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Improved snr based adaptive spectrum sensing For cognitive radio networks

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Abstract:
In Cognitive Radio networks (CRN), spectrum sensing is one of the major issue to enable Dynamic Spectrum Access (DSA) among the (secondary users) SUs. In CR networks, spectrum sensing performance is determined by the probability of detection, probability of false alarm, sensing energy, channel noise level and sensing time. In order to improve the spectrum sensing performance, we propose an adaptive spectrum sensing technique which adaptively selects either Energy detector or Hidden Markov Model (HMM) based sequence detector. This adaptive sensing technique selects Energy detector when it is required to reduce sensing energy in the secondary users (SU) and the primary user's (PU) channel SNR is high to get better detection probability. It selects HMM based sequence detector when the channel SNR is low. As this adaptive sensing technique selects the sensing method based on the received SNR and it optimizes the probability of detection and false alarm both for low and high SNR cases. It provides better spectrum sensing performance for the entire range of SNR and its performance is verified using MATLAB.

Index terms: Cognitive Radio Network (CRN), Dynamic spectrum access (DSA), Adaptive Spectrum sensing, energy detector, HMM (Hidden Markov Model) based sensing.

I. INTRODUCTION

To overcome the spectrum scarcity problem in wireless networks, Cognitive radio networks (CRN) introduce Dynamic Spectrum Allocation (DSA) in the network. In DSA, the licensed spectrum of the primary users are allocated to the unlicensed secondary users when they are not used by the PUs. In order to make use of the idle spectrum of PUs, the SUs should sense the spectrum availability. In general, spectrum sensing is understood as measuring the spectral content, or measuring the radio frequency energy over the spectrum. In Cognitive radio networks, the meaning of spectrum sensing is obtaining the spectrum usage characteristics across multiple dimensions such as time, space, frequency and code. The SUs can sense the availability of the spectrum by any one of the available spectrum sensing techniques such as Energy detector, Matched filter detector, Cyclostationary detector, waveform based detector, HMM based detector, etc [1], [2]. An Energy detector is a simple sensing technique which senses the availability of PU in the channel based on the channel SNR value and involves less complexity. The HMM based sequence detector senses the availability of PUs spectrum by defining the initial model parameter $\lambda 0$ and re-estimating the model parameter (until certain condition is satisfied), using Baum- Welsh algorithm.

The main focus of this paper is to improve the spectrum sensing performance both for low and high SNR regions. The performance of energy detector is better in the high SNR region but it is poor in the low SNR region. At low SNR it is difficult for the energy detector to differentiate PUs channel signal and noise because it measures the energy of the received PU channel. To improve the sensing performance in the low SNR, one of the choice is to increase the number of samples unto SNR wall [14]. But it will increase sensing time and limit the higher layer design considerations. At low SNR the spectrum sensing performance of HMM based sequence detector is good and it is poor at high SNR because all samples are detected as ones [3]. Therefore the proposed adaptive spectrum sensing technique combines both energy detector and HMM based sequence detector to improve the sensing performance for both the low and high SNR regions. The adaptive spectrum sensing technique selects the sensing technique based on the PUs channel SNR. The spectrum sensing performance of the adaptive sensing is better for low and high SNR regions and hence increases the dynamic range of spectrum sensing. This technique also optimizes the spectrum sensing time.

The rest of the paper is organized as follows: Section II discusses about the related work and section III gives an overview of the adaptive spectrum sensing technique. Section IV illustrates about the Energy detector and section V explains HMM based sequence detector. Section VI describes about the performance evaluation of the adaptive spectrum sensing technique and section VII discusses about the conclusion and future work.

II. RELATED WORK

In Cognitive Radio networks, spectrum sensing is an important issue to identify the availability of the PU's idle spectrum. The identified available spectrum can be utilized by the SUs without causing any harmful interference to the PUs. The spectrum sensing in the physical layer is considered as detecting the availability of the spectrum. There are plenty of physical layer sensing algorithms available. Some of the physical layer sensing techniques are Energy detector, Matched filter detector, Cyclostationary detector, Coherent detector, HMM based sequence detector etc. [1], [2].

In [3] for the HMM based sequence detector the risk floor was analyzed but the sensing performance was not dealt. In [5] two stage spectrum sensing was performed among energy detector and cyclostationary detector in which the probability of detection was increased compared to energy and cyclostationary detector. The mean detection time was reduced. In [6] PLL based spectrum sensing is proposed. This technique reduced the mean detection time much more but the sensing performance is not improved for low SNR region. In [7] GLRT based spectrum sensing was proposed. This provides less complexity and better performance for fast slow fading channels of MIMO and OFDM systems. But the probability of detection is very low for below -10dB of SNR value.

Adaptive Lp-norm energy detector was proposed in [8] to improve the sensing performance in non gaussian noise environment. But it increases the number samples, which in turn will increase the sensing time reduce the throughput. In [11] spectrum sensing is performed in on demand basis instead of periodic sensing to improve the channel utilization. In [12] spectrum sensing period is adaptively modified to improve the number of idle channels and channel utilization.

In all the above mentioned adaptive sensing techniques the sensing performance was improved but the probability of detection improvement achieved is less compared to this adaptive sensing technique. This adaptive sensing can also be used to minimize sensing energy and sensing time.

III. ADAPTIVE SPECTRUM SENSING

The proposed adaptive spectrum sensing technique adaptively selects either Energy detector or HMM based sequence detector based on the measured threshold of the PU's channel SNR and energy level of the SUs. This technique selects energy detector when the PU's channel SNR is greater than the threshold and the SU's energy level is low then PU is declared as occupied. If the SNR of the PU's channel is less than the threshold and the SU's energy level is high then it selects HMM based sequence detector. The HMM based sequence detector identifies the PU channel occupied or unoccupied depending on the iterative computations. In general the performance of energy detector is good for higher SNR values ie. above 5dB.Therfore when the PU signal is greater than or equal to 5dB the adaptive sensing techniques selects the energy detector and the sensing performance is also good. When the SNR value is less 5dB this technique selects HMM based sequence detector for sensing. At low SNR the sensing performance of the HMM is better. In HMM based sequence detection the sensing performance is better in the low SNR and it is poor in high SNR because all the symbols are identified as one's. By using this adaptive sensing technique, better spectrum sensing efficiency has achieved even for longer range of SNR ie. From -15dB to 25 dB. As the Adaptive spectrum sensing technique combines both energy detector and HMM based sequence detector, the sensing performance is optimized. This technique optimizes the spectrum sensing parameters such as probability of detection, false alarm and mean detection time. This technique can also be used to save the sensing energy in distributed networks where spectrum sensing energy constraint is a major factor. The block diagram of adaptive spectrum sensing is given in figure.3.

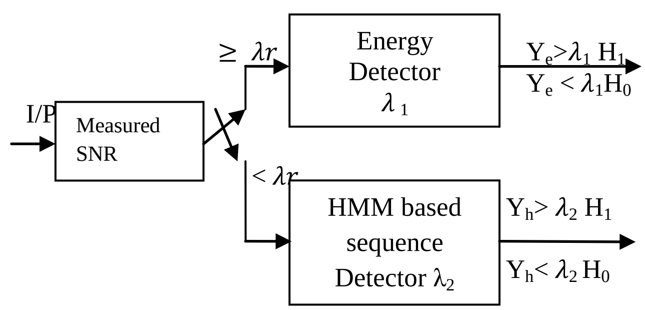

Fig.1. Block diagram of Adaptive spectrum sensing.

Overall probability of detection and probability false alarm for the adaptive spectrum sensing technique are given as follows,

$$P_{d,adapt} = P_r P_{d,\,ener} + (1- P_r)\, P_{d\ hmm} \quad (1)$$

$$P_{f,adapt} = P_r P_{f,\,ener} + (1-P_r)\, P_{f,hmm} \quad (2)$$

where

P_r is the probability of channels having SNR$\geq \lambda$r.
$(1-P_r)$ Probability of channels having SNR < λr.
$P_{d,hmm}$ - Probability of detection of HMM detector.
$P_{d,ener}$ – Probability of detection of energy detector.
$P_{f,hmm}$ - Probability of false alarm of HMM detector.
$P_{f,ener}$ – Probability of false alarm of energy detector.

The mean detection time for this adaptive sensing technique is given as follows,

$$T = T_e + T_{hmm} \quad (3)$$

$$T_e = NP_rT_1 \quad (4)$$

T_{hmm} =N (1-P_r) T_2 (5)

From equation (4) and (5) the mean detection time is given as follows,

$$T = N [P_r T_1 + (1-P_r) T_2] \quad (6)$$

Where

N – the number of channels to be sensed.

T_1 - the mean sensing time for each channel in energy detector.

T_2 –the mean sensing time for each channel in HMM based sequence detector.

IV. ENERGY DETECTOR:

An Energy detector is a simple fast spectrum sensing technique, because it finds only the SNR of the PUs channel and identifies the channel is occupied if the SNR is greater than the threshold (λ) else unoccupied. Due to interference and channel noise in CR networks, spectrum sensing method needs to develop a more accurate detection scheme. Even though the fixed threshold energy detector is simple fast detection method, the performance degrades when the channel noise is high in the Pus. In order to improve the spectrum sensing parameters, when the SNR is less than the threshold it will go to the HMM based sequence detector in the proposed sensing technique.

When the CR users observe the spectrum to detect the primary user activity, the energy detector makes the decision based on M^c observations x(k), k=1,2,3..M^c, given as follows[5],[10]:

$$x(k) = \begin{cases} n(k) & H0 \\ s(k) + n(k) & H1 \end{cases} \quad (7)$$

Where H_0 represents the hypothesis for “no signal transmitted”, H1 for “signal transmitted”. s(k) is the signal waveform and n(k) is a zero mean additive white Gaussian noise (AWGN).

In energy detector noise is assumed to be an i.i.d. Gaussian random process with zero mean and variance σ_n^2 where the signal is assumed to be an i.i.d random process with zero mean and variance σ_s^2.

The decision for the energy detector is given as follows,

$$Y_e = \sum_{k=1}^{M^c} |x_k^2| \quad (8)$$

Ye > λ_1, H_1 else $Y_e < \lambda_1$, H_0

The expression of probability of detection $P_{d,e}$ and false alarm $P_{f,e}$ for the Energy detector are given in terms of Q function as follows [3],[10].

$$P_{d,e} = Q\left(\frac{\lambda 1 - M^c(\sigma s^2 + \sigma n^2)}{\sqrt{2M^c(\sigma s^2 + \sigma n^2)^2}}\right) \quad (9)$$

$$P_{f,e} = Q\left(\frac{\lambda 1 - M^c \sigma n^2}{\sqrt{2M^c \sigma n^4}}\right) \quad (10)$$

For a given probability of false alarm p_f the threshold value is given as follows,

$$\lambda_1 = f(\lambda_2) = Q^{-1}(P_f - \Gamma(\lambda 2/2, N)/\Gamma(N))$$

V. HIDDEN MARKOV MODEL BASED SPECTRUM SENSING

a. Markov chain and Hidden Markov Model:

St is the sequence of random variables taking values from state space S. St is the first order Markov chain if the conditional probability of the current state of the process depends only on the last state with the given previous state and the other past states. Formally,

$$P(St=j|S_0 = s_0, S_1 = s_1, \ldots S_{t-1} = i) = P(St = j|S_{t-1}) = P_{ij} \quad (11)$$

for every $s_0, s_1, \ldots, s_{t-2}$ and t≥ 2.Pij is taken as the transition probability from state i to state j, where i, j ε S. One more element which is required to characterize Markov chain is an initial distribution Π ={π_i} ={P(S_0 =i)}, the set of probabilities that the process starts from a certain state. In Hidden Markov Model (HMM) the state is not directly visible but another set of outputs dependent on the state is visible. The Hidden Markov model (HMM) concept is extended from Markov models, provided the observation being a probabilistic function of the state. A HMM is defined as a doubly embedded stochastic process with an underlying process that is not observable, but can only be observed through another set of stochastic process that produce the sequence of observations [2], [4].

Along with the set of hidden states S_t, the transition matrix P ={Pij} and the initial distribution Π, a critical element to characterize the HMM is the set of emission probabilities f. In HMM, O denotes the observable outputs. The three canonical problems involved with HMM are given as follows,

1. With the given parameters of the model, compute the probability of a particular output sequence with forward algorithm.
2. Compute the state sequence (given the parameters and particular output sequence) using Viterbi and forward and backward algorithm.
3. Derive the maximum likelihood estimate of the parameters of the HMM (with the given set of output sequence) using Baum-Welch algorithm.

Out of these three problems, second is the most suitable for spectrum sensing in DSA network.

This HMM is the first order model with no multipath fading and constant channel gains. The PU access pattern takes slotted structure and the SU is not synchronized with the PU. The HMM model is given fig.2. The PU's activity at any time instant is given by a state which can be either idle or busy. Since the PU's activity has only two states, the transition matrix of the Markov chain is given as follows [3],[4],

$$P_{ij}=\begin{pmatrix} p_{00} & p_{01} \\ p_{10} & p_{11} \end{pmatrix} \quad (12)$$

Where P_{ij} is transition probability from state i to state j. The random variables L_0 and L_1 denote the time duration that the PU resides in an OFF and an ON state respectively. Since the transitions between ON and OFF periods of the PU are assumed to follow a first order Markov process, L_0 and L_1 will be geometrically distributed with parameters p_{01} and p_{10} respectively.

In Markov chain model the true states of the PU are unknown to the SU. But the SUs can observe the signal emitted from a particular state which is modeled as a noisy version of the received PU signal. ie,

$$Y_t = S_tX_t + W_t \quad (13)$$

Where

X_t - the received PU signal, W_t - AWGN noise with zero mean σ_w^2.

In the first order Markov model, the received samples in the observation sequence are conditionally independent given the state sequence, ie[3],[4]

$$f_{Y_t|S^t,Y^{t-1}}\ (y_t|s^t,y^{t-1}) = f_{Y|S}(y_t|s_t) \quad (14)$$

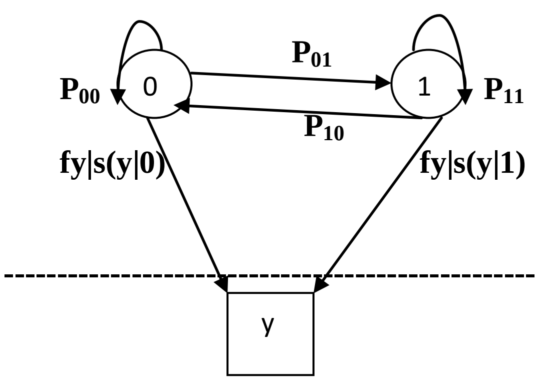

Fig.2. Hidden Markov Model.

Where $f_{Y|S}(y_t|s_t)$ is the conditional probability density function of observing y_t given state s_t at time instant t.

The sequence detection algorithm depends on accurate knowledge of the distribution of the observed samples given by the channel state as well as state transition probabilities. To perform spectrum sensing with HMM, define HMM parameter λ= (P, f, Π) with some initial value λ_0 and reestimate λ value until λ_k= λ_{k-1}.where k is an integer, f ={f_0(y), f_1(y)} set of emission probabilities and Π – is the initial distribution. The output sequence is found by viterbi algorithm and forward and backward probabilities. The HMM parameter is re estimated by Baum-welch algorithm. For this sensing, let us consider that the sequence length as T, the number of states is given by the different status of the PU's channels. The expression for state sequence, forward and backward probabilities are given as follows.

State sequence,Forward and Backward Probabilities:

The highest probability path or state sequence is given by viterbi algorithm, [2],[7]

$$S_T = \arg\max \delta_T(i) \quad (15)$$

Where $\delta_t(i)$ probability of the most probable path ending in state i at time t.

Forward Probabiltiy:

The forward or joint probability density function of the partial observation sequence yt=(y1,y2,…yt) and state i at time t is given as follows,

$$\alpha_t(i) = f_{Y^t,S_t}\ (y^t, i) \quad (16)$$

$\alpha_t(i)$ is proportional to the likelihood of the past observations and can be solved recursively as follows,

$$\alpha_1(i) = \pi_i\ f_{Y|S}(y_1|i)$$

$$\alpha_t(i) = (\sum_{j\epsilon\{0,1\}} \alpha_{t-1}(i))\ f_{Y|S}(y_1|i) \quad (17)$$

For 2≤ t ≤T.

Backward probability:

The backward probability or the conditional probability $\beta_t(i)$ of the partial observation sequence from y_{t+1} to the end produced by all state sequences that start at the ith state is given as follows,

$\beta_t(i) = \sum_{j\epsilon\{0,1\}} p_{ij}\, f_{Y|S}\,(y_{t+1}|j)\, \beta_{t+1}(j)$

For t = T-1,T-2,… ,1.

The a posteriori probability $\gamma_t(i)$ of the hidden state at time t is i for the given observation sequence Y =y up to time T,

$$\gamma_t(i) = \frac{\alpha t(i)\,\beta t(i)}{f_Y(y)} \quad (18)$$

Then the symbol wise state sequence is given as follows,

$$S_t = \underset{i\,\epsilon\{0,1\}}{\arg \text{mim}} \sum_{j\epsilon\{0,1\}} C_{ij}\ \ \gamma_t(j) \quad (19)$$

Where C_{ij} is the cost function.

Estimation of HMM parameters:

.The following steps estimate the HMM parameters:

1. Initialize the model parameter set λ_0. Compute P(O| λ_0), the conditional probability of observation O, given the parameter λ_0.
2. Re estimate the parameter set λ_k given the previous parameter set λ_{k-1} and the observation O, for k=1,2,3,..
3. If model λ_k is significantly better than model λ_{k-1}, continue the procedure else terminate the procedure and λ_k is the final estimation of the parameters.

Let $\xi_t(i, j)$ as the probability of being in state i at time t, and state j at time t+1, given the previous model parameters and the observation sequence, ie.,

$\xi_t(i, j) = P(s_t = i, s_{t+1} = j | O, \lambda_k)$

$\gamma_t(i)$ is related with $\xi_t(i, j)$ as given below,

$\gamma_t(i) = \sum_{j=1}^{2} \xi t(i, j)$

The parameters in λ_k can be re estimated by

π_i = Expected frequency in state i at time(t=0)

$= \gamma_0(i)$

$$\text{Pij} = \frac{\text{Expected number of transitions from state i to state j}}{\text{Expected number of total transitions from state i}}$$

=

$$\text{Fi}(y) = \frac{\sum_{t,s.t.0t \leq y} \gamma_t(i)}{\sum_{t=1}^{T} \gamma_t(i)} \quad (20)$$

Where $\sum_{t.s.t.O_{t \leq y}} \gamma_t(i)$ is the expected number of times in state I and observations smaller than y.

The probability of detection and false alarm are given by the ON and OFF state joint probabilities respectively [9].

$$P(O, 1/\lambda) = P_{d,, hmm} = \sum_{i=1}^{N} \alpha_{t+1}^{1}(i)$$

$$P(O, 0/\lambda) = P_{f,hmm} = \sum_{i=1}^{N} \alpha_{t+1}^{0}(i) \quad 1 \leq i \leq N \quad (21)$$

Where N is the number of PU channel states.

VI. PERFORMANCE EVALUATION

In this section the numerical results obtained by MATLAB simulation demonstrates the increased performance of the proposed adaptive spectrum sensing technique over the existing sensing techniques such as two stage sensing technique [3] and cyclostationary sensing. In this work it is assumed that there are 10 primary user channels to be sensed.

In HMM sensing the following initial parameters are assumed.

State transition matrix $P_{ij} = \begin{pmatrix} 0.2 & 0.8 \\ 0.3 & 0.7 \end{pmatrix}$

Emission probabilities $B = \begin{pmatrix} 0.3 & 0.5 & 0.2 \\ 0.4 & 0.4 & 0.2 \end{pmatrix}$

Initial distribution $\prod$=[0.9, 0.1]

Observable outputs O =[0 1 1]

The performance of adaptive sensing is verified for the following two parameters:

a. **Probability of detection**
b. **Mean detection time**

a. Probability of Detection:

The measured SNR section in fig.1. measures the SNR value of each primary user channel. When the SNR is above 5dB the adaptive spectrum sensing technique selects energy detector for sensing and for below 5dB it selects HMM based spectrum sensing. Fig.3 shows the performance of adaptive spectrum sensing for SNR versus probability of detection. The probability of detection of this proposed sensing

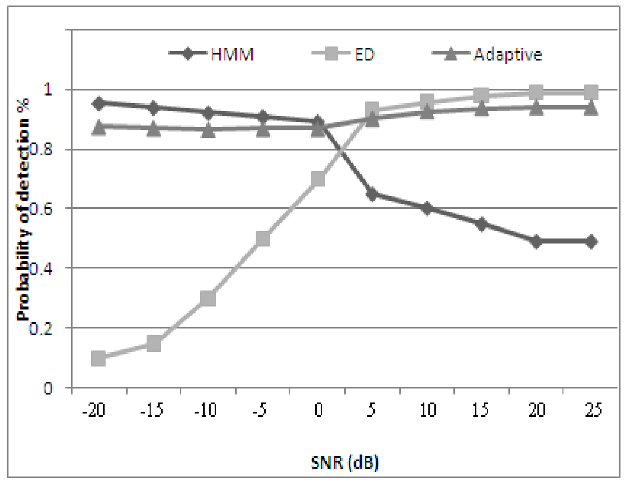

Fig.3. SNR Versus probability of detection for Adaptive sensing.

technique is improved even at low SNR values from -20 dB to 0dB. The probability of detection for the proposed technique ranges from 0.875 to 0.94. for the dynamic range of -20 dB to +25 dB. The proposed technique is compared with cyclostationary and two stage sensing [5] techniques and the performance is shown in fig.4. In the proposed technique the probability of detection is improved better than the other techniques.

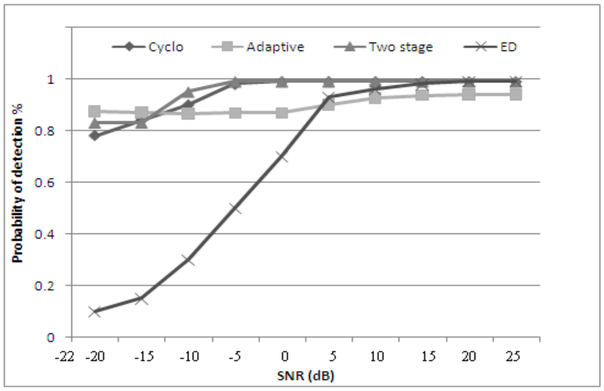

Fig.4. SNR Vs Probability of detection comparison with other sensing techniques.

b. Mean detection time:

The detection time is determined for energy detector at the sensing time of maximum probability of detection.

For HMM based sensing, the highest probability of detection occurs at -17dB and detection time or sensing time for a channel is given by as follows,

Sensing or detection time Ts = {sequence length x Time duration of the sequence}/window size. (22)

Sequence length L =3, time duration of a sequence=1.5 sec. Window size is obtained from HMM parameter estimation process for each SNR value.

For this proposed sensing technique the mean detection time is calculated for 10 channels case from the equation (6). Fig.5 shows the mean detection time performance for the adaptive sensing technique when Pr=0.1 (ie. The probability of channels having SNR> = 5dB). The probability of channels having SNR< 5dB is 0.9 the mean detection time for adaptive sensing is nearer to HMM sensing duration. The mean detection time of adaptive sensing is less than HMM based sensing most of the time. Thus the adaptive sensing technique reduces the sensing time.

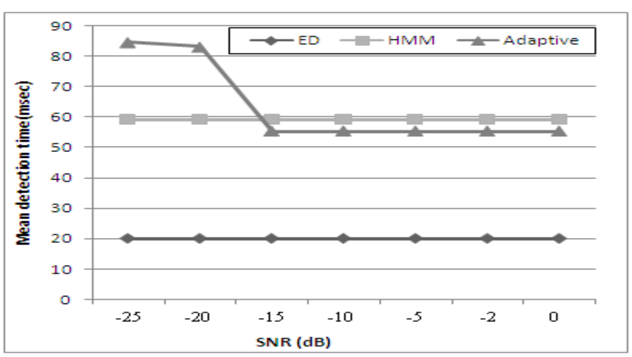

Fig.5.SNR Vs Mean detection time when (Pr=0.1).

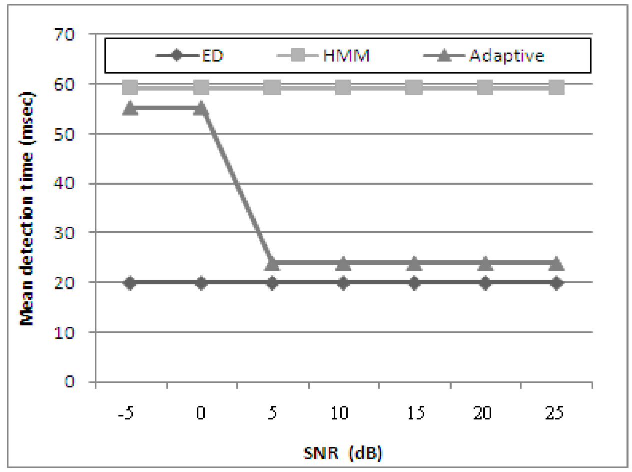

Fig.6. SNR Vs Mean Detection time When (Pr=0.9).

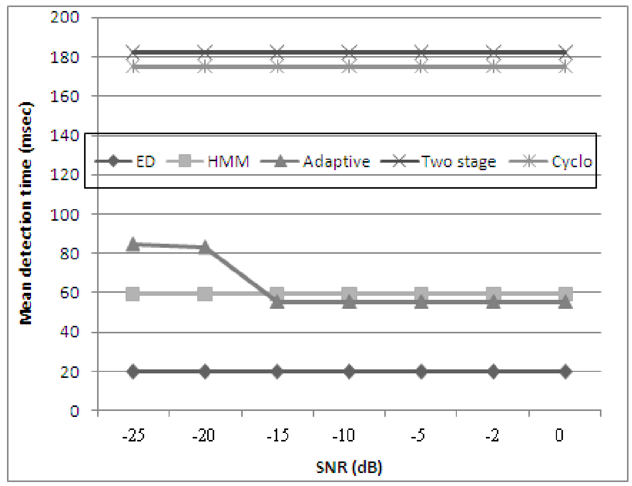

Fig.7. SNR Vs Mean detection time comparison when (Pr=0.1).

Fig.6 shows the mean detection time of the adaptive sensing when Pr=0.9 (ie. The probability of channels having SNR> = 5dB). This means that adaptive sensing technique selects energy detector for sensing with a probability of 0.9.Now the mean detection time of adaptive sensing is nearer to energy detector and the detection time is less compared to HMM based sensing.

The mean detection time of this adaptive sensing is compared with Two stage and cyclo stationary sensing techniques. Fig.7 and fig.8 show the comparison of mean detection time when Pr=0.1 and Pr=0.9 respectively. In both the cases the mean detection time of adaptive sensing is less compared to Two stage and cyclo stationary sensing techniques.

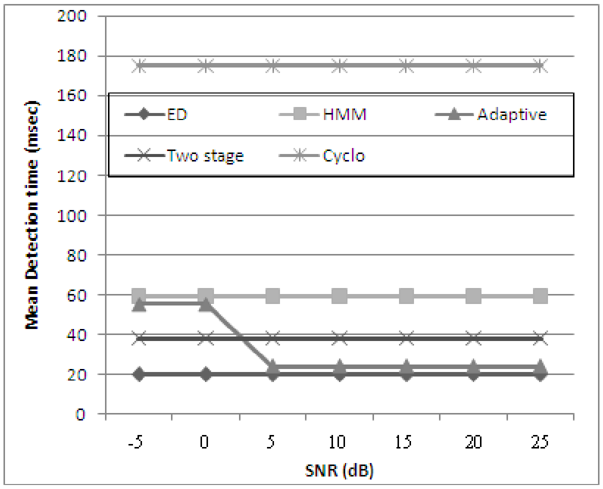

Fig.8. SNR Vs Mean detection time comparison
When (Pr=0.9).

VII. CONCLUSION AND FUTURE WORK:

This Adaptive spectrum sensing technique hasd increased the dynamic range of sensing and improved the sensing parameters such as the probability of detection and mean detection time compared to the two stage and cyclostationary sensing techniques [5].

In future the proposed adaptive sensing technique can also be applied in distributed networks to save the spectrum sensing energy of the nodes.

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