Optimal and Suboptimal Multi Antenna Spectrum Sensing Techniques with Master Node Cooperation for Cognitive Radio Systems

Owayed A. Alghamdi and Mohammed Z. Ahmed
Mobile Communications Research Group
University of Plymouth
Plymouth PL4 8AA, UK
{owayed.alghamdi, m.ahmed}@plymouth.ac.uk

***Abstract*—In this paper, we consider the primary user detection problem in cognitive radio systems by using multi antenna at the cognitive radio receiver. An optimal linear combiner multi antenna based spectrum sensing technique is proposed using the multitaper spectrum estimation method. A suboptimal square law combiner multi antenna based technique, using the multitaper method, is also proposed. The decision statistics' probability density functions of the proposed techniques are derived theoretically. Probabilities of detection and false alarm formulae are presented using the Neyman Pearson criterion. Both proposed techniques are derived when energy detector is used. Based on our results, we found that the general likelihood ratio detector1 (GLRD1) and the blind GLRD that are proposed in the literature, require signal to noise ratios SNRs=7.5 and 9.6 dB, respectively to achieve a probability of detection of 99.99% at false alarm 1% with additive white Gaussian noise (AWGN) using 4 antennas and 16 samples for sensing. In our proposed optimal and suboptimal techniques, the required SNRs are found as −12 and −7.5 dB, respectively to achieve the same probabilities in the same conditions. Of course, this result gives an indication that even GLRD multi antenna based spectrum sensing techniques are blind in their philosophy, but that comes at the expense of their performance. Simulation results that confirm the theoretical work are also presented. An AWGN and Rayleigh flat fading environments are examined in the results. Finally, a new concept of cooperative spectrum sensing, the master node, is introduced.**

***Index Terms*—cognitive radio, spectrum sensing, multitaper spectrum estimation method, multi antenna spectrum sensing, cooperative spectrum sensing**

I. Introduction

Cognitive radio(CR) [1] is a new technology in the wireless communications world that has changed the policy of the spectrum assignment from static to a more flexible paradigm. In a CR network, a spectrum subband that is already licensed to a primary user (PR), can be used opportunistically at a specific time and location by an unlicensed user (i.e., secondary user), which is the CR. This new concept of spectrum access can satisfy the ever increasing demand for spectrum resources, and reduce the underutilized spectrum. Additionally, it can provide communications anywhere at any time [2]. An IEEE 802.22 wireless regional area network (WRAN) is the first CR standard, which operates on the spectrum that is allocated to TV services [3, 4].

In order to use the vacant subband, CR must sense its surrounding radio frequency (RF) environment before using it. Using an accurate spectrum sensing techniques allows CR to opportunistically exploit that unused spectrum, and protect the PR user from interference. Thus, spectrum sensing is a key functional factor in CR systems.

Matched filtering is classified as a high performance spectrum sensing technique. However, it requires a full knowledge of every PR's transmitted signal [5, 6]. A cyclostationary detector has a good performance, but requires knowledge of the PR's cyclic frequencies and requires long time to complete sensing [5-8]. On the other hand, an energy detector (ED), which is called a periodogram or radiometer, is simple, but has a poor performance at a low signal to noise ratio (SNR). The reason behind this, is that ED uses single rectangular tapering, which causes spectral leakage and large variance [9].

The multitaper spectrum estimation method (MTM) [10] produces single spectrum estimate with minimum spectral leakage and variance using an orthonormal family of tapers, the Discrete Prolate Slepian Sequences (DPSS) [11]. Haykin, on the other hand, suggests that MTM is an efficient spectrum sensing technique in CR systems [2]. MTM is an approximation of the optimal spectrum estimate, the maximum-likelihood method but at reduced computation [12, 13]. Haykin in [14], presented MTM's spectrum sensing tutorial and experiment results. The MTM parameters, half time bandwidth product *NW*, and the number of tapers *K* used in MTM, are recommended as ranges in his work. In our previous work, the MTM's parameters have been optimized as in [15]. The optimal *NW* is found as 4 and *K*=5 tapers is the optimal number of tapers. Optimal MTM parameters give the highest performance, and minimize the complexity when using MTM. The probabilities of detection and false alarm formulae of multitaper based spectrum sensing in additive white

Manuscript received January 25, 2011; revised May 1, 2011; accepted June 5, 2011.

Gaussian noise (AWGN) have been derived using the Neyman-Pearson criterion as in our work in [16].

Multi antenna in wireless communications allow for an increased data rate, and improve the spatial diversity [17]. Thus, a CR user can use it for both communications and spectrum sensing. Multi antenna spectrum sensing techniques and issues in CR systems have been investigated in [18-25].

Two main ED-based multi antenna spectrum sensing techniques, the linear coherent combining, and the selection processing are considered in [18]. In [19], each antenna is connected to an ED, where the PR's signal is present when more than one antenna decides so. In [20, 21], using the ED-based square law combining (SLC) technique in orthogonal frequency division multiplexing (OFDM)–multi input multi output (MIMO) based CR, resulted in significant improvements to the performance compared with using a single antenna. Generally, these works depend on ED, which has a poor performance in low SNR, and that is not practical in CR applications.

In [22], general likelihood ratio detectors (GLRDs) using multi antenna are derived with different assumptions. GLRD1 is derived assuming that only the channel gain is unknown, and is estimated using maximum likelihood (ML) estimation. Blind GLRD is derived when, signal variance, noise variance, and channel gain are all unknown to the CR, and it requires estimating these parameters as well. GLRD is derived in [23], assuming that the PR user had three different signal sources. Deriving asymptotic performance of GLRDs at different assumptions can be found in [24]. We can say that even GLRDs, in some cases, do not need prior information about the PR's signal, the channel, and the noise, they depend on estimating, which degrades the performance significantly and requires high SNR to work. In [25], we proposed local-MTM-singular value decomposition (Local-MTM-SVD) multi antenna based spectrum sensing technique as an efficient technique. Our results show a significant improvement in the performance compared to using single antenna.

In this paper, we consider CR spectrum sensing using multi antenna to detect an inverse fast Fourier transform/fast Fourier transform (IFFT/FFT) PR's transmitted signal (e.g., OFDM). Our CR user is assumed to be an IFFT/FFT based signal processing (e.g., OFDM). This will allow for the practical use of MTM in spectrum sensing. We propose the use of linear combiner-MTM based (MTM-LC) spectrum sensing, which is optimal when the channel coefficients can be known by CR, and that is possible when the PR's signaling is known. Blind channel equalization methods can, also, be used in such cases. The linear combining here increases the SNR, and using MTM minimizes the spectral leakage, and improves the variance of the estimate. A suboptimal multi antenna spectrum sensing technique has been proposed, square low combining-MTM based (MTM-SLC). In MTM-SLC, the MTM is performed through each antenna separately, and then the final spectrum estimate can be averaged over all the antennas' estimates. MTM-SLC, improves the performance at low SNR, and does not require coherent detection. Our proposed techniques have been derived theoretically and compared to simulation. The same techniques have been derived as well for ED and comparison between different techniques is presented in the results. Decision statistics' probability density functions (PDFs) of the proposed techniques have been defined for different hypothesis at different cases for both MTM, and ED. Additionally, we introduce a new cooperation concept, the master node (MN) cooperation. In MN, a single CR node can be supported by advanced hardware components, and advanced signal processing. This improves the detection's probability, minimizes the overall CR network complexity, minimizes the over head that is required when all CR's nodes share sensing, and accelerates the decision process.

The rest of the paper is organized as follows: Section II defines the model for the system under consideration, and reviews MTM and ED spectrum sensing techniques. Section III presents the theoretical aspect of the proposed multi antenna MTM-based detectors, and the same detectors when using ED in an AWGN environment. Section IV presents the works in a multipath fading environment. Section V defines the MN-Cooperation concept and compares it to the existing classical cooperation algorithms. Section VI presents the results and Section VII concludes the paper.

II. System Model

In our system model, we consider the OFDM signaling scheme for the PR user. The PR transmitter with N subcarriers (N-IFFT/FFT) transmits OFDM-quadrature phase shift keying (OFDM-QPSK) signal with energy E_s over each subcarrier, and symbol duration T_s. The CR transceiver is supported by the (N-IFFT/FFT) processor as well, so as to perform both tasks of communications and sensing. The number of antennas, M is added to the CR for both spectrum sensing and communications. Fig. 1 shows a representative diagram of multi antenna based spectrum sensing in CR systems.

In the global cooperation scenario, the number of CRs G cooperate their spectrum sensing decisions using binary digits to a main CR base station (CR-BS), which performs the "OR" rule cooperation and declares the final decision to the CR's nodes.

The received PR signal, at the CR receiver, is sampled to generate a finite discrete time samples series $\{x_{t,m}; t = 0,1,\dots,N-1, m = 1,\dots,M\}$, where m denotes the antenna number, and t is the time index. The discrete time samples are dot multiplied with different tapers $v_{(t,k)}(N,W)$ (tapers are DPSS). The associated eigenvalue of the k^{th} taper is $\lambda_k(N,W)$. The product is applied to a Fourier transform to compute the energy concentrated in the bandwidth $(-W,W)$ centered at frequency f. The half time bandwidth product is NW. The total number of generated tapers is $2NW$.

In order to evaluate the performance of the proposed techniques, we review two different types of probabilities at each frequency bin f_i, the probability of detection $P_d(f_i)$ and the probability of false alarm $P_f(f_i)$.

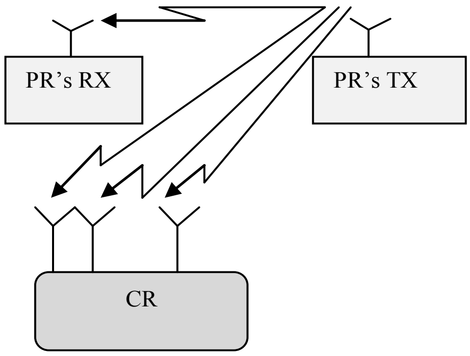

Figure 1. Multi antenna based spectrum sensing in CR systems.

$P_d(f_i)$, is the probability that the CR node (sensor) correctly decides the presence of the PR's signal, and $P_f(f_i)$ is the probability that the CR node (sensor) decides the PR's signal is present when it is absent.

The binary hypothesis test for CR spectrum sensing at the l^{th} time, and using the m^{th} antenna branch is given by:

$$\mathcal{H}_0: \quad x_{t,m}(l) = w_{t,m}(l)$$

$$\mathcal{H}_1: \quad x_{t,m}(l) = s_t(l) + w_{t,m}(l) \qquad (1)$$

where l=0,1,…,L-1 is OFDM block's index, and $x_{t,m}(l)$, $w_{t,m}(l)$, and $s_t(l)$ denote the CR received, noise at the branch m, and PR's transmitted samples. The transmitted PR signal is distorted by the zero mean AWGN, $w_{t,m}(l) \sim \mathcal{CN}(0, \sigma_w^2)$ at the output from the different antenna branches, which are independent and with identical variance σ_w^2. Note that at each frequency bin of CR FFT, $\mathcal{H}_0$ indicates no PR signal present, while $\mathcal{H}_1$ means there is a PR signal present.

The time instant l comes from the samples over different OFDM blocks, and the time instant t comes from the samples from the same OFDM block (i.e., IFFT/FFT samples). Thus, the spectrum sensing time in seconds is $(L)(N)(T_s)$, where T_s represents symbol duration, L represents the number of OFDM blocks that were used in sensing, and N is the number of samples per OFDM block (i.e., FFT size).

For K orthonormal tapers used in the MTM, there will be K different eigenspectrums produced from each antenna defined as:

$$Y_{k,m}(f_i) = \sum_{t=0}^{N-1} v_{(t,k)}(N,W)(x_{t,m}(l))e^{-j2\pi f_i t} \qquad (2)$$

where, $f_i = 0, \frac{1}{N}, \frac{2}{N}, \dots, \frac{N-1}{N}$ are the normalized frequency bins. The power spectrum estimate given by Thomson theoretical work is defined as [10]:

$$S_{MTM}^m(f_i) = \frac{\sum_{k=0}^{K-1} \lambda_k(N,W)\left|Y_{k,m}(f_i)\right|^2}{\sum_{k=0}^{K-1} \lambda_k(N,W)} \qquad (3)$$

On the other hand, the energy detector, when the samples are taken at uniform time spacing, gives the power spectrum density estimation as [9]:

$$S_{ED}^m(f_i) = \left|\sum_{t=0}^{N-1} x_{t,m}(l)e^{-j2\pi f_i t}\right|^2 \qquad (4)$$

The decision statistic over L using MTM is defined for the m^{th}antenna as follows:

$$DEC_{MTM}^m(f_i) = \sum_{l=0}^{L-1} \frac{\sum_{k=0}^{K-1} \lambda_k(N,W)\left|\sum_{t=0}^{N-1} v_{(t,k)}(N,W) x_{t,m}(l) e^{-j2\pi f_i t}\right|^2}{\sum_{k=0}^{K-1} \lambda_k(N,W)} \qquad (5)$$

Using the energy detector, the decision statistic over L is defined for the m^{th} antenna as follows:

$$DEC_{ED}^m(f_i) = \sum_{l=0}^{L-1}\left|\sum_{t=0}^{N-1} x_{t,m}(l)e^{-j2\pi f_i t}\right|^2 \qquad (6)$$

For single antenna MTM-based spectrum sensing, and according to the central limit theorem, if the number of samples L, is large, the decision statistic, $DEC_{MTM}^m(f_i)$ is asymptotically normally distributed with mean (E) [16]:

$$E[DEC_{MTM}^m(f_i)] = \begin{cases} LK\sigma_w^2 & \mathcal{H}_0 \\ LK(E_s + \sigma_w^2) & \mathcal{H}_1 \end{cases} \qquad (7)$$

and variance (VAR)

$$VAR\left(DEC_{MTM}^m(f_i)\right) = \begin{cases} 2LC^2\lambda_\Sigma\sigma_w^4 & \mathcal{H}_0 \\ 2LC^2\lambda_\Sigma\sigma_w^2(\sigma_w^2 + 2E_s) & \mathcal{H}_1 \end{cases} \qquad (8)$$

where λ_Σ, is defined as follows:

$$\begin{aligned} \lambda_\Sigma &= \sum_{k=0}^{K-1} \lambda_k^2(N,W) + 2\lambda_0(N,W)\lambda_1(N,W) \\ &+ 2\lambda_0(N,W)\lambda_2(N,W) + \cdots \\ &+ 2\lambda_0(N,W)\lambda_{K-1}(N,W) \\ &+ 2\lambda_1(N,W)\lambda_2(N,W) + 2\lambda_1(N,W)\lambda_3(N,W) \\ &+ \cdots + 2\lambda_1(N,W)\lambda_{K-1}(N,W) + \cdots \\ &+ 2\lambda_{K-2}(N,W)\lambda_{K-1}(N,W) \end{aligned}$$

and $C = E\left[\frac{1}{\sum_{k=0}^{K-1} \lambda_k(N,W)}\right] = \frac{1}{\sum_{k=0}^{K-1} \lambda_k(N,W)}$

On the other hand for the energy detector, and at the same assumption, the decision statistic, $DEC_{ED}^m(f_i)$ has the mean [26]:

$$E[\,DEC_{ED}^m(f_i)] = \begin{cases} L\sigma_w^2 & \mathcal{H}_0 \\ L(E_s + \sigma_w^2) & \mathcal{H}_1 \end{cases} \qquad (9)$$

and variance

$$VAR\left(DEC_{ED}^m(f_i)\right) = \begin{cases} 2L\sigma_w^4 & \mathcal{H}_0 \\ 2L\sigma_w^2(\sigma_w^2 + 2E_s) & \mathcal{H}_1 \end{cases} \qquad (10)$$

For a normally distributed decision statistic, $DEC(f_i)$, the probabilities of detection, $P_d(f_i)$, and false alarm, $P_f(f_i)$ are defined as follow:

$$\begin{aligned} P_d(f_i) &= P(DEC(f_i) > \gamma / \mathcal{H}_1) \\ &= Q\left(\frac{\gamma - E[DEC(f_i)/\mathcal{H}_1]}{\sqrt{VAR(DEC(f_i)/\mathcal{H}_1)}}\right) \end{aligned} \qquad (11)$$

$$P_f(f_i) = P(DEC(f_i) > \gamma / \mathcal{H}_0)$$

$$= Q\left(\frac{\gamma - E[DEC(f_i)/\mathcal{H}_0]}{\sqrt{VAR(DEC(f_i)/\mathcal{H}_0)}}\right) \quad (12)$$

The probability of miss detection $P_{mi}(f_i)$ can be defined as:

$$P_{mi}(f_i) = P(DEC(f_i) < \gamma / \mathcal{H}_1)$$
$$= 1 - Q\left(\frac{\gamma - E[DEC(f_i)/\mathcal{H}_1]}{\sqrt{VAR(DEC(f_i)/\mathcal{H}_1)}}\right) \quad (13)$$

The term $Q(\xi)$ is the complementary cumulative distribution function, $Q(\xi) = \frac{1}{\sqrt{2\pi}}\int_{\xi}^{\infty} e^{-\frac{t^2}{2}}\,dt$, and γ represents the chosen threshold. Note that γ can be controlled based on $L\sigma_w^2$. The signal to noise ratio is defined as $\mathrm{SNR} = \frac{E_s}{\sigma_w^2}$ for each antenna branch when they are identical.

The different probabilities in (11), (12), and (13) can be calculated based on the means (*Es*), and the variances (*VARs*) for the different techniques at the different hypotheses as in (7) to (10). Thus, the different probabilities of MTM using single antenna can be redefined as follow [16]:

$$P_d^{MTM}(f_i) = Q\left(\frac{\gamma - LK(E_s+\sigma_w^2)}{\sqrt{2LC^2\lambda_\Sigma\sigma_w^2(\sigma_w^2+2E_s)}}\right) \quad (14)$$

$$P_f^{MTM}(f_i) = Q\left(\frac{\gamma - LK\sigma_w^2}{\sqrt{2LC^2\lambda_\Sigma\sigma_w^4}}\right) \quad (15)$$

$$P_{mi}^{MTM}(f_i) = 1 - Q\left(\frac{\gamma - LK(E_s+\sigma_w^2)}{\sqrt{2LC^2\lambda_\Sigma\sigma_w^2(\sigma_w^2+2E_s)}}\right) \quad (16)$$

The number of samples required by MTM using single antenna (L^{MTM}) can be written as [16]:

$$L^{MTM} = \left(\frac{a^{MTM} - b^{MTM}}{KE_s}\right)^2 \quad (17)$$

where

$$a^{MTM} = \sqrt{2C^2\lambda_\Sigma\sigma_w^4}\,Q^{-1}\left(P_f^{MTM}(f_i)\right)$$

and

$$b^{MTM} = \sqrt{2C^2\lambda_\Sigma\sigma_w^2(\sigma_w^2+2E_s)}\,Q^{-1}\left(P_d^{MTM}(f_i)\right)$$

Substituting (9) and (10) in (11), (12), and (13), gives the different probabilities for the ED case.

III. PROPOSED MULTI ANTENNA BASED SPECTRUM SENSING TECHNIQUES

In this section of the paper, we present the theoretical and analytical works of the proposed two spectrum sensing techniques. The first proposed technique is the square law combining-MTM based (MTM-SLC) technique, which can be developed by using number of the antennas, *M* at the CR receiver for spectrum sensing based on MTM. The decision statistic is performed via each antenna branch separately using MTM over *L* samples, and then the overall decision statistic is calculated by summing the outputs decision statistics from the different antenna branches as square law combining. MTM-SLC is compared theoretically and analytically to the energy detector-square law combining (ED-SLC) as can be seen below.

The decision statistics in (5) and (6) can be redefined for square law combining using *M* antennas for both techniques MTM, and ED respectively as follow:

$$DEC_{MTM-SLC}(f_i) = \sum_{m=1}^{M}\sum_{l=0}^{L-1}\frac{\sum_{k=0}^{K-1}\lambda_k(N,W)\left|\sum_{t=0}^{N-1}v_{(t,k)}(N,W)x_{t,m}(l)e^{-j2\pi f_i t}\right|^2}{\sum_{k=0}^{K-1}\lambda_k(N,W)} \quad (18)$$

and

$$DEC_{ED-SLC}(f_i) = \sum_{m=1}^{M}\sum_{l=0}^{L-1}\left|\sum_{t=0}^{N-1}x_{t,m}(l)e^{-j2\pi f_i t}\right|^2 \quad (19)$$

From (18) and (19) the decision statistic using square law combining is a sum of identical and independent normally distributed *M* antennas decision statistics. Thus, the mean of the $DEC_{MTM-SLC}(f_i)$ using *M* antennas can be defined as follows:

$$E[DEC_{MTM-SLC}(f_i)] = \begin{cases} MLK\sigma_w^2 & \mathcal{H}_0 \\ MLK(E_s+\sigma_w^2) & \mathcal{H}_1 \end{cases} \quad (20)$$

and the variance can be defined as follows:

$$VAR\big(DEC_{MTM-SLC}(f_i)\big) = \begin{cases} 2MLC^2\lambda_\Sigma\sigma_w^4 & \mathcal{H}_0 \\ 2MLC^2\lambda_\Sigma\sigma_w^2(\sigma_w^2+2E_s) & \mathcal{H}_1 \end{cases} \quad (21)$$

In the ED case, the mean of the decision statistic, $DEC_{ED-SLC}(f_i)$ using square law combining through *M* antennas can be defined as follows:

$$E[DEC_{ED-SLC}(f_i)] = \begin{cases} ML\sigma_w^2 & \mathcal{H}_0 \\ ML(E_s+\sigma_w^2) & \mathcal{H}_1 \end{cases} \quad (22)$$

and the variance is defined as follows:

$$VAR(DEC_{ED-SLC}(f_i)) = \begin{cases} 2ML\sigma_w^4 & \mathcal{H}_0 \\ 2ML\sigma_w^2(\sigma_w^2+2E_s) & \mathcal{H}_1 \end{cases} \quad (23)$$

The different probabilities can be redefined for the square law combining technique using *M* antennas for both MTM, and ED cases by substituting the means and variances defined in (20), (21), (22), and (23) in (11), (12), and (13). The threshold, γ in this case, is controlled by the term $LM\sigma_w^2$.

The second proposed technique is the MTM based-Linear combiner (MTM-LC) of the received samples from different *M* antennas at the CR receiver. The received data samples at the CR receiver are summed from the different *M* antenna branches in the time domain to be as follows:

$$x_t(l) = \sum_{m=1}^{M} x_{t,m}(l) \quad (24)$$

Then the eigenspectrums of the resulted new received samples, $x_t(l)$, can be written as follows:

$$Y_k(f_i) = \sum_{t=0}^{N-1} v_t^{(k)}(N,W)x_t(l)e^{-j2\pi f_i t} \quad (25)$$

The MTM-LC decision statistic over *L* samples can be defined as follows:

$$DEC_{MTM-LC}(f_i) = \sum_{l=0}^{L-1} \frac{\sum_{k=0}^{K-1} \lambda_k(N,W) \left| \sum_{t=0}^{N-1} v_{(t,k)}(N,W) x_t(l) e^{-j2\pi f_i t} \right|^2}{\sum_{k=0}^{K-1} \lambda_k(N,W)} \quad (26)$$

In order to derive the different probabilities expressions of $DEC_{MTM-LC}(f_i)$, we need to derive the mean (E), and the variance (VAR) for the different hypotheses. We follow our theoretical derivation of the MTM-single based as in [16]. The linear combiner binary hypothesis can be defined as follows:

$$\mathcal{H}_0: \; x_t(l) = w_{t,1}(l) + w_{t,2}(l) + \cdots \; w_{t,M}(l)$$
$$\mathcal{H}_1: \; x_t(l) = s_t(l) + w_{t,1}(l) + \cdots s_t(l) + w_{t,M}(l) \quad (27)$$

The main different in $\mathcal{H}_0$ between MTM, and MTM-LC is the effect of the combined noise signals from different antenna. Thus, the mean for K correlated Gaussian samples of the decision statistic in (26), $E[DEC_{MTM-LC}(f_i)/\,\mathcal{H}_0]$ can be defined as follows:

$$E[DEC_{MTM-LC}(f_i)/\,\mathcal{H}_0] = C.\sum_{l=0}^{L-1}(\sum_{k=0}^{K-1}(\lambda_k(N,W).K\sum_{t=0}^{N-1}\sum_{t'=0}^{N-1}E[v_{(t,k)}(N,W) \\ .v_{(t',k)}(N,W).x_t(l)x_{t'}(l)])) \quad (28)$$

It can be shown that (28) can be simplified as:

$$E[DEC_{MTM-LC}(f_i)/\,\mathcal{H}_0] = \sum_{l=0}^{L-1}\sum_{t=0}^{N-1}(v_{(t,k)}(N,W).v_{(t',k)}(N,W)).K \\ .E[x_t(l)x_{t'}(l)] \quad (29)$$

From the definition of the DPSS, we have [11]:

$$\sum_{t=0}^{N-1} v_{(t,k)}(N,W).v_{(t,k')}(N,W) = \begin{cases} 1, & k = k' \\ 0, & k \neq k' \end{cases} \quad (30)$$

In the remaining parts of the paper, the terms $w_{t,m}(l)$, and $s_t(l)$ will be written as $w_m(l)$, and $s(l)$ respectively for simplification.

The orthonormality of the sequences can be used to simplify (29), over L (L here is for MTM-LC technique, which is different from that for MTM-SLC) sensed samples, when $t = t'$as follows:

$$E[DEC_{MTM-LC}(f_i)/\,\mathcal{H}_0] = \sum_{l=0}^{L-1} K.E[x_t^2(l)]$$

$$= LK.E[(w_1(l) + w_2(l) + \cdots + w_M(l))(w_1(l) + w_2(l) + \cdots + w_M(l))] = LK.E[w_1^2(l) + w_1(l)w_2(l) + w_1(l)w_3(l) + \cdots + w_1(l)w_M(l) + w_2^2(l) + w_2(l)w_1(l) + w_2(l)w_3(l) + \cdots + w_2(l)w_M(l) + \cdots + w_M^2(l) + w_M(l)w_1(l) + w_M(l)w_2(l) + \cdots + w_M(l)w_{M-1}(l)] \quad (31)$$

since $E[w_i(l)w_j(l)] = 0$, for $i \neq j$, and $i, j = 1,2, \ldots M$, then (31) can be rewritten as follows:

$$E[DEC_{MTM-LC}(f_i)/\,\mathcal{H}_0] = LK.(E[w_1^2(l)] + E[w_2^2(l)] + \cdots + E[w_M^2(l)])$$

$$= LK.((E[w_1(l)])^2 + VAR(w_1(l)) + (E[w_2(l)])^2 + VAR(w_2(l)) + \cdots + (E[w_M(l)])^2 + VAR(w_M(l))) \quad (32)$$

Finally, $E[w_m(l)] = 0$, and $VAR(w_m(l)) = \sigma_w^2$, then (32) can be written as follows:

$$E[DEC_{MTM-LC}(f_i)/\,\mathcal{H}_0] = MLK\sigma_w^2 \quad (33)$$

The variance of K correlated Gaussian samples in (26), $VAR(DEC_{MTM-LC}(f_i)/\,\mathcal{H}_0)$ over L sensed samples when $t = t'$, can be defined as follows:

$$VAR(DEC_{MTM-LC}(f_i)/\,\mathcal{H}_0) = \beta L.\left(\sum_{t=0}^{N-1} v_{(t,k)}^2(N,W)\right)^2 .VAR(x_t^2(l)) \quad (34)$$

$$= \beta L\,.VAR(w_1^2(l) + w_1(l)w_2(l) + w_1(l)w_3(l) + \cdots + w_1(l)w_M(l) + w_2^2(l) + w_2(l)w_1(l) + w_2(l)w_3(l) + \cdots + w_2(l)w_M(l) + \cdots + w_M^2(l) + w_M(l)w_1(l) + w_M(l)w_2(l) + \cdots w_M(l)w_{M-1}(l)) \quad (35)$$

where β is defined as follows:

$$\beta = C^2\,\lambda_\Sigma \quad (36)$$

Then, (35) can be simplified as follows:

$$VAR(DEC_{MTM-LC}(f_i)/\,\mathcal{H}_0) = \beta L\,(VAR(w_1^2(l)) + VAR(w_2^2(l)) + \cdots + VAR(w_M^2(l)) + VAR(2w_1(l)w_2(l)) + VAR(2w_1(l)w_3(l)) + \cdots + VAR(2w_1(l)w_M(l)) + VAR(2w_2(l)w_3(l)) + VAR(2w_2(l)w_4(l)) + \cdots + VAR\left(2w_2(l)w_M(l)\right) + \cdots + VAR(2w_M(l)w_{M-1}(l)))$$

$$= \beta L\left(VAR(w_1^2(l)) + VAR(w_2^2(l)) + \cdots + VAR(w_M^2(l)) + \binom{M}{2} VAR\left(2w_i(l)w_j(l)\right)\right) \quad (37)$$

where $VAR(w_m^2(l)) = 2\sigma_w^4$, and $VAR\left(2w_i(l)w_j(l)\right) = 4\sigma_w^4, \forall\; i \neq j, and\; i, j = 1,2, \ldots M$. Finally, (37) can be written as follows:

$$VAR(DEC_{MTM-LC}(f_i)/\,\mathcal{H}_0) = \beta L\,(M(2\sigma_w^4) + 2\binom{M}{2}\,(2\sigma_w^4))$$

$$= \beta L\left(M(2\sigma_w^4) + 2\left(\frac{M!}{(M-2)!\,2!}\right)(2\sigma_w^4)\right)$$

$$= \beta L\,M^2(2\sigma_w^4) \quad (38)$$

When the PR's signal is present, the

$E[DEC_{MTM-LC}(f_i)/\mathcal{H}_1]$ over L sensed samples when $t = t'$, can be defined as follows:

$$E[DEC_{MTM-LC}(f_i)/\mathcal{H}_1] = LK.E[\big(s(l)+w_1(l)+s(l)+w_2(l)+\cdots+s(l)+w_M(l)\big)\big(s(l)+w_1(l)+s(l)+w_2(l)+\cdots+s(l)+w_M(l)\big)]$$

$$= LK.E[M^2s^2(l)+w_1^2(l)+w_2^2(l)+\cdots+w_M^2(l)+s(l)w_1(l)+s(l)w_2(l)+\cdots+s(l)w_M(l)+\cdots+w_M(l)s(l)]$$

$$= LK.(E[M^2s^2(l)]+2M.E[s(l)].E[w_m(l)]+E[w_1^2(l)]+E[w_2^2(l)]+\cdots+E[w_M^2(l)]) \quad (39)$$

where $E[M^2s^2(l)] = M^2E_s$, $E[w_m(l)] = 0$, and $E[w_m^2(l)] = ((E[w_m(l)])^2 + VAR(w_m(l))) = 0 + \sigma_w^2$, then (38) can be simplified as follows:

$$E[DEC_{MTM-LC}(f_i)/\mathcal{H}_1] = LK(M^2E_s + M\sigma_w^2) = MLK(ME_s + \sigma_w^2) \quad (40)$$

The variance, $VAR(DEC_{MTM-LC}(f_i)/\mathcal{H}_1)$ can be defined as follows:

$$VAR(DEC_{MTM-LC}(f_i)/\mathcal{H}_1) = \beta L.VAR\big(M^2s^2(l)+w_1^2(l)+w_2^2(l)+\cdots+w_M^2(l)+s(l)w_1(l)+s(l)w_2(l)+\cdots+s(l)w_M(l)+\cdots+w_M(l)s(l)\big)$$

$$= \beta L\Bigg(VAR\big(2Ms(l)w_1(l)\big)+VAR\big(2Ms(l)w_2(l)\big)+\cdots+VAR\big(2Ms(l)w_M(l)\big)+VAR\big(w_1^2(l)\big)+VAR\big(w_2^2(l)\big)+\cdots+VAR\big(w_M^2(l)\big)+\binom{M}{2}.VAR\Big(2w_i(l)w_j(l)\Big)\Bigg) ,\forall\ i \neq j, and\ i,j = 1,2,\ldots M$$

$$= \beta L(M(4M^2)E_s\sigma_w^2 + M(2\sigma_w^4) + 2\left(\frac{M!}{(M-2)!\,2!}\right)(2\sigma_w^4))$$

$$= \beta L\big(M(4M^2)E_s\sigma_w^2 + M^2(2\sigma_w^4)\big)$$

$$= 2\beta LM^2\sigma_w^2\,(\sigma_w^2 + 2ME_s) \quad (41)$$

Finally, the different MTM-LC hypotheses' mean, and variance can be summarized as follow:

$$E\big(DEC_{MTM-LC}(f_i)\big) = \begin{cases} MLK\sigma_w^2 & \mathcal{H}_0 \\ MLK(ME_s+\sigma_w^2) & \mathcal{H}_1 \end{cases} \quad (42)$$

$$VAR\big(DEC_{MTM-LC}(f_i)\big) = \begin{cases} 2\beta L\,M^2\sigma_w^4 & \mathcal{H}_0 \\ 2\beta LM^2\sigma_w^2\,(\sigma_w^2+2ME_s) & \mathcal{H}_1 \end{cases} \quad (43)$$

The same derivation steps can be followed for $DEC_{ED-LC}(f_i)$, then the different hypotheses' mean, and variance can be written as follow:

$$E[DEC_{ED-LC}(f_i)] = \begin{cases} ML\sigma_w^2 & \mathcal{H}_0 \\ ML(ME_s+\sigma_w^2) & \mathcal{H}_1 \end{cases} \quad (44)$$

$$VAR\big(DEC_{ED-LC}(f_i)\big) = \begin{cases} 2M^2L\sigma_w^4 & \mathcal{H}_0 \\ 2M^2L\sigma_w^2(\sigma_w^2+2ME_s) & \mathcal{H}_1 \end{cases} \quad (45)$$

The different probabilities, P_d^{MTM-LC}, P_f^{MTM-LC}, and P_{mi}^{MTM-LC} shown in (11), (12), and (13) can be calculated based on the means (*E*s), and the variances (*VAR*s) for the MTM-LC at the different hypotheses as in (42) and (43). The same procedures can be done for the ED-LC technique. The threshold, γ, in this case, is controlled by the term $LM\sigma_w^2$.

The MTM's mean is K times ED's mean for both hypotheses, and the difference in the variance is defined as the variance factor (*VF*), which can be written as follows:

$$VF = C^2\,\lambda_\Sigma = \beta \quad (46)$$

The number of samples, $L^{MTM-SLC}$(i.e., OFDM blocks) needed to achieve predefined probabilities of detection, $P_d^{MTM-SLC}$, and false alarm, $P_f^{MTM-SLC}$ in the MTM-SLC technique can be written using the resulted MTM-SLC probabilities of detection and false alarm formulae as follows:

$$L^{MTM-SLC} = \left(\frac{a^{MTM-SLC} - b^{MTM-SLC}}{MKE_s}\right)^2 \quad (47)$$

where

$$a^{MTM-SLC} = \sqrt{2VFM\sigma_w^4}Q^{-1}\left(P_f^{MTM-SLC}(f_i)\right)$$

and

$$b^{MTM-SLC} = \sqrt{2VFM\sigma_w^2(\sigma_w^2+2E_s)}Q^{-1}\left(P_d^{MTM-SLC}(f_i)\right)$$

The derivation of $L^{MTM-SLC}$ is detailed in the Appendix.

The MTM-LC's samples, L^{MTM-LC}, can be defined as follows:

$$L^{MTM-LC} = \left(\frac{a^{MTM-LC} - b^{MTM-LC}}{M^2KE_s}\right)^2 \quad (48)$$

where

$$a^{MTM-LC} = \sqrt{2VFM^2\sigma_w^4}Q^{-1}\left(P_f^{MTM-LC}(f_i)\right)$$

and

$$b^{MTM-LC} = \sqrt{2VFM^2\sigma_w^2(\sigma_w^2+2ME_s)}Q^{-1}\left(P_d^{MTM-LC}(f_i)\right)$$

This can be written in (dB) as follows:

$$L_{dB} = 10log_{10}(L)$$

Substituting VF=1, and K=1 in (47), and (48) produces the number of samples, L for ED-SLC, and ED-LC respectively.

IV. MULTI PATH FADING ENVIORNMENT

The channel model that is assumed in this paper is similar to that in [27], where an AWGN is added to the PR's signal at the CR's receiver. In the multipath fading environment, (1) can be rewritten as follows:

$$\mathcal{H}_0:\quad x_{t,m}(l) = w_{t,m}(l)$$

$$\mathcal{H}_1:\ x_{t,m}(l) = \sum_{p=0}^{P-1} h_{p,m} s_{t-p}(l) + w_{t,m}(l) \quad (49)$$

where the discrete channel impulse response between the PR's transmitter and CR's m^{th} branch is represented by $h_{p,m}$,$p = 0,1,\dots,P-1$, and P is the total number of resolvable paths. The discrete frequency response of the channel through the m^{th} branch is obtained by taking the N point FFT, with $N \geq P$ as follows [28]:

$$H_m(f_i) = \sum_{p=0}^{P-1} h_{p,m} e^{-j2\pi f_i p} \quad (50)$$

In such an environment, using MTM-SLC and ED-SLC does not need co-phasing to cancel the effect of the channel of each antenna branch. Since the decision statistic will be performed via each CR's antenna branch independently, the MTM-SLC's decision statistic can be approximated to Gaussian, and then (20) and (21) can be rewritten as:

$$E\big(DEC_{MTM-SLC}(f_i)\big) = \begin{cases} MLK\sigma_w^2 & \mathcal{H}_0 \\ LK\big(E_s(\sum_{m=0}^{M-1}|H_m(f_i)|^2) + M\sigma_w^2\big) & \mathcal{H}_1 \end{cases} \quad (51)$$

$$VAR\big(DEC_{MTM-SLC}(f_i)\big) = \begin{cases} 2MLC^2\lambda_\Sigma\sigma_w^4 & \mathcal{H}_0 \\ 2LC^2\lambda_\Sigma\sigma_w^2\big(M\sigma_w^2 + 2E_s(\sum_{m=0}^{M-1}|H_m(f_i)|^2)\big) & \mathcal{H}_1 \end{cases} \quad (52)$$

In practice, $|H_m(f_i)|^2$ can be estimated a priori during the time that PR's transmitter occupies a specific band with specific power [28]. In this paper, we assume that the channel gain between the PR's transmitter and the CR's receiver is constant during the spectrum sensing duration, and this is useful for application like in IEEE802.22. When applying MTM-LC and ED-LC, the CR wants to coherently add up the signals from different branches by co-phasing, which requires knowing the channel coefficients a priori via training sequences or pilot signals. Blind channel equalization techniques [29] are very useful in such cases.

V. MASTER- NODE COOPERATION

In order to resolve the multipath fading effect, shadowing, and noise uncertainty on the CR's spectrum sensing, different cooperative spectrum sensing techniques have been proposed in literature. Fig. 2 shows the cooperative spectrum sensing scenario in a centralized CR networks. Basically, these techniques are classified into soft and hard cooperation techniques. In the soft technique, a number of CR users sense the PR's signal and then resend the real measurements to the main CR-BS that applies a specific fusion rule, and then declares the final decision. In hard cooperation, each CR's user decides about the PR's signal locally and independently from the other CRs, then a binary digit represents the state of the PR's signal in a specific band is sent to the CR-BS that applies a binary fusion rule to declare the final decision to the CR network.

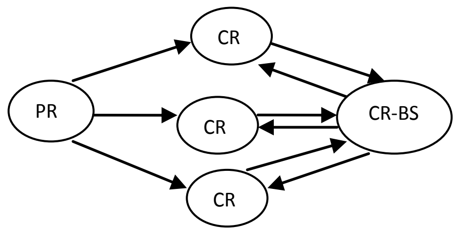

Figure 2. Classical cooperative spectrum sensing scenario in a centralized CR network.

An optimal linear soft cooperation algorithm has been proposed in [26], where the performance is optimized by linearly combining the individual CRs' local test statistics at the CR-BS. In [30], the authors propose an optimal soft cooperation algorithm based on the deflection coefficient maximization criterion. The cooperative spectrum sensing performance using likelihood ratio test (LRT)-soft combination has been evaluated in [31]. It is found that the LRT-soft cooperation outperforms AND-hard cooperation in term of performance.

An OR-hard cooperation algorithm has been proposed in [32], where the CR-BS declares that the PR's signal is present in the band under sensing when at least one CR user decides the signal is present.

The joint probability of detection, Q_d, and the joint probability of false alarm, Q_f, of the OR rule combining at the CR-BS using G CR nodes (sensors) with identical probabilities of detection and false alarm are given by:

$$Q_d = 1 - \prod_{g=1}^{G}(1 - P_{d,g}) \quad (53)$$

$$Q_f = 1 - \prod_{g=1}^{G}(1 - P_{f,g}) \quad (54)$$

where $P_{d,g}$, $P_{f,g}$ represent the probabilities of detection and false alarm achieved by the g^{th} CR node (sensor).

The multitaper singular value decomposition spectrum sensing technique (MTM-SVD) [2, 14], can be classified as soft cooperation with multi measurements from different tapers [7]. Our work in [25], ends the need for huge overhead feedback to the CR-BS in MTM-SVD by proposing the efficient multi antenna based spectrum sensing technique, the Local-MTM-SVD.

The work in [33] shows that, including the decision from CR user with a low SNR in the cooperation at the CR-BS degrades the probability of detection. Thus, the authors propose a fusion rule at the CR-BS that uses only the reliable decisions, which come from the CR users with a high SNR. The main drawbacks here are the requirements for SNR estimation, and in addition to sending decisions from different CR users to the CR-BS, each CR has to send its own estimated SNR to the CR-BS. Different hard cooperation optimization algorithms have been proposed in [34-38]. The common objectives of these works are minimizing the number of binary bits sent to the CR-BS that would require wideband control channel, or by choosing the CRs with the reliable decisions to cooperate at the main station, while at the same time, keeping the probability of opportunity high.

Generally, implementing spectrum sensing at each CR in the cooperative CR network, decoding or amplifying the sensed signals and then sending the results to a main CR-BS, have the following main challenges:

1) The need for sensing units at each CR that will increase the hardware cost, the system complexity, the sensing delay and power consumption.
2) The need for sending the sensed information or decisions to a main CR-BS, which requires more signal processing at both sides, the CR's terminals and CR-BS.
3) The need for control channels and huge overhead feedback to send the sensed information from all CRs to the CR-BS. Additionally, algorithms for information sharing and coordination are required in such cases [39].
4) Additional information such as the SNRs at different CRs has to be sent to the main CR-BS in optimized cooperative sensing.
5) The availability of some CRs in the network with reliable decisions is not guaranteed at all time. Thus, cooperating the sensed information produces more errors.

In order to face such challenges, the CR system needs to minimize the spectrum sensing processing in the CR network and insure that the performance is kept high. Supporting the CR network with an ideal CR node can satisfy the two above conditions. Adding highly advanced hardware and software components to a single CR node in the CR network, and excluding the others CRs is a good solution. In this solution, the spectrum sensing using advanced high performance techniques such as those proposed in this paper is performed at this ideal CR, and the final decision can be sent to the main CR-BS. The hardware components here should allow the ideal CR node to sense different frequency bands at the same time. Prior information about the different PR's signals must be known at this ideal node in order to resolves multipath fading. Training sequences and pilot signals are examples of this information.

Fig. 3 shows the MN-cooperative spectrum sensing scenario in a centralized CR networks. The work in [40], proposes implementing spectrum sensing using devices that are separate from the CR network and can be provided by the CR's service provider. In addition to the PR's and CR's system, a separate sensing system appears in their work. Of course, that would increase the overall system complexity, require more technical and management coordination protocols and sensing devices cannot be used in the CR's cycle.

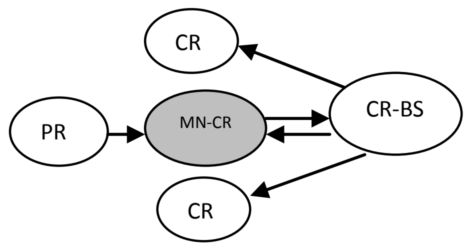

Figure 3. MN cooperative spectrum sensing scenario in a centralized CR network.

VI. SIMULATION RESULTS

In our system, each node of the CR network uses 64-FFT with a sampling frequency 20 MHz. The PR user's transmitter uses 64-IFFT with symbol duration T_s =0.05μs, and transmits QPSK signal with normalized energy equal to 1 over each subcarrier. The CR nodes use the MTM and ED with *M*=1 antenna. The multi antenna techniques considered in this paper, MTM-SLC, MTM-LC, ED-SLC, ED-LC, and Local-MTM-SVD are examined with a different number of antennas *M*=2, and 4. In MTM techniques, the used half time bandwidth product is *NW*=4, and the number of tapers is *K*=5 [15]. In all cases of simulations, the results are averaged over 10^6 realizations. The channels considered in the simulation are AWGN with zero mean and variance σ_w^2, and Rayleigh flat fading. The performance is evaluated over a chosen frequency bin, when it is assumed that, the whole band under sensing is occupied by the PR's signal.

Fig. 4, and Fig. 5 show the probability of detection, P_d versus probability of false alarm, P_f using the different spectrum sensing techniques with a different number of antennas at AWGN with SNR=-10dB and 20 OFDM blocks (i.e., $L = 20$) used in sensing. Note that the number of samples used is $(L = 20) \times (N = 64) = 1280$, which approximately corresponds to the sensing time 64μs. Both figures show significant improvement in the performance using the proposed MTM with multi antenna techniques. Additionally, we can see how the Local-MTM-SVD technique has the same performance that is achieved by MTM-SLC in the same conditions. This suggests that MTM-SLC is more practical as it does not need the SVD process and gives the same performance with lower complexity. Using *M*=2 antennas, when $P_f = 10\%$, MTM-SLC, MTM-LC, ED-SLC, and ED-LC techniques have P_d =80, 95, 21, and 29% respectively. The MTM-LC outperforms MTM-SLC in terms of P_d by 5% for *M*=4 case, and by 14% for *M*=2 case, when $P_f = 10\%$ in the same conditions. ED techniques have a poorer performance compared to the others under the same conditions.

Fig. 6 shows the probability of detection, P_d versus probability of false alarm, P_f , using the different considered spectrum sensing techniques with number of antennas *M*=2 at Rayleigh flat fading with average SNR=-5dB and $L = 20$. It is clear that the MTM-LC and ED-LC' performances are affected by fading more than that in MTM-SLC and ED-SLC. This is due to the destructive adding of the received signals from different antennas without co-phasing the channels coefficients. There is a significant outperforming of MTM against ED even in a fading environment, and the Local-MTM-SVD still has the same performance when using MTM-SLC in the same conditions. The probability of detection P_d's percentages when the false alarm is fixed to $P_f=10\%$ using MTM-LC, MTM-SLC, ED-LC, ED-SLC, and Local-MTM-SVD are 77, 93, 62, 81, and 93 % respectively.

Fig. 7 shows the probabilities of detection, P_d that meet probability of false alarm, $P_f=10\%$, versus the SNR at AWGN using MTM with single antenna, MTM-SLC, and MTM-LC with *M*=4 antennas, and $L=50$ for spectrum sensing. We can see a noticeable improvement in the performance using both proposed techniques compared to MTM with single antenna. At SNR=-15dB, MTM-SLC outperforms MTM with single antenna in terms of probability of detection, P_d by 30%. On the other hand, MTM-LC outperforms MTM with single antenna by 66%. It can be seen from the figure that, our simulations match the theory.

Fig. 8 shows the comparison between the number of OFDM blocks, L required to achieve $P_d=99\%$, and $P_f=1\%$ at AWGN environment with different SNR using the different considered techniques with *M*=1, and 4 antennas. It is clear that the number of OFDM blocks used in the sensing process in the MTM system is lower than that for ED in all cases. Additionally, LC techniques require a lower number of OFDM blocks compared to SLC for both MTM, and ED cases in the same conditions. For example, from the figure at SNR=-15dB, the number of OFDM blocks L in dB that are required by ED only, ED-SLC, ED-LC, MTM only, MTM-SLC, and MTM-LC are 50, 42, 35, 32, 27, and 20 , or in *milli seconds* as 5, 0.792, 0.158, 0.08, 0.025, and 0.005 respectively. It is clear that the MTM-multi antenna based spectrum sensing techniques proposed in this paper, are faster than the others. For example, MTM-LC is faster than MTM only by 93.75% (i.e., faster by 0.075 $m\ seconds$), and ED-LC by 96.85%.

In OR-rule based cooperation, the resulted spectrum sensing decisions from the individual CR nodes are relayed to the main CR-BS, which applies the OR rule cooperation algorithm to declare the final decision to the CR network. Five CR nodes (i.e.,*G*=5) share the cooperation, with each supported by *M*=3 antennas. Fig. 9 shows the OR rule joint probability of detection, Q_d versus the joint probability of false alarm, Q_f for MTM-SLC, MTM-LC, ED-SLC, and ED-LC with *M*=3 antennas, and *G*=5 CR users at AWGN with SNR= $-$ 12dB and *L*=20 OFDM blocks. At joint probability of false alarm, $Q_f=10\%$, the joint probability of detection is $Q_d=100\%$ using the MTM-LC, 92% using MTM-SLC, 45% using ED-LC, and 25% using ED-SLC.

The resulted probabilities of detection for MTM-SLC, MTM-LC, GLRD1 [22], and blind GLRD detector [22] using *M*=4 antennas at AWGN with SNR=-10dB when the false alarm is 1% and *L*=16, can be summarized as follow:

- Using MTM-SLC and MTM-LC gives a probability of detection 70, and 98% respectively.
- In the same conditions, the GLRD1 and the blind GLRD detectors have a probability of detection of 0%.

Therefore, our main conclusion here is that, the latter techniques can produce large harmful interference to PR users, or a very low probability of opportunity.

Additionally, the required SNRs in (dB) for MTM-SLC, MTM-LC, ED-SLC, ED-LC, GLRD1[22], and blind GLRD detector [22] to achieve a probability of detection of 99.99%, using *M*=4 antennas at AWGN when the false alarm is 1% and *L*=16 sensed samples, can be summarized as follow:

- The GLRD1 gives a probability of detection of 99.99% when the SNR=7.5 dB, and the blind GLRD, gives the same probability when the SNR =9.6 dB.
- The MTM-SLC and MTM-LC give the same probability of detection, when the SNR for them is -7.5, and -12dB respectively.

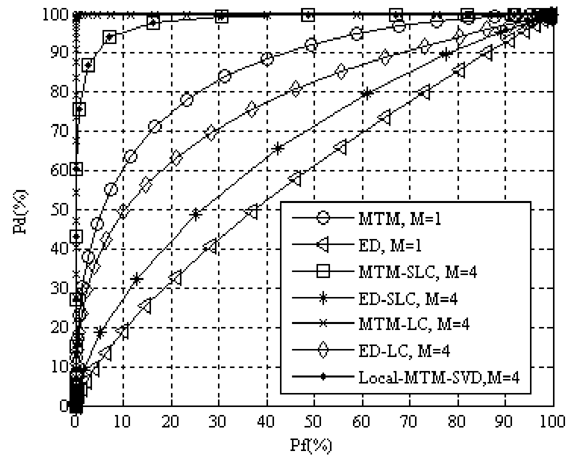

Figure 4. Probability of detection versus probability of false alarm using MTM and ED with *M*=1, and MTM-SLC, MTM-LC, ED-SLC, and ED-LC with *M*=4 antennas at AWGN with SNR=-10dB and $L=20$.

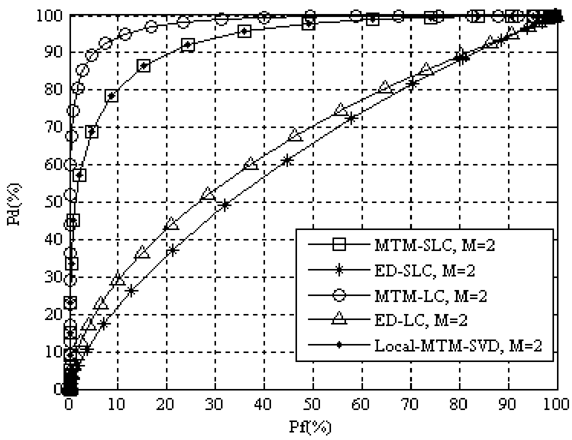

Figure 5. Probability of detection versus probability of false alarm using MTM-SLC, MTM-LC, ED-SLC, and ED-LC with number of antennas *M*=2, at AWGN with SNR=-10dB and $L=20$.

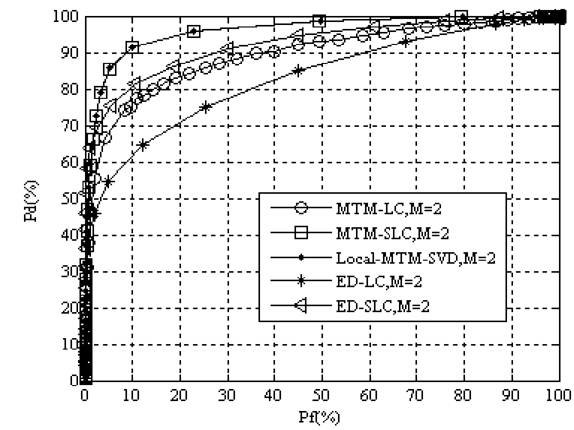

Figure 6. Probability of detection versus probability of false alarm using MTM-SLC, MTM-LC, ED-SLC, and ED-LC with M=2 antennas at Rayleigh flat fading with average SNR=-5dB and$L = 20$.

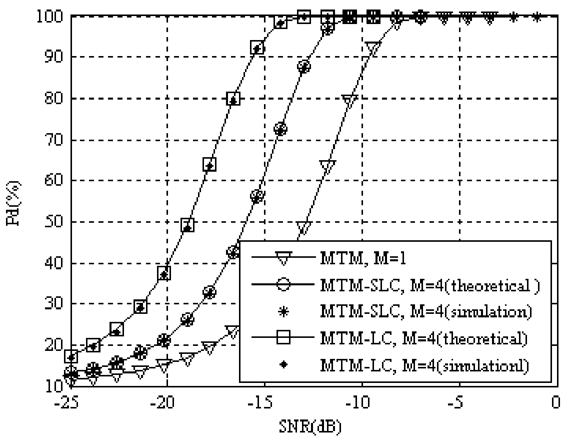

Figure 7. Probability of detection that meets $P_f = 10\%$ versus the SNR at AWGN using MTM, MTM-SLC, and MTM-LC spectrum sensing techniques with number of antennas M=4 and $L = 50$.

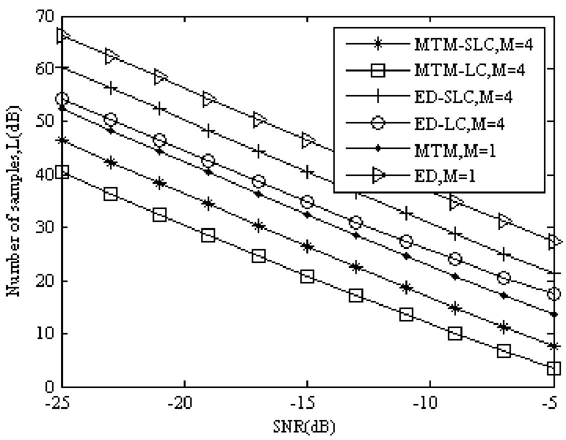

Figure 8. Numbers of samples (L) required to achieve $P_d = 99\%$, and $P_f = 1\%$ at AWGN with different SNR using MTM, MTM-SLC, MTM-LC, ED, ED-SLC, and ED-LC spectrum sensing techniques with number of antennas M=1, and 4.

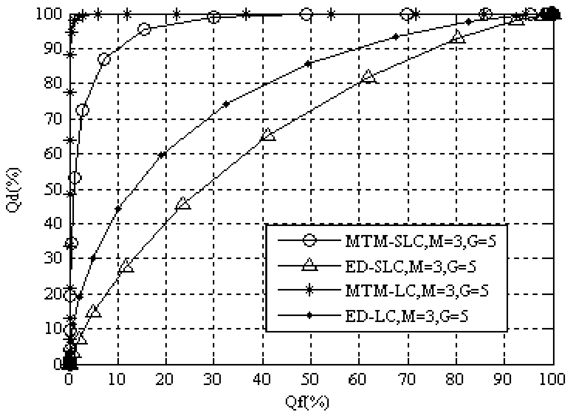

Figure 9. OR rule Joint Probability of detection versus joint probability of false alarm using MTM-SLC, MTM-LC, ED-SLC, and ED-LC spectrum sensing techniques with number of antennas M=3using 5 CR users (G=5) at AWGN with SNR=-12dB and L=20.

- The ED-SLC and ED-LC achieve the same probability of detection in the same conditions, when their SNRs are 5, and 0 dB respectively.

Thus, these techniques do not give a high performance unless the SNR is high, which is not practical in CR. It is clear that the MTM-LC has a 10dB SNR's gain compared to ED-LC, and 15dB compared to ED-SLC.

VII. Conclusion

In this paper, we propose different MTM-multi antenna based techniques as efficient CR spectrum sensing techniques. Theoretical work has been derived for the proposed techniques in AWGN, and multipath fading wireless environments. The ED-multi antenna based spectrum sensing techniques has been derived as well and compared to that of MTM, and the Local-MTM-SVD.

Using multi antenna in MTM-LC, and MTM-SLC gives more improvement in performance compared to that for ED-LC, ED-SLC. The Local-MTM-SVD spectrum sensing technique has the same performance when of MTM-SLC under the same conditions. Therefore, we can say that the MTM-SLC is more practical than Local-MTM-SVD as it does not need SVD processors, and that minimizes the complexity and the cost of the system. Moreover, based on our results, we found that the GLRD1 and the blind GLRD that are proposed in the literature, require SNRs=7.5 and 9.6 dB, respectively to achieve a probability of detection of 99.99% at false alarm 1% with AWGN using 4 antennas and 16 samples for sensing. In our proposed optimal and suboptimal techniques, the required SNRs are found as -12 and -7.5 dB, respectively to achieve the same probabilities in the same conditions.

In the multipath fading environment, adding the PR's signals received from different CR antennas might degrades the resulted combined signal destructively in MTM-LC, and ED-LC. Thus, such combining needs co-phasing to tolerate the multi path effects. However, we believe that this is a main challenge in CR spectrum sensing and is still open issue. Blind equalization methods can be considered in such cases.

The proposed techniques represent local cooperation using multi antenna. These techniques can be added to one CR node to work as MN in the CR network. This is a practical solution to minimize the complexity of the CR network. The different hard and soft cooperation algorithms in the literature can be used here to improve the overall performance. The OR rule cooperation is used to cooperate the generated binary decisions from the individuals CR nodes at a main CR-BS. Then the final decision is declared to the CR nodes.

APPENDIX

The probabilities of detection and false alarm, $P_d^{MTM-SLC}(f_i)$, and $P_f^{MTM-SLC}(f_i)$ using MTM-SLC technique are defined as:

$$P_d^{MTM-SLC}(f_i) = Q\left(\frac{\gamma - L^{MTM-SLC}KM(E_s+\sigma_w^2)}{\sqrt{2LMC^2\lambda_\Sigma\sigma_w^2(\sigma_w^2+2E_s)}}\right) \tag{55}$$

$$P_f^{MTM-SLC}(f_i) = Q\left(\frac{\gamma - L^{MTM-SLC}KM\sigma_w^2}{\sqrt{2LMC^2\lambda_\Sigma\sigma_w^4}}\right) \tag{56}$$

In order to calculate the number of samples, $L^{MTM-SLC}$, which are required to achieve specific probabilities of detection and false alarm, the threshold, γ that used in both (55), and (56) are the same. Thus, after mathematical manipulation, the threshold form (55) can be defined as follows:

$$\gamma = Q^{-1}\left(P_d^{MTM-SLC}(f_i)\right)\sqrt{2LMC^2\lambda_\Sigma\sigma_w^2(\sigma_w^2+2E_s)} + LKM(E_s+\sigma_w^2) \tag{57}$$

using (56), the threshold can be defined as:

$$\gamma = Q^{-1}\left(P_f^{MTM-SLC}(f_i)\right)\sqrt{2LMC^2\lambda_\Sigma\sigma_w^4} + LKM\sigma_w^2 \tag{58}$$

Since the thresholds in (57) and (58) are equals, then $L^{MTM-SLC}$ can finally be defined as in (47). The same steps can be followed to derive the number of required samples, when MTM-LC, ED-SLC, and ED-LC are used for sensing.

REFERENCES

[1] J. Mitola and G. Q. Maguire, "Cognitive radio: making software radios more personal," *IEEE personal communications,* vol. 6, pp. 13-18, 1999.

[2] S. Haykin, "Cognitive radio: brain-empowered wireless communications," *IEEE journal on selected areas in communications,* vol. 23, pp. 201-220, 2005.

[3] C. Cordeiro, K. Challapali, D. Birru and N. Sai Shankar, "IEEE 802.22: the first worldwide wireless standard based on cognitive radios," in *New Frontiers in Dynamic Spectrum Access Networks, 2005. DySPAN 2005. 2005 First IEEE International Symposium on*, 2005, pp. 328-337.

[4] C. Stevenson, G. Chouinard, L. Zhongding, H. Wendong, S. Shellhammer and W. Caldwell, "IEEE 802.22: The first cognitive radio wireless regional area network standard," *Communications Magazine, IEEE,* vol. 47, pp. 130-138, 2009.

[5] I. F. Akyildiz, W. Y. Lee, M. C. Vuran and S. Mohanty, "NeXt generation/dynamic spectrum access/cognitive radio wireless networks: a survey," *Computer Networks,* vol. 50, pp. 2127-2159, 2006.

[6] T. Yucek and H. Arslan, "A survey of spectrum sensing algorithms for cognitive radio applications," *Communications Surveys & Tutorials, IEEE,* vol. 11, pp. 116-130, 2009.

[7] M. Jun, G. Y. Li and J. Biing Hwang, "Signal Processing in Cognitive Radio," *Proceedings of the IEEE,* vol. 97, pp. 805-823, 2009.

[8] Y. Zeng, Y. C. Liang, A. T. Hoang and R. Zhang, "A review on spectrum sensing for cognitive radio: challenges and solutions," *EURASIP Journal on Advances in Signal Processing,* vol. 2010, p. 2.

[9] D. B. Percival and A. T. Walden, *Spectral analysis for physical applications: multitaper and conventional univariate techniques*: Cambridge Univ Pr, 1993.

[10] D. J. Thomson, "Spectrum estimation and harmonic analysis," *Proceedings of the IEEE,* vol. 70, pp. 1055-1096, 1982.

[11] D. Slepian, "Prolate spheroidal wave functions, Fourier analysis, and uncertainty. V- The discrete case," *Bell System Technical Journal,* vol. 57, pp. 1371–1430, 1978.

[12] P. Stoica and T. Sundin, "On nonparametric spectral estimation," *Circuits, Systems, and Signal Processing,* vol. 18, pp. 169-181, 1999.

[13] D. J. Thomson, "Jackknifing multitaper spectrum estimates," *IEEE Signal Processing Magazine,* vol. 24, pp. 20-30, 2007.

[14] S. Haykin, D. J. Thomson and J. H. Reed, "Spectrum Sensing for Cognitive Radio," *Proceedings of the IEEE,* vol. 97, pp. 849-877, 2009.

[15] O. A. Alghamdi, M. A. Abu-Rgheff and M. Z. Ahmed, "MTM Parameters Optimization for 64-FFT Cognitive Radio Spectrum Sensing using Monte Carlo Simulation," in *EMERGING 2010 : The Second International Conference on Emerging Network Intelligence*, Florence-Italy, 2010, pp. 107-113.

[16] O. A. Alghamdi, M. Z. Ahmed and M. A. Abu-Rgheff, "Probabilities of Detection and False Alarm in Multitaper Based Spectrum Sensing for Cognitive Radio Systems in AWGN," presented at the The IEEE International Conference on Communication Systems (IEEE ICCS 2010), Singapore, 2010.

[17] A. Goldsmith, *Wireless communications*: Cambridge Univ Pr, 2005.

[18] A. Pandharipande and J. P. M. G. Linnartz, "Performance Analysis of Primary User Detection in a Multiple Antenna Cognitive Radio," in *Communications, 2007. ICC '07. IEEE International Conference on*, 2007, pp. 6482-6486.

[19] L. Jong-Hwan, B. Jun-Ho and H. Seung-Hoon, "Collaborative Spectrum Sensing using Energy Detector in Multiple Antenna System," in *Advanced Communication Technology, 2008. ICACT 2008. 10th International Conference on*, 2008, pp. 427-430.

[20] V. Kuppusamy and R. Mahapatra, "Primary user detection in OFDM based MIMO Cognitive Radio," in *Cognitive Radio Oriented Wireless Networks and Communications, 2008. CrownCom 2008. 3rd International Conference on*, 2008, pp. 1-5.

[21] M. Wei, W. Mu Qing, L. Dong and W. Meng Ling, "User sensing based on MIMO cognitive radio sensor networks," in *Computer Science and Information Technology, 2009. ICCSIT 2009. 2nd IEEE International Conference on*, 2009, pp. 205-208.

[22] A. Taherpour, M. Nasiri-Kenari and S. Gazor, "Multiple antenna spectrum sensing in cognitive radios," *Wireless Communications, IEEE Transactions on,* vol. 9, pp. 814-823, 2010.

[23] Z. Rui, L. Teng, L. Ying-Chang and Z. Yonghong, "Multi-antenna based spectrum sensing for cognitive radios: A GLRT approach," *Communications, IEEE Transactions on,* vol. 58, pp. 84-88, 2010.

[24] W. Pu, F. Jun, H. Ning and L. Hongbin, "Multiantenna-Assisted Spectrum Sensing for Cognitive Radio," *Vehicular Technology, IEEE Transactions on,* vol. 59, pp. 1791-1800, 2010.

[25] O. A. Alghamdi and M. A. Abu-Rgheff, "Local MTM-SVD based spectrum sensing in SIMO OFDM cognitive radio under bandwidth constraint," in *Cognitive Radio Oriented Wireless Networks & Communications (CROWNCOM), 2010 Proceedings of the Fifth International Conference on*, 2010, pp. 1-6.

[26] Q. Zhi, C. Shuguang and A. H. Sayed, "Optimal Linear Cooperation for Spectrum Sensing in Cognitive Radio Networks,"

Selected Topics in Signal Processing, IEEE Journal of, vol. 2, pp. 28-40, 2008.

[27] F. Sheikh, S. Masud and B. Bing, "Harmonic power detection in wideband cognitive radios," *Signal Processing, IET,* vol. 3, pp. 40-50, 2009.

[28] Q. Zhi, C. Shuguang, A. H. Sayed and H. V. Poor, "Optimal Multiband Joint Detection for Spectrum Sensing in Cognitive Radio Networks," *Signal Processing, IEEE Transactions on,* vol. 57, pp. 1128-1140, 2009.

[29] T. Lang and S. Perreau, "Multichannel blind identification: from subspace to maximum likelihood methods," *Proceedings of the IEEE,* vol. 86, pp. 1951-1968, 1998.

[30] B. Shen, S. Ullah and K. Kwak, "Deflection coefficient maximization criterion based optimal cooperative spectrum sensing," *AEU - International Journal of Electronics and Communications,* vol. 64, pp. 819-827, 2009.

[31] E. Visotsky, S. Kuffner and R. Peterson, "On collaborative detection of TV transmissions in support of dynamic spectrum sharing," in *New Frontiers in Dynamic Spectrum Access Networks, 2005. DySPAN 2005. 2005 First IEEE International Symposium on*, 2005, pp. 338-345.

[32] A. Ghasemi and E. S. Sousa, "Collaborative spectrum sensing for opportunistic access in fading environments," in *New Frontiers in Dynamic Spectrum Access Networks, 2005. DySPAN 2005. 2005 First IEEE International Symposium on*, 2005, pp. 131-136.

[33] Y. Zheng, X. Xie and L. Yang, "Cooperative Spectrum Sensing Based on SNR Comparison in Fusion Center for Cognitive Radio," 2009, pp. 212-216.

[34] Z. Wei, R. K. Mallik and K. Ben Letaief, "Cooperative Spectrum Sensing Optimization in Cognitive Radio Networks," in *Communications, 2008. ICC '08. IEEE International Conference on*, 2008, pp. 3411-3415.

[35] L. Wang, "Novel scheme for cooperation spectrum sensing in cognitive radio networks," in *Computer and Automation Engineering (ICCAE), 2010 The 2nd International Conference on*, 2010, pp. 371-375.

[36] A. Jamshidi, "Performance analysis of low average reporting bits cognitive radio schemes in bandwidth constraint control channels," *Communications, IET,* vol. 3, pp. 1544-1556, 2009.

[37] S. Chunhua, Z. Wei and K. B. Letaief, "Cooperative Spectrum Sensing for Cognitive Radios under Bandwidth Constraints," in *Wireless Communications and Networking Conference, 2007.WCNC 2007. IEEE*, 2007, pp. 1-5.

[38] S. Chunhua, Z. Wei and K. Ben, "Cluster-Based Cooperative Spectrum Sensing in Cognitive Radio Systems," in *Communications, 2007. ICC '07. IEEE International Conference on*, 2007, pp. 2511-2515.

[39] S. Hussain and X. Fernando, "Spectrum sensing in cognitive radio networks: Up-to-date techniques and future challenges," in *Science and Technology for Humanity (TIC-STH), 2009 IEEE Toronto International Conference*, 2009, pp. 736-741.

[40] H. Zhu, F. Rongfei and J. Hai, "Replacement of spectrum sensing in cognitive radio," *Wireless Communications, IEEE Transactions on,* vol. 8, pp. 2819-2826, 2009.

Owayed A. Alghamdi received the B.Sc. and M.Sc. degrees in Electrical Engineering with communications major from King Saud University, Riyadh, Saudi Arabia, in 2000 and 2007. Since 2001, he has worked with the Ministry of Interior (MOI) of Saudi Arabia as a telecommunication engineer, where he has gained theoretical and practical experience in different kinds of telecommunications.

Currently, he is a Ph.D. candidate in the Department of Electrical and Computer Engineering at University of Plymouth, Plymouth, UK. His research interests include statistical signal processing, detection and estimation theories, wireless communications and networking, cognitive radio, and cooperative communications.

Mohammed Zaki Ahmed graduated with a Master of Engineering (Information Engineering) and a Bachelor of Engineering (Communication Engineering) from the University of Plymouth, getting both degrees in 1999. He completed his PhD at the University of Plymouth(2003) and has been employed as a lecturer there since 2001.

He is currently an Associate Professor in the School of Computing and Mathematics. His current research includes error correction and signal processing as applied to communication, storage and wireless networks.