereas, a secondary user has lower priority and gains spectrum access without interfering with the PU. Hence the SU must be equipped with this cognitive sensing ability and must ensure a certain degree of PU protection. As soon as the SU detects that the PU signal level is above a given threshold, it should immediately vacate the particular band and shift to other suitable vacant bands, if available.

The detection of spectral occupancy by CR can be viewed as a binary hypothesis testing problem. H_0 corresponds to the case where only additive noise is present, whereas H_1 corresponds to the case when the PU signal is present along with noise. The challenge of spectrum sensing lies in accurately distinguishing between these two hypotheses. Several spectrum sensing techniques have been reported in the literature. These include: energy detection [3], matched filtering [4], waveform based sensing, cyclo stationary feature detection [5], eigen value based detection [6], etc.

The matched filter detector is an optimal technique that maximizes the signal to noise ratio (SNR), but it requires a priori knowledge of the PU signal like modulation type/order, etc. [4]. The energy detection is very popular because of its low computational complexity along with the fact that it does not require knowledge of the PU signal. However, the drawback of this technique is degradation of sensing performance due to noise uncertainty [7].

Cyclo stationary feature detection, by virtue of its robustness to noise, can detect PU signals in very low SNR conditions [5]. However, the high computational complexity involved is the main limiting factor in the implementation of cyclo stationary feature detection. Eigen value based detection [6] is a state-of-the-art sensing technique which takes the ratio of maximum to minimum eigen values of the covariance matrix of received signal.

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The performance of spectrum sensing techniques degrades due to the dynamic characteristics of wireless channels like multipath fading and shadowing [8]. Due to these effects, individual cognitive radios may not be able to reliably detect the presence of a primary user. In order to improve the reliability of spectrum sensing, radio cooperation exploiting spatial diversity among multiple secondary users has been proposed in the literature [8]. A network of cognitive radios, each experiencing different channel conditions, would have a better chance of detecting a PU if they fuse their individual sensing information.

Another problem that must be considered in CR is that of energy efficiency. Recently the explosive growth in multimedia communications has led to a drastic increase in energy consumption of wireless networks. This leads to an increase in demand for battery capacity, besides causing severe electromagnetic pollution to the global environment [9]. Increased energy consumption in wireless is one of the major reasons for greenhouse gas emissions, with reports that Information & Communications Technology (ICT) generates about 2 percent of worldwide CO2 emissions [10]. Also, ICT power usage is increasing by 16 to 20 percent every year. In this scenario, 'Green Wireless Communications' is an emerging paradigm which seeks to find novel solutions to improve the energy efficiency of wireless applications in terms of the bits- per- Joule metric [11].

This paper is organized as follows. Section II describes the effects of fading and shadowing on spectrum sensing. Section III describes the improvements in sensing performance resulting from the use of cooperative sensing. Section IV describes an energy efficient two stage spectrum sensing scheme for CR. Section V discusses improvements in detection performance as well as energy efficiency resulting from the application of compressed sensing techniques to the algorithm presented in Section IV. Finally Section VI concludes the paper.

II. SPECTRUM SENSING OVER FADING CHANNELS

The goal of spectrum sensing is to accurately decide between the following two hypotheses:

$$x(t) = n(t) \qquad H_0$$

$$x(t) = hs(t) + n(t) \quad H_1$$

where x(t) is the signal received by secondary user and s(t) is primary user's transmitted signal, n(t) is the additive white gaussian noise and h is the amplitude gain of the channel. A common method for detection of unknown signals is energy detection [12]. Fig 1 depicts a block diagram for energy detector.

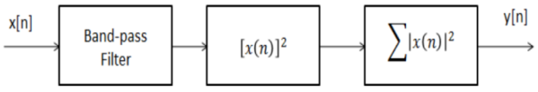

Fig 1 Energy Detection

Following the work of [12], it can be shown that the decision metric for energy detection is central chi-squared distributed in case of H_0 and non-central chi-squared distributed in case of H_1. In a non-fading environment, the detection and false alarm probabilities are given by [12]:

$$P_d = P\{Y > \lambda \mid \mathrm{H}_1\} = Q_m\left(\sqrt{2\gamma}, \sqrt{\lambda}\right)$$

$$P_f = P\{Y > \lambda \mid H_0\} = \frac{\Gamma(m, \lambda/2)}{\Gamma(m)}$$

where $\Gamma(.)$ and $\Gamma(.,.)$ are the complete and incomplete gamma functions and $Q_m(.,.)$ is the generalized Marcum-Q function, Y is the decision metric, λ is the threshold and γ is the SNR. In case of fading channels, detection probability may be derived as [13]:

$$P_d = \int_x Q_m(\sqrt{2\gamma}, \sqrt{\lambda}) \mathrm{f}_\gamma(x) dx$$

where $f_\gamma(\mathrm{x})$ is the probability distribution function of SNR under fading. In the following, we study the performance of energy detection over Rayleigh fading and Lognormal shadowing channels, in terms of the complementary ROC curves (plot of P_m vs P_f).

II A *Rayleigh Fading*

Under Rayleigh fading, the SNR has an exponential distribution. The closed form expression for the detection probability is [13]:

$$P_d = e^{-\lambda/2} \sum_{k=0}^{m-2} \frac{1}{k!} (\lambda/2)^k + \left(\frac{1+\bar{\gamma}}{\bar{\gamma}}\right)^{m-1}$$

$$* \left(e^{-\frac{\lambda}{2(1+\bar{\gamma})}} - e^{-\frac{\lambda}{2}} \sum_{k=0}^{m-2} \frac{1}{k!} \left(\frac{\lambda\bar{\gamma}}{2(1+\bar{\gamma})} \right)^k \right)$$

Fig. 2 depicts complementary ROC under AWGN and Rayleigh fading. SNR and m are assumed to be -10 dB and 5 respectively. It can be seen that Rayleigh fading degrades the performance of energy detector significantly.

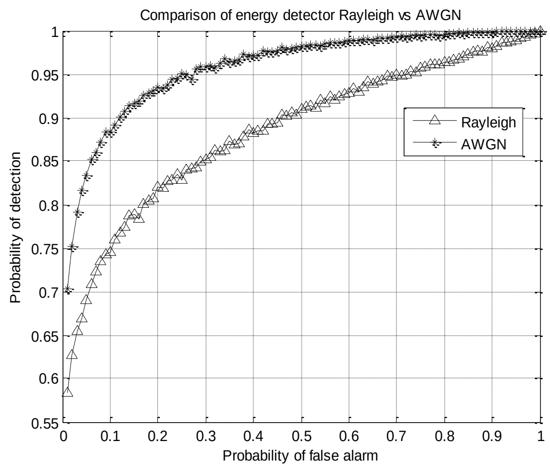

Fig 2 Energy detection over AWGN and Rayleigh channels

II B *Lognormal Shadowing*

Medium scale fluctuations of received power when expressed in dB units, follow a normal distribution [13]. Thus the linear channel gain may be modelled as a

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lognormal random variable e^X, where X is normally distributed. Fig 3 shows complementary ROC plots over AWGN vs lognormal shadowing. SNR and m are again assumed as -10 dB and 5 respectively. Comparing the AWGN curve to that due to shadowing, it is evident that spectrum sensing is much harder in the presence of shadowing.

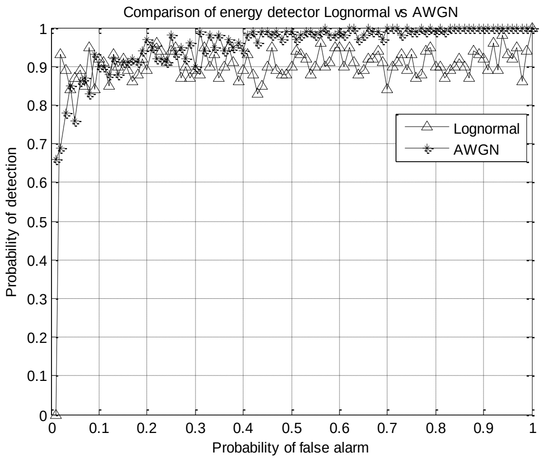

Fig 3 Energy Detection over AWGN and lognormal channels

III. CO-OPERATIVE SPECTRUM SENSING IN COGNITIVE RADIO

In order to improve the performance of spectrum sensing, we allow different secondary users to collaborate by sharing their information [14]. Let n denote the number of users collaborating. We assume that all n users experience independent and identically distributed fading/shadowing with same average SNR. Recent works [14] show that cooperative sensing can greatly increase the probability of detection over fading channels. Cooperative sensing works as follows: Every CR performs local spectrum measurements independently and makes a binary decision; All CRs forward their binary decisions to a common receiver; The common receiver combines those binary decisions and makes a final decision on the presence or absence of the primary user in the given spectral band..

Now we examine via simulations, using energy detection as the sensing technique, the performance of two popular hard decision rules for cooperative sensing over wireless fading channels - the OR rule and the AND rule. With a hard decision counting rule, the fusion center implements a k-out-of-n rule that decides in favour of H_1 if atleast k out of n decisions indicate H_1. The overall probability of detection at the fusion center is given by [14]:

$$P_d = \sum_{i=k}^{n} \frac{n!}{i!(n-i)!} P_{d,i}{}^{i} (1-P_{d,i})^{n-i}$$

where $P_{d,i}$ is the detection probability for each individual node. Setting k=1, we get the OR fusion rule.

$$P_{d,OR} = 1-(1-P_{d,i})^n$$

Cooperative detection performance with AND rule can be evaluated by setting k=n.

$$P_{d,AND} = P_{d,i}{}^{n}$$

Fig 4 shows the performance of OR fusion rule and Fig 5 shows the performance of AND fusion rule. Fig 5 compares the sensing performance of AND,OR and local spectrum sensing. Clearly, the performance of cooperative spectrum sensing is much better than local spectrum sensing.

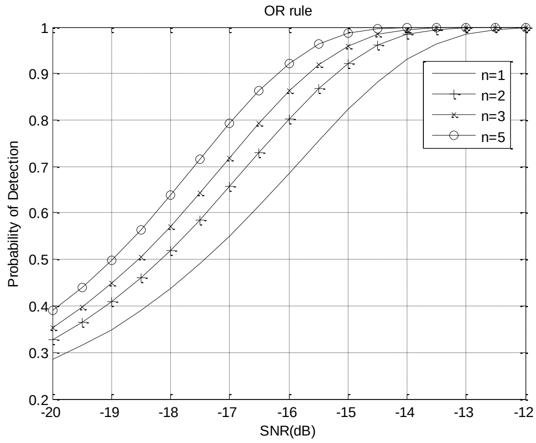

Fig 4 OR fusion rule performance

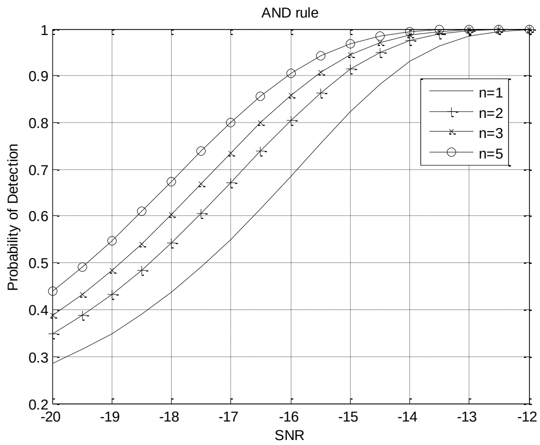

Fig 5 AND fusion rule performance

In the above figures, the detection probabilities of OR and AND fusion rules have been depicted for various values of number of collaborating nodes n, against the signal to noise ratio (SNR). As can be seen from Fig 6, at a false alarm probability of 0.1, the detection probability of AND and OR rules are around 0.8, compared to only 0.45 for local sensing. This demonstrates the effectiveness of cooperative sensing.

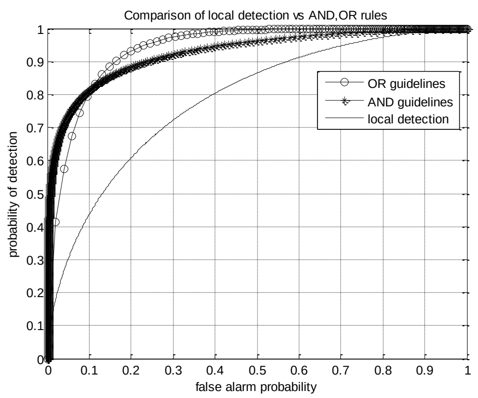

Fig 6 Comparison between OR,AND and local sensing

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IV. A TWO STAGE ENERGY EFFICIENT COOPERATIVE SPECTRUM SENSING SCHEME

We now consider a two stage energy efficient one bit cooperative spectrum sensing (TSEEOB CSS)algorithm described in [15]. The TSEEOB-CSS algorithm has high sensing accuracy as well as low sensing time and energy consumption, especially in high SNR conditions or when no PU exists. In this algorithm, the energy consumption of conventional cooperative sensing with N_S samples can be reduced by designing two TSEEOB-CSS schemes αN_S sample first stage detection and $(1\text{-}\alpha)N_S$ sample second stage detection. It can be expressed by the following steps [15]:

1. Perform the first stage coarse energy detection with αN_S samples at each SU, where $\alpha<0.5$. The sensing result of SU_i can be given as:

$$T1_i = \frac{1}{\alpha N_S}\sum_{n=1}^{\alpha N_S}|x_i(n)|^2$$

where $x_i(n)$ is the nth sample of signal to be sensed at SU_i. If $T1_i > \lambda_1+\Delta$, sends the local decision $D1_i=1$ to the fusion center i.e. H_1. If $T1_i < \lambda_1\text{-}\Delta$, sends the local decision $D1_i=0$ to fusion center indicating H_0.If $\lambda_1\text{-}\Delta < T1_i < \lambda_1+\Delta$, nothing will be sent. λ_1 and Δ are two positive parameters that determine the upper and lower thresholds.

2. The first stage local decisions are fused at the fusion center, and the final decision DF can be found as:
DF = 1, More than K/2 SUs indicate H_1
DF = 0, More than K/2 SUs indicate H_0
DF = Final decision not obtained, otherwise
If final decision DF can be obtained, it is sent each SU. If final decision cannot be obtained, nothing will be done.

3. If DF is received by the SUs, go to step 6. If DF is not obtained by SUs after some time period, perform second stage fine energy detection with $(1\text{-}\alpha)N_S$ samples, and sensing result of SU_i can be given as:

$$T2_i = \frac{1}{(1-\alpha)N_S}\sum_{n=1}^{(1-\alpha)N_S}|x_i(n)|^2$$

4. Local decision $D2_i$ is obtained through second stage fine energy detection as:
$D2_i = 1,\ T2_i > \lambda_2$
$D2_i = 0,\ T2_i < \lambda_2$
Then the local decisions $D2_i$ are sent to the fusion center.

5. The second stage decisions are fused and final decision DF is given as:

$$DF = 1,\quad \sum_{i=1}^{K} D2_i \geq K/2$$
$$DF = 0,\quad Otherwise$$

DF is sent to each SU, and goes to step 6.

6. Current detection ends.

The above algorithm achieves almost the same performance as conventional cooperative sensing, while its sensing time and energy consumption are reduced considerably when no PU exists or SNR of PU is high [15].

V. PROPOSED IMPROVED ALGORITHM WITH COMPRESSED SENSING BASED CYCLOSTATIONARY FEATURE DETECTION

The TSEEOB-CSS algorithm suffers from the drawback that it uses energy detection in both sensing stages. Energy detection technique is not suitable in low SNR conditions and it suffers from the SNR wall problem [16]. Hence an improvement to TSEEOB-CSS could be obtained by modifying the second fine sensing stage from energy detection to a more sophisticated cyclostationary feature detection (CFD) [5]. CFD outperforms energy detector in terms of detection performance and is reliable in low SNR and does not suffer from SNR wall problem [5]. However, the energy consumption will significantly increase while using CFD in second stage, as it involves more sensing time. Hence we propose to circumvent this problem by applying Compressed Sensing (CS) to the second stage CFD as explained in [17]. With CS based CFD as the second stage sensing technique, we demonstrate that both detection performance as well as energy efficiency are improved compared to TSEEOB-CSS algorithm.

V. A *Cyclostationary Feature Detection*

Cyclostationarity feature detection [2] is a method for detecting primary user transmissions by exploiting the cyclostationarity features of the received signals. Cyclostationary features are caused by the periodicity in the statistics like mean and autocorrelation. Cyclic correlation function is used for detecting signals present in a given spectrum [2]. The cyclostationarity based detection algorithms can differentiate noise from primary users' signals. This is a result of the fact that noise is wide-sense stationary (WSS) with no correlation while modulated signals are cyclostationary with spectral correlation due to the redundancy of signal periodicities [2]. The cyclic spectral density (CSD) function of a received signal can be calculated as [2] :

$$S(f,\alpha) = \sum_{\tau=-\infty}^{\infty} R_y^{\alpha}(\tau)e^{-j2\pi f\tau}$$

where

$$R_y^{\alpha}(\tau) = E[y(n+\tau)y^*(n-\tau)e^{j2\pi\alpha n}]$$

is the cyclic autocorrelation function (CAF) and α is the cyclic frequency. The CSD function outputs peak values when the cyclic frequency is equal to the fundamental frequencies of transmitted signal $x(n)$. This suggests that a peak detector can be used after calculating the CAF or CSD to detect the primary user. A schematic for feature detection is as given below [7]:

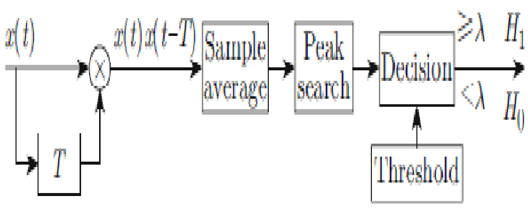

Fig 7 Cyclostationary Feature Detector

V. B *Compressed Sensing based CFD*

The drawback of CFD is the high computational complexity and sensing time/energy consumption

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involved. To reduce the energy consumption of CFD, a technique known as Compressed Sensing [18] may be applied. It works on the principle of simultaneous data acquisition and data compression [18]. Since the communication signals are sparse due to spectral correlation, compressed sensing can exploit this sparsity. To reduce the energy consumption in cyclostationary spectrum sensing, we employ the compressive sensing technique explained in [17]. Let y(t) be a zero mean cyclostationary process that is characterized by the fact that its time varying autocorrelation $r_{yy}(t,\tau) = E[y(t)y(t+\tau)]$ is periodic in time with a period called cycle period T_0. Then it has a Fourier Series (FS) with respect to t [17]:

$$r_{yy}(t,\tau) = \sum_{\alpha \in A_\alpha} R_{yy}(\alpha,\tau) e^{j2\pi\alpha t}$$

where $A_\alpha = \{\alpha = k/T_0, k \in \mathbb{Z}\}$ is the set of cyclic frequencies and the Fourier coefficient $R_{yy}(\alpha,\tau)$, called the cyclic autocorrelation function is given by:

$$R_{yy}(\alpha,\tau) = \lim_{T\to\infty} \frac{1}{T} \sum_{t=0}^{T-1} r_{yy}(t,\tau) e^{-j2\pi\alpha t}$$

The function takes nonzero values for few $\alpha \neq 0$. An unbiased estimator of the above is given by:

$$\hat{R}_{yy}^{(N)}(\alpha,\tau) \triangleq \frac{1}{N} \sum_{t=0}^{N-1} y(t) y(t+\tau) e^{-j2\pi\alpha t}$$

We define

$$f_\tau(t) = y(t)y(t+\tau)$$

Then above equation can be written as

$$\hat{R}_{yy}^{(N)}(\alpha,\tau) \triangleq \frac{1}{N} \sum_{t=0}^{N-1} f_\tau(t) e^{-j2\pi\alpha t}$$

Thus we note from the above equation that the cyclic autocorrelation vector of the received signal in the cyclic frequency domain, $\hat{R}_{yy}^{(\tau_0)}(\alpha)$, is nothing but a scaled version of the DFT of f_{τ_0} [17].The function $\hat{R}_{yy}^{(\tau_0)}(\alpha)$ takes nonzero values for α =0 and some specific values of α. Hence we can reconstruct the vector $\hat{R}_{yy}^{(\tau_0)}(\alpha)$ of length N using only n samples, where n << N [17]. For the reconstruction to be successful, n should satisfy the Restricted Isometry Property:

$$n \succ S\log(N)$$

with S being the number of nonzero entries in $\hat{R}_{yy}^{(\tau_0)}(\alpha)$. Then we apply a sparse representation approach based on representing the first n elements of f_{τ_0} on the column vectors of the (n,N) matrix A, formed by taking the first n rows of the conjugate of the N by N DFT matrix F [17]. Define $b^{(\tau_0)}$ as an (n,1) column vector composed of the first n elements of f_{τ_0}. The problem consists of solving the system $Ar^{(\tau_0)} = b^{(\tau_0)}$. Then the (N,1) vector solution $\hat{r}^{(\tau_0)}$ represents the estimated CAF $\hat{R}_{yy}^{(\tau_0)}(\alpha)$. In this paper, we solve the inverse problem by Basis Pursuit (BP), as opposed to Orthogonal Matching Pursuit (OMP) used in [17], due to its simplicity. The problem can be expressed as:

$$\hat{r}^{(\tau_0)} = \min \left\| r^{(\tau_0)} \right\|_1 \text{ such that } Ar^{(\tau_0)} = b^{(\tau_0)}$$

To distinguish between H_0 and H_1, we take two successive slots of size n each, s_1 and s_2, and assume that these slots belong to the same hypothesis. Then we compute the CAFs of slots s_1 and s_2, and then compare the indices of maximum values. If these indices are same or close, we choose H_1, otherwise H_0 [17]. The algorithm according to [17] can be written as follows:

$$s_1 \leftarrow [y_1(0),\ldots,y_1(n-1)]^t$$
$$s_2 \leftarrow [y_2(0),\ldots,y_2(n-1)]^t$$

for i = 1 to M do

$b_1^{(\tau_i)} \leftarrow$ calculation of first n elements of $f_1^{(\tau_i)}$

$b_2^{(\tau_i)} \leftarrow$ calculation of first n elements of $f_2^{(\tau_i)}$

$\hat{r}_1^{(\tau_i)} \leftarrow BP(A, b_1^{(\tau_i)})$

$\hat{r}_2^{(\tau_i)} \leftarrow BP(A, b_2^{(\tau_i)})$

$\text{index}_1 \leftarrow index(\max(|\hat{r}_1^{(\tau_i)}|))$

$\text{index}_2 \leftarrow index(\max(|\hat{r}_2^{(\tau_i)}|))$

if $|\text{index}_1 - \text{index}_2| \prec k$ then

$\Delta_i = 1$

else

$\Delta_i = 0$

end if

$\Gamma \leftarrow \sum_{l=1}^{i} \Delta_l$

if $\Gamma \geq V$ then

H_1 is chosen

end if

end for

H_0 is chosen

Now we draw a comparison between the above algorithm and the conventional cyclostationary feature detector, under the same SNR, as shown in Fig 8. Clearly, the above detector gives better detection performance than the cyclostationary detector, under the same conditions.

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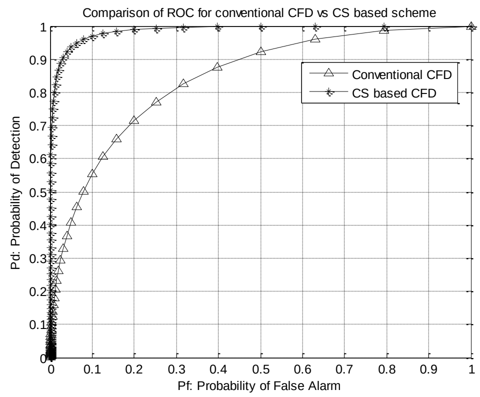

Fig 8 Comparison between CFD and CS-CFD

We now show the reduction in sensing time of CS-CFD compared to CFD in Fig 9.

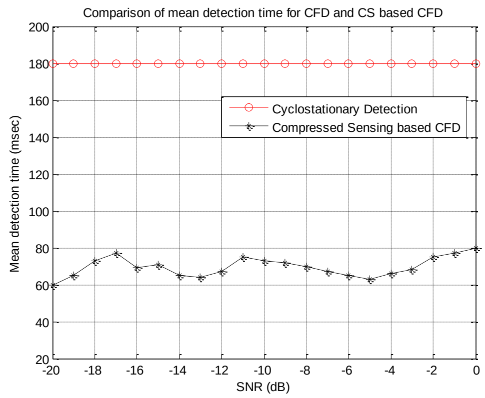

Fig 9 Mean detection time CFD vs CS-CFD

V. C *CS-CFD applied to second stage of TSEEOB-CSS*

Now we modify the TSEEOB-CSS algorithm by changing its second fine sensing stage from energy detection to Compressed Sensing-CFD. This has twofold advantages. The detection performance improves as the second stage is based on feature detection rather than energy detection. Also, because of compressed sensing, the energy consumption is also reduced compared to the original TSEEOB-CSS algorithm. Fig 10 below shows the improvement in detection performance achieved by our modified algorithm compared to TSEEOB-CSS, energy detection and conventional cooperative sensing. We assume the number of samples N_S to be 768 in all cases.

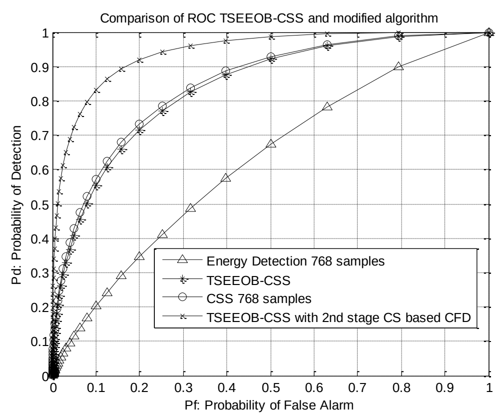

Fig 10 Comparison between ED, CSS, TSEEOB-CSS and modified algorithm

Next we plot, in Fig 11, the energy efficiency improvement due to our algorithm over TSEEOB-CSS algorithm. We do this by comparing the percentage energy savings of both algorithms over conventional cooperative spectrum sensing algorithm. Specifically, at an SNR of -10 dB, TSEEOB-CSS energy saving is 30%, whereas our algorithm achieves 42%, which is a 12% improvement in energy efficiency.

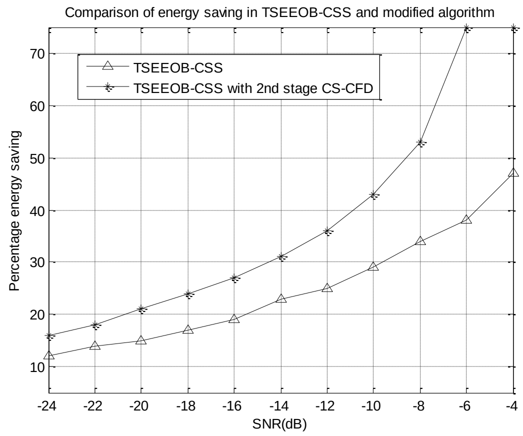

Fig 11 Energy Saving comparison TSEEOB-CSS vs modified algorithm

VI. CONCLUSION

This paper evaluated the effect of wireless channel phenomena like fading and shadowing on the spectrum sensing process for cognitive radio. It was shown that collaborative spectrum sensing greatly improves the detection performance in the presence of channel imperfections. An energy efficient two stage spectrum sensing algorithm was reviewed, which was based on energy detection in both stages. The potential for cyclostationary feature detection based on compressed sensing was explored. Subsequently, the above algorithm was modified to include compressed sensing based feature detector in the second stage. Notable improvements in both sensing performance as well as energy efficiency were observed.

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