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# Cooperative Subcarrier Sensing Using Antenna Diversity Based Weighted Virtual Sub Clustering

Bushra Mughal · Sajjad Hussain · Abdul Ghafoor

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Abstract The idea of cooperation and the clustering amongst cognitive radios (CRs) has recently been focus of attention of research community, owing to its potential to improve performance of spectrum sensing (SS) schemes. This focus has led to the paradigm of cluster based cooperative spectrum sensing (CBCSS). In perspective of high date rate 4th generation wireless systems, which are characterized by orthogonal frequency division multiplexing (OFDM) and spatial diversity, there is a need to devise effective SS strategies. A novel CBCSS scheme is proposed for OFDM subcarrier detection in order to enable the non-contiguous OFDM (NC-OFDM) at the physical layer of CRs for efficient utilization of spectrum holes. Proposed scheme is based on the energy detection in MIMO CR network, using equal gain combiner as diversity combining technique, hard combining (AND, OR and Majority) rule as data fusion technique and antenna diversity based weighted clustering as virtual sub clustering algorithm. Results of proposed CBCSS are compared with conventional CBCSS scheme for AND, OR and Majority data fusion rules. Moreover the effects of antenna diversity, cooperation and cooperating clusters are also discussed.

**Keywords** Cooperative spectrum sensing  $\cdot$  MIMO based clustering  $\cdot$  OFDM subcarrier detection  $\cdot$  Energy detection.

### 1 Introduction

There has been an unprecedented rise in wireless data traffic in the last few years, which is mainly attributed to the widespread use of smart devices. This increased wireless activity has resulted in a plethora of wireless communication standards. These wireless standards have not only contributed in increased data rates and reliable communication links but has also led to an overcrowded spectrum, thus causing the spectrum scarcity. It has further accelerated research on concepts of software defined radio [1] and cognitive radio (CR) [2], which has laid the foundation of intelligent spectrum access for unlicensed users. For practical implementation of this concept, IEEE 802.22 wireless regional area network (WRAN) group established 802.22 WRAN CR standard [3] for communication over the unused spectrum.

B. Mughal · A. Ghafoor

College of Signals, National University of Sciences and Technology (NUST), Islamabad, Pakistan

E-mail: bushramughal\_020@yahoo.com, abdulghafoor-mcs@nust.edu.pk

S. Hussain

School of Engineering, University of Glasgow, UK

E-mail: sajjad.hussain@glasgow.ac.uk

A significant and most vital feature of CR is the spectrum sensing (SS). CR, while acting as a secondary user or unlicensed user, uses parts of spectrum which are not occupied by licensed primary users (PUs). CRs should make sure that SS results are highly reliable to avoid intolerable interference to PUs. Occupied frequency bands are called black spaces and unutilized frequency bands are termed as white spaces or spectrum holes. CRs search for white spaces in the spectrum and use them to their own advantage till PUs reclaim these spaces. The performance metrics of SS techniques are probability of detection  $(P_d)$ , probability of false alarm  $(P_f)$ , and probability of missed detection  $(P_m)$ . The SS techniques present in literature include energy detection [4–6], cyclostationary detection [7], matched filter detection [8], covariance based detection [9], autocorrelation based sensing [10], and joint time frequency based detection [11].

Individual sensing has the drawback of low  $P_d$  due to multi-path fading, shadowing and receiver uncertainty. To cope with this problem, CRs cooperate with each other for sensing white spaces called cooperative SS (CSS). The cooperation among CRs provides increase in agility, reduces false alarms and ensures more accurate signal detection than individual SS. CSS is classified into three categories [12] based on the method of sharing sensed data: centralized [13–16], distributed [17], and relay-assisted [18–20]. Distributed and relay-assisted CSS schemes have the disadvantage of increased complexity but enjoy better performance as compared to centralized CSS schemes.

As an important element of CSS, we have also focused on data fusion schemes [12]. Data fusion is the method of uniting the reported SS results (received from individual CRs) for achieving the cooperative decision. In literature there are two main types of data fusion schemes, soft and hard combining. To obtain the cooperative decisions it is simpler to apply hard combining, also known as linear fusion rule, as compare to soft combining. The widely used types of hard combining fusion rules are AND, OR and Majority rules. In proposed work all these types are explored for the proposed algorithm.

Wireless communication systems can be divided in to four forms with respect to antenna diversity: Single input single output (SISO), single input multiple output (SIMO), multiple input single output (MISO) and multiple input multiple output (MIMO). Use of multiple antennas at the receiver side to have receive diversity is used to receive signals from several independent channels to combat the effects of fading and hence improve the signal to noise ratio (SNR). There are several methods to combine the multipath signals called diversity combining techniques [21,22] such as selection combining (SC), equal gain combining (EGC) and maximal ratio combining (MRC). SC and MRC both require knowledge of SNR at the receiver where as EGC does not need the knowledge of SNR at the receiver and is one of the simplest linear combining technique. The output SNR of EGC is the sum of SNRs on all branches [4], which helps increasing  $P_d$  of the received signal. In proposed scheme it is assumed that PUs are working with single antennas where as the CRs present in environment are of both types single antenna and multiple antennas. CRs with multiple antennas use EGC as diversity combining technique in proposed scheme.

For large number of cooperating CR users, CSS may result into excessive overhead. To overcome this problem, CRs are grouped into clusters for more efficient cooperative sensing i.e. cluster based CSS (CBCSS). Grouping CRs into clusters improves performance and reduces computational cost, workload on individual nodes, cooperation delay, and induced overhead. CBCSS techniques [23] need specific clustering algorithms like random, reference based, statistical based and distance based [24], on the basis of which CRs are grouped together. Random clustering can easily be implemented while being unreliable. The remaining are location based clustering. In this paper, a novel two level clustering strategy is proposed. In level 1 it is assumed that main clustering has been done by upper layers and that any of energy efficient geographical based algorithms may be adopted to avoid performance degradation and propagation delays. In level 2 virtual sub clustering within main clusters (MCs) is performed on the basis of a new concept of antenna diversity based weighted clustering. In this concept CRs with same number of antennas are virtually grouped together to form a virtual sub cluster (VSC) and thus inside a MC we have several VSCs. Each VSC is comprised of the CRs with the same number of antennas e.g., VSC1 is made of CRs with 1

TX/RX antenna, VSC2 of 2 TX/RX antennas and so on. As discussed earlier, the CRs with more number of antennas give more reliable sensing results hence weights are assigned to the decision of each VSC according to the number of antennas they are equipped with. The term VSC is used for discriminating the radios with different number of antennas and for assigning the weights to the cluster results accordingly. It is important to note that idea of sub clustering is presented here because sub clustering allows us to weight certain decisions and thus to improve the overall performance.

CSS techniques for orthogonal frequency division multiplex (OFDM) signals already exist in literature [25,26]. The underlying idea of this work is to develop an efficient CBCSS technique for the OFDM signal environment like 3GPP LTE [27,28] and LTE-Advanced. In this paper subcarrier detection of OFDM signals is explored to exploit the advantages of using non-contiguous OFDM (NC-OFDM) [29] modulation technique in CR systems. After sensing free holes in the spectrum, CRs make sure to start communication over free holes while keeping the minimum interference to the occupied spectrum used by the PUs. This process can be easily done by the CRs by utilizing NC-OFDM as their modulation technique. In our scenario, CRs sense the free subcarriers of the PU's OFDM signal and using NC-OFDM the CRs assign zero to the occupied subcarriers and send data on free subcarriers. In this paper it is assumed that PUs are using OFDM for transmission and CRs are using NC-OFDM as their modulation technique.

The main focus of this paper is to analyze the effects of antenna diversity reception, cooperation of single antenna CRs, cooperation of multiple antenna CRs, hard combining data fusion techniques and weighted virtual sub clustering on the SS performance of a MC (within which virtual sub clustering is performed). Later on  $P_d$  and  $P_f$  of MC of proposed scheme is presented with and without assigning weights to the VSCs. The results of MC of proposed scheme are also compared with the MC of conventional CBCSS scheme [23]. The results are presented for all three hard data fusion schemes.

# 2 System Model

Consider an environment in which CRs with different number of antennas are randomly deployed. A cluster is formed of these CRs following any efficient geographical based clustering algorithm. In Figure 1(a) a scenario with down link transmission of PU OFDM signals is shown in which there are several MCs which are transmitting their SS information to main head (MH) through their respective main cluster heads (MCHs). In Figure 1(b) a typical MC is shown with single and multiple antennas CRs which are transmitting their SS decisions to MCH. Here CR[1x1] is 1 TX and 1 RX antenna CR, CR[2x2] is 2 TX and 2 RX antennas CR and CR[4x4] is 4 TX and 4 RX antennas CR. Thus inside a MC, we have, for instance, VSC1, VSC2 and VSC3 of 1, 2 and 4 TX/RX antenna CRs respectively. MCH takes SS decisions based on decisions sent from CRs present inside MC.

PU time domain discrete OFDM symbol [27,28], which is to be sensed by the CRs, is represented by following equation:

$$x[n] = \frac{1}{N} \sum_{k=1}^{N} \left[ d_k e^{\frac{j2\pi kn}{N}} \right], \tag{1}$$

where N is the the inverse discrete fourier transform (IDFT) size,  $d_k$  are the data symbols to be sent over N subcarriers, and n = 1, 2, ..., N.

The time domain discrete OFDM signal along with AWGN is received at CR RX. The CR RX converts the received serial stream of data to parallel stream and passes it through the Q point discrete fourier transform (DFT) block hence transforming time domain signal to frequency domain as follows:

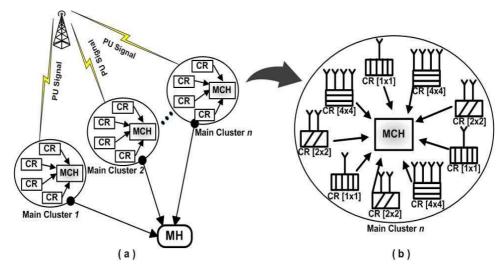


Fig. 1 (a) Overview of System Model. (b) Main Cluster (MC).

$$c[q] = \sum_{p=1}^{Q} \left[ x_p e^{\frac{-j2\pi pq}{Q}} \right], \tag{2}$$

where  $x_p$  is the received OFDM sampled signal, and q = 1, 2, ..., Q. After Q point DFT block we get L signal samples against each subcarrier. L signal samples over the n-th subcarrier are extracted from total Q samples of c[q] as follows:

$$s_n[l] = c[(nL - L) + l], \tag{3}$$

where l = 1,2,...,L, and L is the number of samples per subcarrier and L can be called as over sampling factor also, which equals to Q/N hence Q should be greater than or equal to N.

After passing from an AWGN channel, the received L samples of n-th subcarrier are given as:

$$r_n[l] = \begin{cases} G_n[l] & H_0 \\ s_n[l] + G_n[l] & H_1 \end{cases}$$
 (4)

where hypothesis  $H_0$  means that only AWGN is present at the n-th subcarrier i.e. subcarrier is vacant. Hypothesis  $H_1$  means that signal is present i.e. frequency band at the n-th subcarrier is occupied.  $G_n[l]$  represents L samples of AWGN against n-th subcarrier. The CR energy computation block forms the decision statistics  $E_n$  by computing energy using L signal samples corresponding to the n-th subcarrier as follows:

$$E_n = \sum_{l=1}^{L} \left[ | \, r_n[l] \, | \, \right]^2. \tag{5}$$

 $E_n$  is compared with threshold value ( $\lambda$ ) to detect the presence/absence of PU signal. Threshold is a common parameter for the  $P_f$ ,  $P_d$  and  $P_m$ . The common practice of setting threshold is based on  $P_f$  [30]. The decision making block at CR marks subcarrier as vacant when  $E_n$  is less than threshold and occupied when  $E_n$  is greater than threshold. This procedure is repeated for all subcarriers and subsequently CR determines number of free and used subcarriers.

### 3 Antenna Diversity and Cooperative Subcarrier Detection

In this section we discuss SS performance based on antenna diversity and then we discuss the effects of cooperative subcarrier detection on the SS performance.

### 3.1 Antenna Diversity

As discussed earlier there are two types of CRs present in the environment and hence in the MC: single antenna CRs and CRs with multiple antennas. In this section the effect of number of antennas on the expressions of  $P_d$  and  $P_f$  is discussed. Because of more number of antennas and use of EGC as diversity reception technique, the SNR of the received signal increases and hence the  $P_d$  also improves along with reduction in  $P_f$  as discussed below.

### 3.1.1 Single Antenna CRs

Now we discuss  $P_d$  and  $P_f$  for the single antenna CRs. Since AWGN obeys Gaussian distribution of zero mean and variance  $\sigma_n^2$ , therefore, on computing energy  $E_n$ , the distribution is changed. So under hypothesis  $H_0$ ,  $E_n$  obeys central chi-square distribution ( $\chi^2$ ) with 2L degrees of freedom (L real components plus L imaginary components) and under hypothesis  $H_1$ ,  $E_n$  obeys non-central chi-square distribution with 2L degrees of freedom and non centrality parameter  $\Upsilon$  [31] which is equal to SNR [6]. DFT and IDFT blocks do not affect the gaussian distribution [32].

 $P_f$  is defined as the probability that the received energy at n-th subcarrier  $(E_n)$  is greater than threshold when signal is not present. By using definition of upper incomplete gamma function  $\Gamma(u,v)$  [31],  $P_f$  is given as:

$$P_f = \frac{\Gamma(L, \lambda/2)}{\Gamma(L)} \tag{6}$$

 $P_d$  is defined as the probability that  $E_n$  is greater than threshold when signal is present. By using definition of generalized marcum Q function  $Q_a(u, v)$  [33],  $P_d$  is given as:

$$P_d = Q_L(\sqrt{\Upsilon}, \sqrt{\lambda}) \tag{7}$$

## 3.1.2 Multiple Antennas CRs

Now we discuss the SS performance for multiple antenna CRs. From (3), the received L samples of n-th subcarrier, from the m-th antenna, are given as:

$$r_n^m[l] = \begin{cases} G_n^m[l] & H_0 \\ s_n^m[l] + G_n^m[l] & H_1 \end{cases}$$
 (8)

where hypothesis  $H_0$  means n-th subcarrier is vacant. Hypothesis  $H_1$  means n-th subcarrier is occupied. Using EGC spatial diversity technique energy computation block computes energy for M antennas of the CR for the n-th subcarrier as follows

$$E_n = \sum_{m=1}^{M} \sum_{l=1}^{L} \left[ |r_n^m[l]| \right]^2 \tag{9}$$

where M are the number of antennas the CR is equipped with. Adding M independent non central  $\chi^2$  variates with 2L degrees of freedom and non-centrality parameter  $\Upsilon_m$ , results in another non-central  $\chi^2$  variate with 2ML degrees of freedom and non-centrality parameter  $\Upsilon_t$ . As EGC increases SNR of the signal by adding SNRs at all M branches [4] hence

$$\Upsilon_t = \sum_{m=1}^{M} \Upsilon_m \tag{10}$$

As the degree of freedom of both distributions is changed from L to ML,  $P_f$  and  $P_d$  for multiple antenna CRs are given as follows:

$$P_f = \frac{\Gamma(ML, \lambda/2)}{\Gamma(ML)} \tag{11}$$

$$P_d = Q_{ML}(\sqrt{\Upsilon_t}, \sqrt{\lambda}) \tag{12}$$

### 3.2 Cooperative Subcarrier Detection

In this sub section, the effect of cooperation of CRs on the expressions of  $P_d$  and  $P_f$  for all three AND, OR and majority data fusion rules [34] are discussed. The CRs present in z-th VSC  $(VSC_z)$  of each MC start the process of cooperation, after individual sensing, for achieving maximum cooperative probability of correct detection  $P_{d_{VSC_z}}$  and minimum cooperative probability of false alarm  $P_{f_{VSC_z}}$  of the VSC. In the process of cooperation the CRs share their sensing results with their respective MCH in the form of zeros and ones. The MCH then makes decision by applying specific data fusion rule on the received results against each VSC.

In OR data fusion rule if any one of the members of z-th VSC send decision as logical one against n-th subcarrier, then the MCH also makes the final decision as logical one against that subcarrier for z-th VSC. In this way the cooperative probability of false alarm using OR data fusion rule for z-th VSC is as below [12]:

$$P_{f_{VSC_z}}^{OR} = 1 - \prod_{b=1}^{B} (1 - P_{f_z,b})$$
(13)

where B is the number of CR members in the z-th VSC, z is the cluster number and  $P_{fz,b}$  is the probability of false alarm of the b-th CR member in the z-th VSC, which is given in (6) for the case of VSC with single antenna CRs and (11) for the case of VSC with multiple antennas CRs respectively. The cooperative probability of correct detection using OR data fusion rule for z-th VSC is

$$P_{d_{VSC_z}}^{OR} = 1 - \prod_{b=1}^{B} (1 - P_{dz,b})$$
(14)

where  $P_{dz,b}$  is the probability of detection of the b-th CR member in the z-th VSC, which is given in (7) for the case of VSC with single antenna CRs and (12) for the case of VSC with multiple antennas CRs respectively. In AND data fusion rule if even one of the members of z-th VSC send decision as logical zero, the final decision taken by MCH is also zero against that n-th subcarrier for z-th VSC. The cooperative probability of false alarm using AND data fusion rule for z-th VSC

$$P_{f_{VSC_z}}^{AND} = \prod_{b=1}^{B} (P_{fz,b})$$
 (15)

The cooperative probability of correct detection using AND data fusion rule for z-th VSC is

$$P_{d_{VSC_z}}^{AND} = \prod_{b=1}^{B} (P_{dz,b})$$
 (16)

In majority hard decision data fusion rule, if half or more than half of the members of z-th VSC send decision as one against n-th subcarrier, then the MCH also finalizes the decision as one against that subcarrier for z-th VSC and vice versa. The cooperative probability of false alarm using majority data fusion rule for z-th VSC is

$$P_{f_{VSC_z}}^{Maj} = \sum_{b=B/2}^{B} {B \choose b} P_{f_z,b}^b (1 - P_{f_z,b})^{B-b}$$
 (17)

The cooperative probability of correct detection using majority data fusion rule for z-th VSC is

$$P_{d_{VSC_z}}^{Maj} = \sum_{b=B/2}^{B} {B \choose b} P_{dz,b}^b (1 - P_{dz,b})^{B-b}$$
 (18)

### 4 Proposed Antenna Diversity Based Weighted Cooperative Subcarrier Detection

In conventional CBCSS [23] scheme all the CRs spread in the environment are equipped with single antenna. One level of clustering is performed which may be done on the basis of some location based algorithm. All the CRs within clusters first perform the individual SS and report their individual spectrum observations to the randomly chosen cluster head (CH). All the CHs then apply any of hard combining data fusion scheme on the received results and send their decisions to the randomly chosen MH. Finally the MH gives the verdict on the free and occupied spectrum by applying the same data fusion rule and inform the lower levels. All the CRs are equipped with single antenna so they have the same  $P_f$  and  $P_d$  given in equation (6) and (7) respectively. MH and all the CHs use same equations as (13 - 18) to fuse the received results and to give the verdicts. In proposed scheme we have single and multiple antenna CRs and two level of clustering: Main clustering and virtual sub clustering.

The proposed CBCSS scheme is conducted through the following steps:

- 1. Choosing main head (MH): First of all, a CR with the largest reporting channel gain is selected as MH of all CRs in a cluster to reduce the reporting errors [12].
- 2. Level 1 Clustering: Then two level clustering is performed in which level 1, main clustering, is assumed to be performed using any of energy efficient geographical location based algorithms. In level 1 MCs are formed.
- 3. Choosing MCH: The members of each MC would again choose their respective main clusters heads (MCHs) independently amongst themselves on the basis of largest reporting channel gain.
- 4. Level 2 Clustering: Under MCs, VSCs are created by MCHs based on the number of antennas i.e., CRs with same number of antennas are virtually grouped together to form a VSC within the MC. Here we assume that the number of antennas of each node (CR) are known to the MCH.
- 5. Individual SS: CRs present in each VSC perform individual subcarrier sensing using energy detection based SS technique.
- 6. Sending Results to MCH: All CRs present in a MC then send their binary decisions to the respective MCH in form of ones (if received signal energy > threshold then the subcarrier is occupied) and zeros (if received signal energy < threshold then the subcarrier is free).
- 7. Data fusion for each VSC: The MCHs fuse results of members of VSCs, making cooperative decision against each VSC by applying hard combining data fusion rule on the received decisions.
- 8. Assigning Weights: Now each MCH assigns weight to the decisions of VSCs according to the number of antennas of CRs in that VSC i.e., maximum weight is assigned to the decision of VSC with maximum number of antennas and vice versa. Hence assigning more weight to the decisions of CRs having greater SNR improves the SS performance i.e., increased  $P_d$  of the VSC  $(P_{d_{VSC}})$  and reduced  $P_f$  of the respective VSC  $(P_{f_{VSC}})$  is achieved.

9. Data fusion at MC: After getting decisions against each VSC and assigning the appropriate weights, the MCHs (using same or any other data fusion rule) fuse the weighted results of VSCs and obtain cooperative decision of their corresponding MC.

- 10. Sending results to MH: Then all the MCHs send their respective MC's decisions to the MH.
- 11. Data fusion at MH: MH then takes final decision by fusing the results of all MCHs (using same or any other data fusion rule) and passes it to the subordinate levels in reverse order.
- 12. CR TX/RX using NC-OFDM: Upon receipt of final decision all CRs know the detected free subcarriers and can use them for their transmission using NC-OFDM as their physical layer modulation scheme. NC-OFDM is the method in which zeros are assigned to the occupied subcarriers and data is transmitted over free subcarriers hence assuring minimized interference to the licensed PUs along with efficient bandwidth utilization.

The focus of this paper is from step 4 to step 9.

### 4.1 Without Weight Virtual Sub Clustering

In this section we discuss the effect of fusing the decisions of VSCs without applying any weights to the decisions. When the subcarrier sensing decisions of the VSCs are combined using the OR data fusion rule by the MCH then the  $P_f$  of the MC is given as

$$P_{f_{MC}}^{OR} = 1 - \prod_{z=1}^{Z} (1 - P_{f_{VSC_z}}^{OR})$$
(19)

where Z is the total number of VSCs present in a MC. The  $P_d$  of the MC using OR data fusion rule is

$$P_{d_{MC}}^{OR} = 1 - \prod_{z=1}^{Z} (1 - P_{d_{VSC_z}}^{OR})$$
 (20)

The  $P_f$  of the MC using AND hard decision data fusion rule is

$$P_{f_{MC}}^{AND} = \prod_{z=1}^{Z} (P_{f_{VSC_z}}^{AND})$$
 (21)

The  $P_d$  of the MC using AND data fusion rule is

$$P_{d_{MC}}^{AND} = \prod_{z=1}^{Z} (P_{d_{VSC_z}}^{AND})$$
 (22)

The  $P_f$  of the MC using majority data fusion rule is

$$P_{f_{MC}}^{Maj} = \sum_{z=Z/2}^{Z} {Z \choose z} (P_{f_{VSC_z}}^{Maj})^z (1 - P_{f_{VSC_z}}^{Maj})^{Z-z}$$
 (23)

The  $P_d$  of the MC using majority data fusion rule is

$$P_{d_{MC}}^{Maj} = \sum_{z=Z/2}^{Z} {Z \choose z} (P_{d_{VSC_z}}^{Maj})^z (1 - P_{d_{VSC_z}}^{Maj})^{Z-z}$$
 (24)

#### 4.2 Weighted Virtual Sub Clustering

In weighted combining of decisions of VSCs, the MCH assigns weight to the VSC decision according to the number of antennas of the CRs present in that VSC i.e., the VSC with CRs having maximum number of antennas is assigned with the highest weight hence giving more value to the decisions of that VSC because of having more number of antennas and hence because of providing more reliable results. When the subcarrier sensing decisions of the VSCs are assigned weights and combined using the OR data fusion rule then the  $P_f$  of the MC is given as

$$P_{f_{MC}}^{OR} = 1 - \prod_{z=1}^{Z} (1 - P_{f_{VSC_z}}^{OR})^{w_z}$$
 (25)

where  $w_z$  is the weight assigned to the z-th VSC. The  $P_d$  of the MC using OR data fusion rule is

$$P_{d_{MC}}^{OR} = 1 - \prod_{z=1}^{Z} (1 - P_{d_{VSC_z}}^{OR})^{w_z}$$
 (26)

The  $P_f$  of the MC using AND hard decision data fusion rule is

$$P_{f_{MC}}^{AND} = \prod_{z=1}^{Z} (P_{f_{VSC_z}}^{AND})^{w_z}$$
 (27)

The  $P_d$  of the MC using AND data fusion rule is

$$P_{d_{MC}}^{AND} = \prod_{z=1}^{Z} (P_{d_{VSC_z}}^{AND})^{w_z}$$
 (28)

The  $P_f$  of the MC using majority data fusion rule is

$$P_{f_{MC}}^{Maj} = \sum_{z=Z/2}^{Z} {Z \choose z} (P_{f_{VSCz}}^{Maj})^{zw_z} (1 - P_{f_{VSCz}}^{Maj})^{(Z-z)w_z}$$
(29)

The  $P_d$  of the MC using majority data fusion rule is

$$P_{d_{MC}}^{Maj} = \sum_{z=Z/2}^{Z} {Z \choose z} (P_{d_{VSC_z}}^{Maj})^{zw_z} (1 - P_{d_{VSC_z}}^{Maj})^{(Z-z)w_z}$$
(30)

The set of weights assigned to Z number of VSCs present in a MC is given as

$$\mathbf{w} = \{w_1, w_2, ..., w_Z\} \tag{31}$$

where  $w_i$  is the weight assigned to the VSCi. The set of sizes of Z VSCs is given below

$$\mathbf{B} = \{B_1, B_2, ..., B_Z\} \tag{32}$$

where  $B_i$  is the size (number of CR members) of VSCi. The assigned weights can be a function of  $P_{d_{MC}}$ ,  $P_{f_{MC}}$  and sizes of all VSCs i.e.

$$\mathbf{w} = f(P_{d_{MC}}, P_{f_{MC}}, \mathbf{B}) \tag{33}$$

The weight vector can be optimized as per the given network size and SS performance requirements.

# 4.3 Complexity Analysis of the Proposed Scheme

In this section we shall provide the complexity analysis of the proposed scheme and its comparison with the existing CBCSS schemes.

In this analysis, for the sake of consistency, we assume that all the CBCSS schemes (including ours) use the same method for spectrum sensing thus taking the sensing algorithm complexity comparison out of equation. We shall compare the complexity at the fusion center level while performing the fusion of the received results. The novelty of this paper rests at the same level where we improve the sensing decisions by proposing an improved decision fusing mechanism.

Considering the cases where we use AND/OR fusion rules, there are  $B \times Z$  multiplications required to find  $P_d$  or  $P_f$  where B is the number of CRs in a VSC and Z is the total number of VSCs. This number is equal to the total number of CRs present in a MC thus the computational complexity of without weight virtual sub-clustering is the same as that of a conventional CBCSS scheme. In fact, without weight virtual sub-clustering is the same as conventional CBCSS without any VSCs in the scenario where all CRs have single antenna.

As far as the complexity with weighted virtual sub clustering is concerned, it is little more that CBCSS. The only difference in number of multiplications which come due to the weight factor in Eq. 25-30. Fortunately, this difference is not much. We have to perform  $x^n$  operation in order to give weight to the decisions from different VSCs. The complexity of performing this operation using 'exponentiation by squaring' is  $\lfloor \log_2 n \rfloor$  squarings and at most  $\lfloor \log_2 n \rfloor$  multiplications, where  $\lfloor \rfloor$  denotes the floor functions. For instance, for  $w_i = 4$ , there are 2 squarings and 2 multiplications required. Thus there is a little more complexity of this algorithm but the performance improvement eclipses this complexity increment.

## 4.4 Effect of OFDM Mapping Scheme

In this sub section we shall discuss about the effects of mapping schemes (QPSK, QAM etc.) used by OFDM based primary transmitter on the performance of our algorithm.

In our paper, we have considered energy detection as the sensing algorithm by the CRs present in the MC. Each CR makes decision about the present or absence of primary user based on the energy level of the primary signal. Assuming that the primary transmission power is kept fixed or in other words, the average bit energy is kept constant, the change in mapping scheme would not affect the performance of energy detection algorithm and in turns the performance of our proposed algorithm. Since with constant average bit energy, energy level of primary signal mapped using any mapping scheme would be same for the sensing radios, the energy detector results would be same.

However, if the average bit energy is not kept constant, the detection results would improve with increased primary transmitted power and vice versa.

# 4.5 Feasibility for different OFDM based standards

Here, we shall discuss the feasibility of applying our proposed algorithm to different OFDM based standards like IEEE 802.11, IEEE 802.16, LTE etc.

The differences with regard to sensing performance in different standards include the channel bandwidth, carrier frequencies, subcarrier spacing, transmitted energy levels etc. As far as the parameters related to bandwidth/frequency are concerned, these are related to the sensing capabilities of the CRs which may include the analog and digital front end performance of the radio. Assuming that the CRs are able to process any spectral band of any width, our algorithm can be implemented for any OFDM based standard. Regarding different power levels of different standards, the algorithm can be implemented by variation of few parameters like energy detector threshold to get the optimal sensing results.

In short, the proposed algorithm is feasible for any OFDM based standard with little modifications.

### 5 Simulation Results

In this section first we show the effect of antenna diversity on the SS performance then the effect of cooperation for both single and multiple antennas CRs, antenna diversity based cooperation with and without weights, and then the effect of VSCs size is shown. Simulation parameters are PU modulation scheme = QPSK, N=64 and Q=2048. For simulation results it is assumed that 3 types of CRs are present in environment: single antenna (1x1), dual antenna (2x2) and quadruple antenna (4x4) CRs. Hence for simulations of proposed scheme we are having 3 VSCs in each MC. In our simulations VSC1 has 3 CRs with single antenna, VSC2 has 3 CRs with 2 antennas and VSC3 has 3 CRs with four antennas, unless mentioned otherwise. The proposed scheme is valid for any number of VSCs and any number of CRs inside each VSCs. It is important to note that for simulation results, at step 7 and step 9 of the proposed scheme we have used same data fusion rule. It is important to note that the proposed scheme works for any combination of fusion rules. Also, any SS algorithm can be used for individual SS, but we have used energy detection due to its simple implementation. Please note that VSC without weight is the theoretically the same as conventional CBCSS in the SISO context.

#### 5.1 Diversity Effect

In this section effect of number of antennas on  $P_d$  and  $P_f$  are shown. As the number of diversity paths increases the sensing results become more reliable because of increased SNR, and hence  $P_d$  also increases as shown in Figure 2. It can be noticed from Figure 3 that as the number of antennas of CR increases the  $P_f$  reduces as the CR with 4 antennas has the least  $P_f$  as shown in Figure 3. These results illustrate possible gains that can be achieved by increasing number of antennas of a CR.

#### 5.2 Cooperation Effect

# 5.2.1 Cooperation of Single Antenna CRs

In this section effect of cooperation with AND, OR and Majority data fusion techniques for single antenna CRs is shown i.e., results of VSC1 are shown. When cooperation is done using OR rule,  $P_{d_{VSC_1}}$  increases with increasing number of CRs as shown in Figure 4. But  $P_{f_{VSC_1}}$  also increases [35] with increasing number of CRs using OR rule because even if one CR gives the false decision, the MCH finalizes that false verdict which can cause a certain increase in  $P_{f_{VSC_1}}$  as shown in Figure 5.

When cooperation is performed using AND rule,  $P_{f_{VSC_1}}$  decreases with increasing number of cooperating CRs as shown in Figure 5. But  $P_{d_{VSC_1}}$  also decreases [35] with increasing number of CRs because the MCH gives the verdict as zero (unoccupied) even if one cooperating CR gives the decision zero hence reducing  $P_{d_{VSC_1}}$  as shown in Figure 4.

Majority rule provides better results at high SNRs with increasing number of CRs as shown in Figure 4 and Figure 5. Results of majority data fusion rule lies in between the AND and OR rule as it depends on the decision of the half or more than half of the CRs present in the VSC.

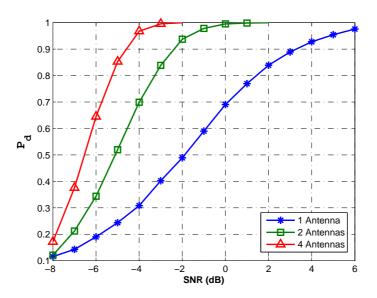


Fig. 2 Increasing  $P_d$  with increasing number of receive antennas of single CR.

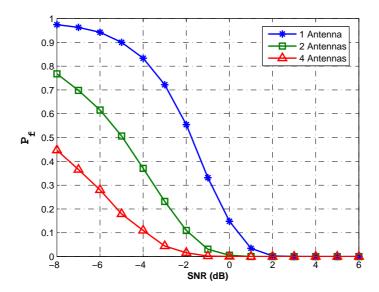


Fig. 3 Decreasing  $P_f$  with increasing number of receive antennas of single CR.

# 5.2.2 Cooperation of Multiple Antenna CRs

In this section results of VSC2 and VSC3 are provided and discussed. For CRs cooperation with multiple antenna, the results are shown in Figure 6 and Figure 7 with different data fusion schemes. It can be seen that when CRs with 4 antennas cooperate with each other (VSC3), they give better

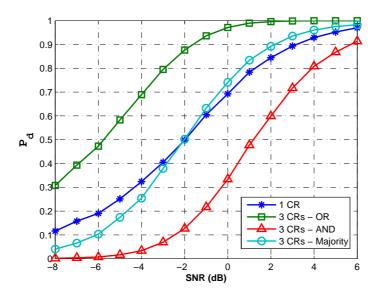


Fig. 4 Effect of cooperation of single antenna CRs on  $P_d$  with comparison of data fusion rules.

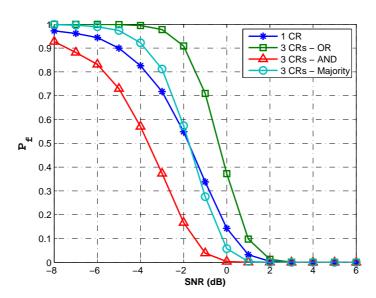


Fig. 5 Effect of cooperation of single antenna CRs on  $P_f$  with comparison of data fusion rules.

results than the 2 antenna (VSC2) and single antenna cooperating CRs (VSC1) i.e., effect of diversity is visible.

In addition, the effect of data fusion schemes is also visible in the figures.  $P_d$  with AND rule is the worst where as it is better for majority rule and the largest for OR data fusion rule. On the other hand  $P_f$  with AND rule is the best where as it is in middle for majority rule and the worst for OR data fusion rule.

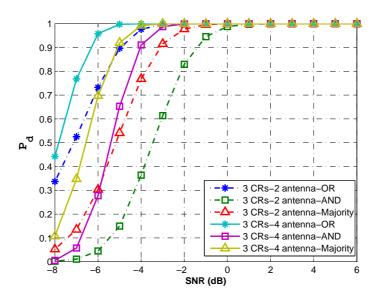


Fig. 6 Effect of cooperation of multiple antenna CRs on  $P_d$  with comparison of data fusion rules.

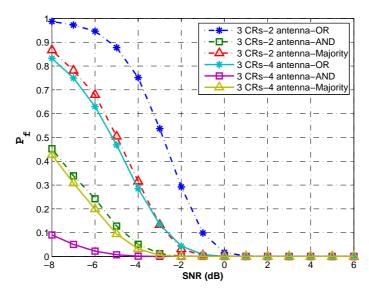


Fig. 7 Effect of cooperation of multiple antenna CRs on  $P_f$  with comparison of data fusion rules.

# 5.3 Antenna Diversity based Cooperation Effect

As discussed earlier MCH fuses results of VSC1, VSC2 and VSC3 using AND, OR and majority data fusion rules. In this section results of MC with and without weights are provided and discussed. Here the results of  $P_d$  and  $P_f$  of the MC of proposed scheme is compared with the  $P_d$  and  $P_f$  of MC of conventional CBCSS scheme.

#### 5.3.1 Without Weights

For conventional CBCSS scheme it is assumed that each MC has 9 single antenna CRs. Figure 8 and Figure 9 show the results of conventional MC as compared with proposed scheme MC in which we have 3 VSCs with 1, 2 and 4 number of antenna CRs. It can be seen from the figures that  $P_d$  and  $P_f$  of the MC of proposed scheme have better results than  $P_d$  and  $P_f$  of the MC of conventional scheme. Moreover the most favorable  $P_d$  is with OR data fusion rule and the least  $P_f$  is with AND data fusion rule for MC of the proposed scheme.

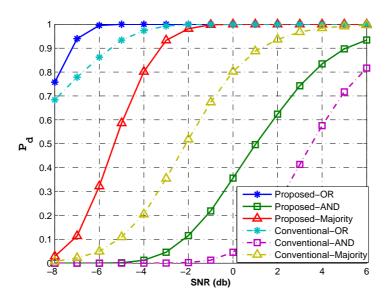


Fig. 8 Comparison of  $P_d$  of proposed scheme's MC with conventional scheme's MC with comparison of data fusion rules (without weight virtual sub clustering).

# 5.3.2 With Weights

As the most favorable rule for better  $P_d$  is OR data fusion rule followed by Majority rule, so the effect of weighted virtual sub clustering on  $P_d$  is analyzed for OR and Majority data fusion rules only as shown in Figure 10. It can be seen that still OR data fusion rule is giving the largest  $P_d$ . For the least  $P_f$  AND data fusion rule performs the best so for analyzing effects of weighted virtual sub clustering on  $P_f$ , results are shown for both AND and Majority data fusion rule. It can be seen from Figure 11 that AND data fusion rule is the best for minimized  $P_f$ . In this case w1 = 1 (weight assigned to VSC1), w2 = 2 (weight assigned to VSC2) and w3 = 3 (weight assigned to VSC3). It can be seen from Figure 10 and Figure 11 that  $P_d$  of MC with weights is better than  $P_d$  of MC without weights. Similarly  $P_f$  of MC is reduced with assigning weights than the results without weights.

In this paper we have assigned arbitrary weights however assigning optimal weights can further improve the performance of our algorithm. Since optimal weights shall be assigned to the decisions at the fusion center, the sensing performance shall further be improved.

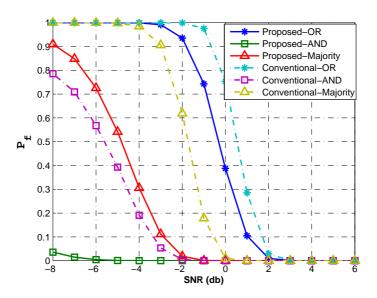
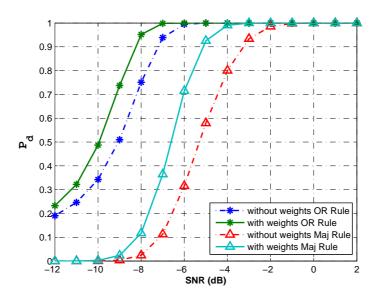


Fig. 9 Comparison of  $P_f$  of proposed scheme's MC with conventional scheme's MC with comparison of data fusion rules (without weight virtual sub clustering).



 $\textbf{Fig. 10} \ \ \text{Effect of weights on} \ P_d \ \text{of proposed scheme's MC using OR and Majority rule (w1=1, w2=2, w3=3)}.$ 

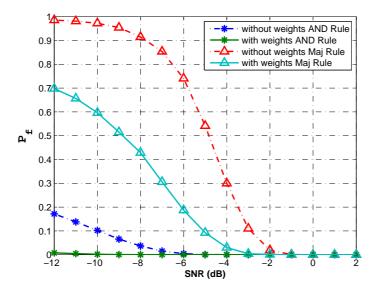


Fig. 11 Effect of weights on  $P_f$  of proposed scheme's MC using AND and Majority rule (w1=1, w2=2, w3=3).

## 5.4 Effect of Virtual Sub Clusters Size

Figure 12 and Figure 13 show effect of size of sub clusters on the results of MC. It can be seen from the figures that when the number of CRs in VSC2 and VSC3 increases, the  $P_d$  improves and the  $P_f$  reduces. In Figure 12 and Figure 13 three types of combinations of VSCs is used. The first combination of VSCs is with 3 CRs in VSC1 (single antenna), 1 CR in VSC2 (2 antennas) and 1 CR in VSC3 (4 antenna). The second combination consists of 1 CR in VSC1, 1 CR in VSC2 and 3 CRs in VSC3. It can be seen that second combination with 3 quadruple antenna CRs has better performance than the first combination which means that larger the number of multiple antennas, larger would be the received SNR which in turns results better SS performance. The third combination with 1 CR in VSC1, 3 CRs in both VSC2 and VSC3 outperforms the first two combinations as number of multiple antenna CRs are increased further hence increasing  $P_d$  and reducing  $P_f$  further. It should be noted that the weight optimization can further improve the SS performance.

### 6 Conclusion

This paper focuses three significant characteristics of CBCSS scheme which are subcarrier energy detection of OFDM signals, antenna diversity based weighted virtual sub-clustering, and hard combining data fusion rules. From above simulation results it can be concluded that proposed CBCSS scheme outperforms the conventional CBCSS scheme. By virtually grouping the CRs with same number of antennas and assigning weights to the SS decisions according to the number of antenna, can improve the SS performance of the conventional CBCSS scheme. For better  $P_d$  the OR data fusion scheme should be preferred as it gives better  $P_d$  as compared to other fusion schemes. For reduced  $P_f$  requirements, AND data fusion rule should be preferred.

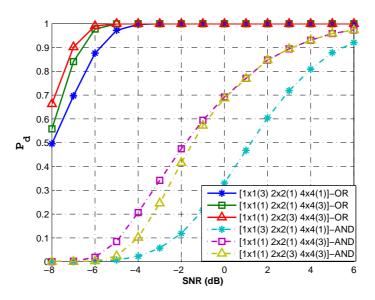


Fig. 12 Effect of VSCs' size on  $P_d$  of proposed scheme's MC (where [axb(c)] is c number of axb CRs).

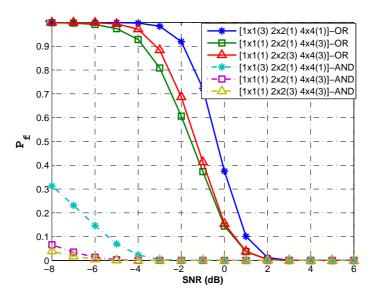


Fig. 13 Effect of VSCs' size on  $P_f$  of proposed scheme's MC (where [axb(c)] is c number of axb CRs).

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Bushra Mughal is Communication System Design Engineer at AIR University, Islamabad. She did MS in 2014 from MCS, NUST Islamabad in Electrical engineering with specialization in Telecommunication. She is focused to research in cooperative communication in Cognitive Radio Networks, OFDM and MIMO.



Sajjad Hussain is University Teacher at School of Engineering, University of Glasgow, UK. He did his PhD in 2009 from University of Rennes 1, Rennes in Electrical Engineering. He is focused to research in sensing algorithms for Cognitive Radios, cross layer optimization in Cognitive Radio networks along with demand response of Smart Grids.

**Abdul Ghafoor** is Associate Professor at Electrical Engineering Department, National University of Sciences and Technology (NUST), Islamabad. He did his PhD in Model Reduction research area from the University of Western Australia in 2007. His current research interests include Model Reduction, Controller Reduction, Image Enhancement, Image Fusion, Through-Wall Imaging and Cognitive Radios. He was awarded NUST Best Teacher Award - 2009 and NUST Best Researcher Award 2013.