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Framework for Cognitive Radio Systems

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Abstract: The proposed system gives the calculation of number of samples and SNR in OFDM and SSB modulation and can calculate available throughput in cognitive radio transmission and normalize minimum sensing time. The system gives appropriate throughput for OFDM and system algorithms suggest better miss detection probability. The aggregate interference is constant in all systems while it changes in opportunistic throughput. Considering a periodic sensing scheme, with uniform channel sensing durations, the detection problems are formulated as joint optimization of the sensing duration and individual detector parameters to maximize the aggregate achievable secondary throughput capacity given some limits on the overall interference imposed on the primary network. Result shows that cognitive radio implemented using orthogonal frequency division multiplexing technique has better performance than using single side band technique.

Index Terms: Cognitive radio, multiband sensing-time-adaptive joint detection, nonlinear optimization, periodic sensing, spectrum sensing, throughput maximization, wideband sensing.

I. INTRODUCTION

According to Federal Communications Commission (FCC), temporal and geographical variations in the utilization of the assigned spectrum range from 15% to 85%. Although the fixed spectrum assignment policy generally served well in the past, there is a dramatic increase in the access to the limited spectrum for mobile services in the recent years. This increase is straining the effectiveness of the traditional spectrum policies. The limited available spectrum and the inefficiency in the spectrum usage necessitate a new communication paradigm to exploit the existing wireless spectrum opportunistically. Dynamic spectrum access is proposed to solve these current spectrum inefficiency problems and so called Next Generation program aims to implement the policy based intelligent radios known as cognitive radios. The Cognitive Radio technology will enable the user to determine which portion of the spectrum is available, detect the presence of primary user (spectrum sensing), select the best available channel (spectrum management), coordinates the access to the channel with other users (spectrum sharing) and migrate to some other channel whenever the primary user is detected (spectrum mobility) [3].

Cognitive Radio will enable the user to determine the presence of primary user, which portion of spectrum is available, in other words to detect the spectrum Holes or white spaces and it is called spectrum sensing, select the best available channel or to predict that how long the white spaces are available to use for unlicensed users also called spectrum management.

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To distribute the spectrum holes among the other secondary users which is called Spectrum sharing and switch to other channel whenever primary user is detected and this functionality of CR called spectrum mobility [4].Among these function Spectrum Sensing is considered to be the one of the most important critical task to establish Cognitive Radio Networks.

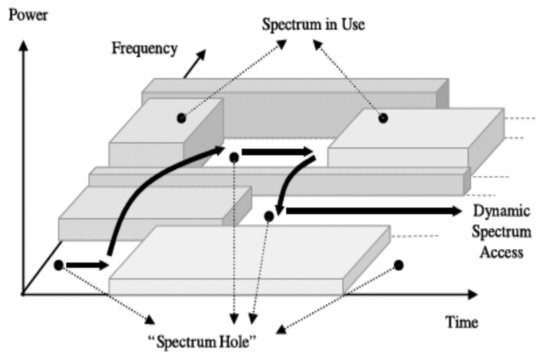

Fig.1 Illustration of spectrum hole.

Cognitive Radio is characterized by the fact that it can adapt, according to the environment, by changing its transmitting parameters, such as modulation, frequency, frame format, etc. [4]. The main challenges with CRs or secondary users (SUs) are that it should sense the PU signal without any interference. This work focuses on the spectrum sensing techniques that are based on primary transmitter detection [5]. The focus of this work is on the comparative study of an important spectrum sensing detection methods namely Energy detection (ED), The energy detection technique is known to be optimal when the only information available about the primary received signal is the noise power density and the received primary signal samples are independent and identically distributed Matched filter detection (MFD). Cyclostationary feature detector may be exploited in order to have more robust sensing. A survey on spectrum sensing algorithms can be found in, however, due to its low computational complexities and its fast detection ability. Maximum Eigenvalue to Minimum Eigenvalue ratio detector (ERD) an Eigenvalue-based algorithm which exploits the ratio of the maximum and minimum eigenvalues of the sample covariance matrix can be used. Maximum Eigenvalue to Minimum Eigenvalue ratio detector is Mean Eigenvalue ratio detector (MERD

II. SYSTEM MODEL

As a primary work on joint Wideband sensing, first we start the multiband joint Detection Framework of Where the sensing decision are made jointly over multiple frequency bands. The MJD framework, a set of individual secondary detectors is optimized so as to enhance the cognitive radio performance while protecting the primary network from harmful interference. Considering a periodic sensing structure as a crucial system model and adding the sensing time slot duration to the design parameters, we present the novel “multiband sensing-time-adaptive joint detection framework within which we find the optimal sensing slot duration and individual channel parameters so as to maximize the secondary capacity given a bound on the aggregate interference to the primary network. We also present some results which prove that the formulated optimization problem can be made convex if particular practical conditions are assumed. Finally, we propose another optimal joint detection framework, assuming that the aggregate interference on the primary network is excluded from the constraints and the individual interference protection constraints are restrictive enough to protect the primary network. Consequently, we reformulate the optimization problem in a much simpler form compared to the MSJD.

A. wideband sensing

We consider a Wideband channel which is divided into N non overlapping narrowband sub channels and we assume that a number of primary users share the spectrum. Multiuser orthogonal OFDM modulation is a very good candidate for such scenarios since it has been recognized as an excellent candidate for high data rate transmission over wideband channels and its nature makes the interpretation of sub channels easy. Depending on the location and time is not use in primary users and are available for secondary transmission.

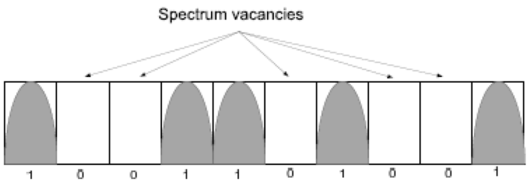

Fig 2. An illustrative example of a wideband channel and its sub channel Occupancies.

The detection on each sub channel k, binary hypothesis H_0, k represents the absence of the primary signal and $H_0 k$ represents the present of the primary signal considering a single sub band at a time may not be optimal. This relative importance is regarded as secondary capacity throughput for cognitive radio users and is reflected as primary interference protection priority for the primary network. Thus, instead of sensing each channel independently and identifying the spectrum vacancies in each sub Channel separately, we develop a wideband spectrum sensing framework which jointly detects the opportunities for secondary transmission over the entire target spectral bandwidth.

B. Periodic sensing

Once a secondary user detects an opportunity for transmission, its transmission parameters to access the channel yet, it should continue sensing the spectrum every T seconds in order to vacate the channel if the primary user reoccurrence. The sensing channel and transmitting the same channel cannot be done simultaneously the sensing period T determines the maximum time that the secondary user disregards the primary user activity and may impose harmful interference on the legacy network.

Therefore, the choice of T forces a delay on the primary transmission and hence a degradation of the quality of service. The selection of T should depend on the type of the primary service and should be set by the regulator. We fragment primary services into two types considering their sensitivity to transmission delay, 1) Small period category in which the frequency of primary user reoccurrence is high, forcing T to be selected relatively small. 2) Large period category where larger valves of T are endured since the reoccurrence of the primary signals occurs on a large time scale.

Fig. 3 represents the frame structure considered for the Periodic spectrum sensing. Each frame consists of one sensing slot τ and one data transmission slot T –τ For a given sensing time τ, the number of samples used for sensing of one sub channel is M =τfs where fs is the sampling frequency.

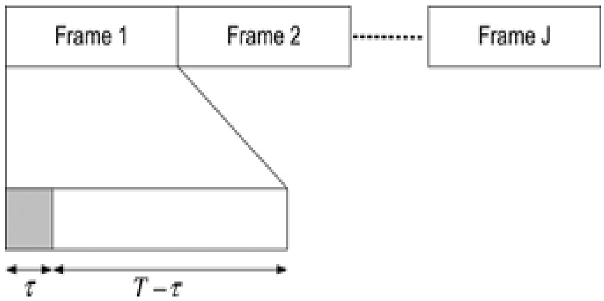

Fig 3. Periodic spectrum sensing.

C. Optimal Spectrum Sensing Framework

In this paper we develop an optimal spectrum sensing framework, which is illustrated in Figure 4. The proposed framework consists of the optimization of sensing parameters.

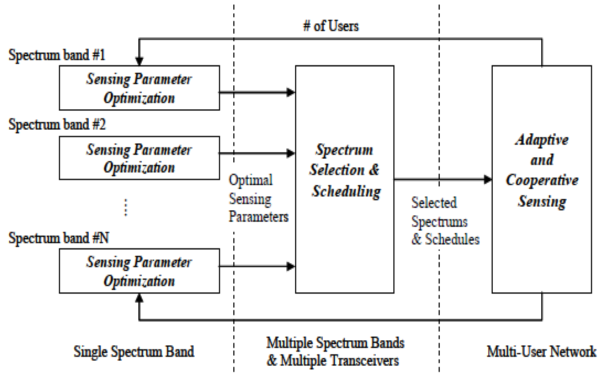

Fig 4 .the proposed optimal spectrum sensing framework

In a single spectrum band, spectrum selection and scheduling, and an adaptive and cooperative sensing method. The detailed scenario for the optimal sensing framework is as follows. According to the radio characteristics, base-stations initially determine the optimal sensing parameters of each spectrum band through the sensing parameter optimization. When CR users join the CR networks, they select the best spectrum bands for sensing and configure sensing schedules according to the number of transceivers and the optimized sensing parameters by using spectrum selection and scheduling methods. Then, CR users begin to monitor spectrum bands continuously with the optimized sensing schedule and report sensing results to the base-station. Using these sensing results, the base-station determines the spectrum availability. If the base-station detects any changes which affect the sensing performance, sensing parameters need to be re-optimized and announced to its CR users through the adaptive and
Cooperative sensing.

D. Received Signals

Consider a multipath fading channel in which $h(l)=, l=0,1,.........L-1$, represents the discrete time channel response between primary transmitter and cognitive user where L denotes the number of resolvable paths. Considering s (n) as the wideband signal transmitted by primary users, the received signal at the secondary user is given by,

$$r(n)=\sum_{l=0}^{l-1} h(l)s(n)+v(n) \qquad (1)$$

Where v(n) is additive complex white Gaussian noise with zero means variance. In fading environments, since the multipath delay spread is comparable to the transmitted signal duration, the wideband wireless channel exhibits frequency selectivity and its frequency response is represented as,

$$H_k=\frac{1}{\sqrt{N}}\sum_{n=0}^{L-1} h(n)e^{-j2\pi nk/N},$$
$$k=1,2,............N \qquad (2)$$

Where $N \geq L$. In the frequency domain, the received signal at each sub channel can be calculated, by computing the N-point discrete Fourier transform (DFT) of the received signal, as

$$R_k=\frac{1}{\sqrt{N}}\sum_{n=0}^{N-1} r(n)e^{-j2\pi nk/N}$$
$$H_kS_k+v_{k,}, \qquad k=0,1,........k-1 \qquad (3)$$

Where s_k the primary is transmitted signal at sub channel k and v_k is the DFT of received noise. We assume the transmitted signal, s_k the channel response H_k, and the noise v_k to be mutually independent.

E. signal detection in Individual Bands

After decomposing the received signal into N parallel waveforms, we are able to independently sense each individual band. Consequently, we perform signal detection in each sub-channel available for the joint detection framework. Thus, signal detection in the k-th sub channel may be formulated as a binary hypothesis test as

$$H_{0,K}: R_K = v_K$$
$$H_{1,K}: R_K = H_K S_K + v_K$$

K=1, 2 ….N (4)

As a common method for detecting unknown signals, energy.

Detection for each sub band is performed, i.e.

$$T_K=\frac{1}{M}\sum_{m=0}^{M=1}|R\kappa(m)|^2,$$

Is the decision statistic. Furthermore, we define the received signal-to-noise ratio (SNR) of the k^{th} sub channel as

$$\gamma\kappa=\frac{E(S\kappa)^2 H\kappa^2}{\sigma^2{}_w} \qquad (5)$$

In which E(.) Denotes expectation. For a large number of samples we shall use a central limit theorem to approximate the probability distribution function of T_k as a normal distribution under both hypotheses. Accordingly, the probability of false alarm $p_f^{(k)}(\varepsilon_k,\lambda)$ and the probability of detection $p_d^{(k)}(\varepsilon_k,\lambda)$ for the k-th channel are approximated

$$p_f^{(k)}(\varepsilon_k,T)=p_r(T_k>\varepsilon_k/H_{0,k})$$
$$=Q((\frac{\varepsilon_k}{\sigma_w^2}-1)\sqrt{\lambda F_s})$$

(6)

$$p_d^{(k)}(\varepsilon_k,T)=p_r(T_k>\varepsilon_k/H_{1,k})$$
$$=Q((\frac{\varepsilon_k}{\sigma_w^2}\gamma_k-1)\sqrt{Tf_s/2\gamma k+1})$$

Where Q (·) denotes the complementary distribution function of the standard Gaussian distribution. In the context of sensing algorithms, one of the design criteria is to make the probability of false alarm Pf as low as possible, since it measures the percentage of vacant spectrum which is misclassified as busy. On the other hand, in order to limit the probability of interfering with primary users, it is

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desired to keep the probability of missed detection Pm = 1 − Pd, with Pd given in, low .The threshold $\in_k$ is a tradeoff factor between the probabilities of false alarm and missed detection; a low threshold value will result in high false alarm probability in favor of low missed detection probability and vice versa. Alternatively, the choice of the sensing time τ offers a tradeoff between the quality and speed of sensing. By increasing the sensing time, the test decision is more accurate but the available time for cognitive transmission is reduced, in consequence.

IV. JOINT SPECTRUM SENSING FRAMEWORK

In next sections, we aim to optimize the aforementioned sensing design parameters within the so called joint detection frameworks. As pointed out before, a separate detection framework is not optimal, since the relative priorities and importance's of the sub channels are different from both the secondary and primary network viewpoints. Thus, optimal frameworks which jointly consider detection of spectrum vacancies over all sub channels are indicated.

4.1 Problem Formulation

In a vector-based format, the probabilities of false alarm and detection are represented as

$$p_f(\varepsilon,\lambda)=[p_f^{(1)}(\in_1,\lambda),............p_f^{(1)}(\in_N,\lambda)]^{\lambda} \quad (7)$$

$$p_d(\varepsilon,\lambda)=[p_d^{(1)}(\in_1,\lambda),............p_d^{(1)}(\in_N,\lambda)]^{\lambda} \quad (8)$$

In which ε = $[\in_{1,}\in_2 \,............\, \in_N]^T$ denotes threshold vector.

To formulate the problem, let denote the opportunistic throughput of the secondary user over sub channel when it operates in the absence of the primary users and Recall that represents the Percentage of spectrum vacancies detected by the cognitive user and represents the portion of the frame duration available for opportunistic transmission. Hence, we define the available throughput as,

$$R(\in,\lambda)=(\frac{T-\lambda}{T})r^T(1-p_f(\in,\lambda)) \quad (9)$$

Where1 denotes the all-ones vector.

For a given frame duration □ and threshold vector €, the larger the sensing time λ, the smaller the available time for data transmission $(T-\tau)$ and on the contrary, the larger the probability of opportunities detection $(1-p_f)$. Hence, we observe that there is an inherent trade-off in the sensing time that affects the available throughput. On the other hand, for a given sensing time τ , maximizing $R(\in,\tau)$ results in a large probability of miss-detection p_m and large interference with primary users. As a result, the interference to primary users must be constrained. In order to quantify the effect of interference on primary services, we assign some relative interference protection priorities to different sub channels. In particular, we define c_k as the cost of interfering with a primary user in the K-th sub channel & $c=[c_1,c_2 ....c_N]$ furthermore, we assume that J primary users share the whole spectrum where each user occupies subset S_j the N sub bands. Given the fact that primary users may demand different levels of protection, the aggregate interference to primary user j is defined as,

$$I_j(\in,\tau)=\sum\nolimits_{i\in s_j} c_i p_m^{(i)}(\in_i,\tau) \quad (10)$$

To proceed, we formulate the opportunistic secondary throughput and aggregate interference. Particularly, these functions will determine the performance of different sensing schemes and thus should be considered as the optimization objective functions. Intuitively, one would like to maximize the opportunistic secondary capacity and, at the same time, minimize the aggregate interference to the primary network. To do so, the sensing design parameters $\{\in_k\}_k^N=1$ and τ, which are effective in determining these functions, should be calculated and optimized during the sensing process. Although it is reasonable and somewhat crucial to consider the sensing time τ as an optimization variable, in some applications, it is indicated as a fixed value and should not be varied during the optimization process. Given this assumption, a wideband sensing framework referred to as multiband joint detection is presented in the next section.

A Minimum Value of sensing Time λ

Before solving the optimization problem, we explore a hidden lower bound on the sensing time λ. More specifically, we present an algorithm for deriving the sensing time required to meet the constraints [29]. That is, the smallest possible sensing time needed to satisfy the expectation of each individual sub channel is derived in this section. This investigation is motivated by several factors. First, we gain valuable insight into the range of values that an optimum value of can assume. Second, we make use in to solve the problem (P2) for a special range of values of frame duration. For further investigation, we need to explicitly express the relation between the probabilities of false alarm and missed detection. As a rule of thumb, in order to calculate, we fix the probability of false alarm vector at its maximum tolerable value. From, and for a given probability of false alarm at sub channel, the probability of missed detection is shown to be,

$$p_m^{(k)}(\lambda)=Q(\frac{1}{\sqrt{2\gamma_k+1}}(\sqrt{\lambda f_s\gamma_k}-Q^{-1}(\beta_k))) \quad (11)$$

B Algorithm 1 to calculate the minimum sensing time $\lambda_{\min}$

1) Assign the zero valves for Minimum Value of Sensing Time λ.
2) For J=1: J do.
3) For k-th Decision threshold in s_j do.

4) Assign the one valve for probability of miss detection.
5) Probability of miss detection is greater than Maximum allowable probability of interference in Channel k.
6) Minimum Value of Sensing Time λ solve the summation of probability of miss detection in sensing time λ.
7) $k_s \leftarrow \arg\min k \in s_j$
8) If Minimum Value of Sensing Time λ greater than minimum valve of sensing time (j).
9) Assign the Minimum Value of Sensing Time λ greater than minimum valve of sensing time (j).
10. End

V. LOW-COMPLEXITY ALGORITHM

The sensing time τ is constant which restricts the multiband joint detection framework we present an efficient algorithm for calculating the optimal threshold vector ε. Then, taking advantage of the algorithm, we propose another efficient algorithm for solving the original multiband sensing-time-adaptive joint detection framework in which ε and τ are both optimization variables.

A. Multiband Joint Detection

Here, we would like to find the optimal primal and dual parameters $\bar{\varepsilon}$ λ_1 $\boldsymbol{\lambda}_2$, and $\boldsymbol{\lambda}_3$ by satisfying the KKT conditions. Aiming to further simplify the problem, we first assume that all the optimal thresholds $\{\in_k\}_k^n = 1$ lie strictly between the specified maximum and minimum values, i.e., $\in_{k,\min} < \in_k < \in_{k,\max}$ for all k. In other words, we assume that is valid even if the equality is removed. This assumption may not be generally valid and some of the thresholds must assume the boundary values in order to satisfy all the KKT conditions. However, for the interim, we present results based on the aforementioned assumption and will deal with the Boundary thresholds in the next stages of the algorithm. Based on the assumption, it is seen that $\lambda_2^{(k)}$ and $\lambda_3^{(k)}$ are zero for all $k = 1...N$. As a result, only the exponential factors remain in, i.e., we have

$$\text{Exp}\left(\frac{0.5t_k^{-2}}{2\gamma_k+1} - \frac{(t_k+\gamma_k\sqrt{\lambda f_s})}{2}\right) = \frac{\lambda_1 c_k}{\gamma_k\sqrt{2\gamma_k+1}} \quad (12)$$

After taking the logarithms of both sides of the equation and doing some simplifications, is transformed into,

$$(t_k + \frac{\sqrt{\lambda fs}}{2} + \lambda k\sqrt{\lambda f_s})^2 \quad (13)$$

$$= -\frac{2\gamma_k+1}{\gamma_k}\log\left(\frac{\lambda 1 c_k}{\gamma_k\sqrt{2\gamma k+1}}\right) + \frac{\lambda fs}{4}(2\gamma k+1) \quad (14)$$

Generally, has two solutions, but only one of them is valid for our problem as can easily be shown using. Substituting, we can write the detection threshold

$$\in_k = \sigma_w^2\left[\frac{1}{2} + \sqrt{\frac{2\gamma_k+1}{\gamma_k}}\left[\frac{-1}{\lambda fs}\log\left(\frac{\lambda 1 c_k}{\gamma_k\sqrt{2\gamma k+1}}\right) + \frac{\gamma_k}{4}\right]\right. \quad (15)$$

$\{\varepsilon_{k,\min}\}^N_{=1}$,

This is a closed-form function of λ1. Having such a function enables us to substitute into the KKT condition and obtain the optimal λ1. Note that is an equality condition and can easily be solved using various fast and efficient numerical root-finding methods such as the Newton-Raphson method, fixed point iteration method,etc. Once λ1 is obtained, the detection thresholds $\{\in_k\}_k^N = 1$ are accordingly obtained. Note that these computed threshold values are optimal only if they satisfy the assumption of strictly lying between the specified values, i.e.….. $\in_{k,\min} < \in_k < \in_k, \max$ *forall* k=1 ….N since the Other KKT conditions are easily shown to be satisfied. That is, if some of the computed threshold values $\{\in_k\}_k^N = 1$ take values outside of the admissible range [$\in_{k,}$ min, $\in_{k,}$ max] it means that's neither is the solution optimal nor is the assumption of λ2 and λ3 being zeros valid .This means that's, there might be some $\{\lambda_2^{(k)}\}_k^N = 1$ Which must have nonzero values and accordingly, the associated thresholds must take the boundary values $\{\in_k, \min\}_k^N = 1$. This fact is easily concluded from the KKT conditions. Generally ,there is no way to know which $\{\lambda_2^{(k)}\}_k^N = 1$ are nonzero and in the worst case an Exhaustive search may be needed .
However ,we observe that once a specific subset of $\{\lambda_2^{(k)}\}_k^N = 1$ are known to be non –zero ,than the thresholds associated with s_p must take the boundary values.

A. Algorithm.2 Low-Complexity Implementation of the MJD Framework
1) For i= 1to 2N plus 1 do.
2) For k=1 to N do.
3) Lagrangian dual variable associated with maximum is greater than equal $A_{i+1.}$
4) Lagrangian dual variable associated with minimum is less than equal $A_{i.}$
5) Calculate the allowable detection threshold in the k-th channel for the MJD framework.
6) If Lagrangian dual variable associated with minimum is greater than equal A_{i+1} than Lagrangian dual variable associated equal to Minimum allowable detection threshold in the k-th channel for the MJD framework.
7) If Lagrangian dual variable associated with maximum is greater than equal A_{i+1} than Lagrangian dual variable associated equal to Maximum allowable detection threshold in the k-th channel for the MJD framework.
8) $D_i = (I(\in(A_i)) - \varsigma) * (I(\in(A_{i+1})) - \varsigma)$.
9) If D_i is less than equal to zeros.
10) Than Lagrangian dual variable associated solve the $I(\in(\lambda))$ equal to Maximum aggregate Interference tolerated by the primary network.

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11) Decision threshold is assign valve substitute Lagrangian dual variable associated in all Decision thresholds in the k-th channel.

VI. MULTIBAND SENSING-TIME-ADAPTIVE JOINT DETECTION

In this section, we propose an algorithm which computes the optimal detection threshold vector ε and sensing time τ as given in. The basic idea is that, instead of jointly optimizing the optimization variables, we optimize them in a disjoint two-stage algorithm. In the first stage of the algorithm, we assume that the sensing time τ is a constant value. In the second stage, we update the sensing time τ based on the information obtained from the previous stage.

We also use iteration in our algorithm in order to refine the information used in each stage. That is, after completing stage 2, we repeat stage 1 based on the updated sensing time τ obtained from the previous iteration and so on. However, it is shown that the number of required iterations is small and, most likely, on the second or third iteration, the optimal solution is obtained. Since the first stage of the algorithm has already been explained. We focus on the second stage here. In order to implement stage 2, we need some information from the previous stage. We specifically exploit probabilities of missed detection for this purpose.

There are four main parameters which are effective in determining probabilities of missed detection $P_m(\varepsilon\tau)$. These parameters are the achievable throughput r_k, the interference cost c_k, the channel SNR γ_k and the sensing time τ. This is an intuitive result which can be easily extracted from the objective and constraint functions in the problem. To be more specific, determines how to assign different values to every P_m based on the aforementioned four main parameters in order to achieve the maximum secondary aggregate throughput. In other words, these parameters determine the relation of different miss-detection probabilities and accordingly fix them at specific values. Having this fact in mind, we observe that the parameters $\gamma_k c_k$ and r_k are channel-dependent values and can vary in each sub channel but the sensing time τ is a global value and is the same in each sub channel. Therefore, we can intuitively conclude that the channel-dependent parameters are more effective in determining the miss-detection probabilities than the channel-in-dependent sensing time τ. That is, the relative proportion of different miss-detection probabilities is mostly dependent on the parameters which are different in each sub channel rather than the globally constant sensing time τ. On the other hand, it is seen that these so called channel-dependent parameters are fixed values and depend only on the system model. Thus, the computed missed detection probabilities in the first stage will re-main almost unchanged even if the sensing time τ changes in the next iteration. We exploit this information to implement the second stage of the algorithm. Accordingly, in the second stage, we assume that probabilities of missed detection are fixed at the values P_m () obtained from the first stage. Thus, we can write the probability of false alarm as

$$p_f^{(k)}(\tau) = Q(\sqrt{2\gamma_k + 1Q^{-1}(1-p_m^{(k)})} + \sqrt{\tau f_s \gamma_k} \qquad (16)$$

Accordingly, the optimization problem is converted to

$$Rmiss(\lambda) = \sum_{k=1}^{N} r_k((1-\frac{\tau}{T})p_f^{(k)}(\lambda) + \frac{\tau}{T}) \quad (17)$$

s.t $p_f(\tau) \le \beta$

Which has been proved to be convex if $0 \le \beta_k \le 0.5$. Since the only optimization variable is τ, we can rewrite the problem as

Min $\tau . R_{miss\,(\tau)}$
s.t $\tau \ge$ argmax $\{\tau_{min}^{(1)}, \tau_{min}^{(2)}, \tau_{min,}^{(3)} \ldots\ldots \tau_{min}^{(N)}\}$
in which

$$\lambda_{\min}^{(k)} = \frac{1}{\gamma_k^2 f_s}[Q^{-1}(\beta_k) - \sqrt{2\gamma_k + 1Q^{-1}}(1-p_m^{(k)})]^2 \quad (18)$$

Is the minimum required sensing time at sub channel k obtained from. The optimization problem can easily be solved by taking the derivative of the objective function and setting it to zero in order to obtain the optimal value of τ. The calculated value of τ is the optimal solution if it satisfies constraint. Otherwise the boundar y value given in is chosen. After solving the problem, the second stage of the algorithm is complete and we can repeat the first stage based on the updated value of τ until the solution is accurate enough. However, we intuitively showed that the probabilities of missed detection are not very dependent on the sensing time τ, thus the Number of iterations would be very small.

Algorithm.3 Low-Complexity Implementation of the proposed MSJD Framework

1) Choose an initial sensing time λ.
2) $\partial =$ Accuracy threshold.
3) Repeat runs Algorithm 2.
4) Comput $R_{miss}(\in, \lambda)$ put the value in R_{miss}^{old}
5) Calculate $p_m^{(k)}$.
6) Comput $R_{miss}(\lambda)$ put the value in R_{miss}^{new}.
7) 7 R_{miss}^{new} - R_{miss}^{old} greater than the Accuracy threshold.

VII. SIMULATION RESULTS

In this section, computer simulation results are presented to evaluate the proposed spectrum sensing schemes. Consider a single primary user communication (i.e., $J = 1$) over a wide-band spectrum of 6.4 MHz in which OFDM modulation with 16 subcarriers is adopted (i.e., $N = 16$).

A. Simulation result for number of samples vs. SNR increment.

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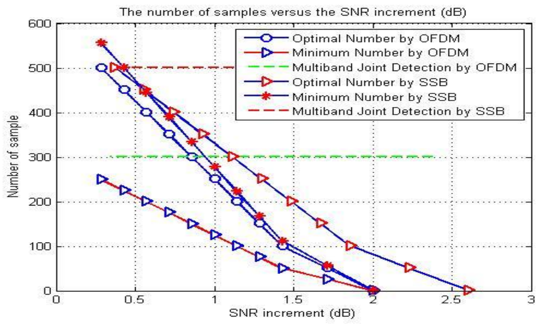

Fig .7 the number of samples M versus the SNR increment (dB)

In Fig .7, the number of samples M is plotted versus the SNR increment above the γ_k 's we observe that as the channel condition improves, the optimal number of samples is decreased. From this graph it can be concluded that multiband joint detection by single side band modulation gives maximum number of samples of 500 at 0.3db to 2.5db SNR. At lower value of SNR minimum number by SSB gives maximum number of samples of 560.when the value of SNR is 2 dB minimum numbers by SSB, optimal number by OFDM, minimum number by OFDM gives zero number of samples. By comparing multiband joint Detection by OFDM and multiband joint Detection by SSB, SSB method gives maximum number of samples

B. simulation result for normalized minimum sensing time vs. opportunistic throughput**.**

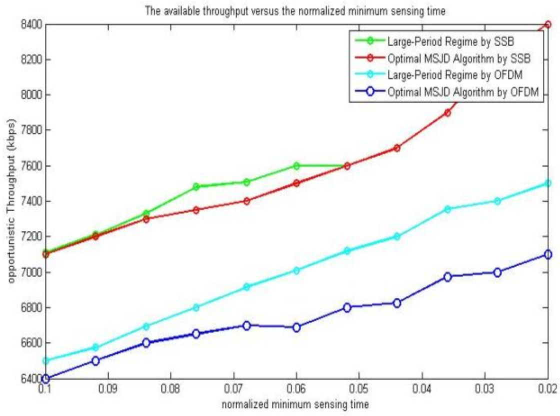

Fig.8 The available throughput for cognitive transmission versus the normalized minimum sensing $\lambda_{\min}^{norm}$

Fig.8 shows the available throughput versus the normalized minimum sensing time$_{norm}$. It can be seen that for minimum sensing time of 0.02 optimal MSJD algorithm by SSB gives maximum throughput of 8400 kbps while large period regime by OFDM gives throughput of 7500kbps and optimal MSJD algorithm by OFDM gives lower throughput of 7000 kbps.

Large period regime by SSB and optimal MSJD algorithm by SSB gives approximately equal results for sensing time of 0.1 to 0.08 with throughput of 7100 kbps and increase throughput as sensing time decreases.

C. Simulation result for sensing time vs. probability of miss-detection

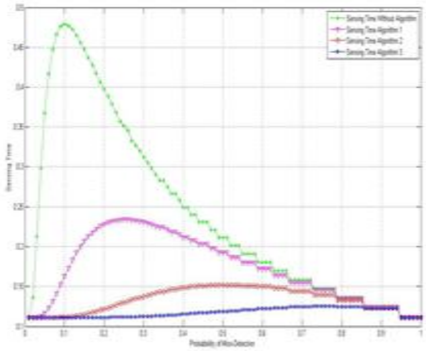

Fig.9 sensing time vs. probability of miss-detection

From above graph it can be conclude that for minimum probability of Miss Detection without algorithm gives maximum sensing time of 0.48 whereas the algorithm 1 , algorithm 2 and Algorithm 3 gives minimum sensing time of 0.12.As probability of Miss Detection increases sensing time decreases in without algorithm. From 0.6 to1 probability of Miss Detection for all algorithms reaches to nearly equal values.

A.Simulation result for available opportunistic throughput versus the aggregate interference.

The low-complexity algorithms are used for solving both the MSJD and MJD framework. Algorithm 2 optimizes the detection threshold vector ε when the sensing time τ is a predetermined value which better suits the MJD framework.

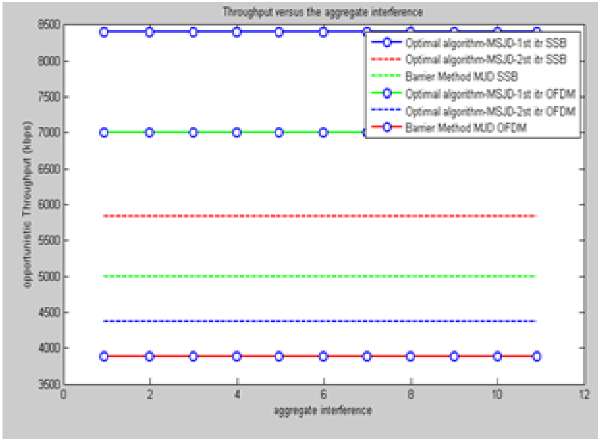

Fig.10 available opportunistic throughput versus the aggregate interference to the primary network

The parameter set used for simulation is the same as the one given in Table II. As depicted in the figure, the optimal solutions can easily be achieved by the algorithms. Optimal algorithm MSJD1st iterations SSB gives maximum throughput of 8500 kbps while barrier methods MJD OFDM give minimum throughput of 3800kbps.Optimal algorithm MSJD 2st iterations SSB gives maximum throughput of 5900 kbps while Optimal algorithm MSJD 2st OFDM give minimum throughput of 4400kbps. Barrier methods MJD SSB gives maximum throughput of 5000 kbps while barrier methods MJD OFDM give minimum throughput of 3800kbps.

VIII. CONCLUSION

The sampling time decreases from 0.47 to 0.14, for sensing time algorithm in the proposed system sampling time achieved is for algorithm 1 is 0.23 and algorithm 2 is 0.15 and algorithm 3 is 0.17 The proposed algorithm gives better miss detection probability, as we increase the SNR number of sample required for detection decreases. OFDM is having better opportunity throughput than that of SSB. Opportunity throughput constant as aggregate interference increases. It is minimum for barrier method MJD SSB and maximum for MJD OFDM.

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