DISTRIBUTED COOPERATIVE SPECTRUM SENSING WITH DOUBLE-TOPOLOGY

Francisco C. Ribeiro Jr.[⋆] *Marcello L. R. de Campos*[⋆] *Stefan Werner*[†]

[⋆] Program of Electrical Engineering, Federal University of Rio de Janeiro
[†] Department of Signal Processing and Acoustics, Aalto University, School of Electrical Engineering
E-mails: {francisco.junior, campos}@lps.ufrj.br, stefan.werner@aalto.fi

ABSTRACT

This paper addresses the problem of correlation due to redundancy in cooperative spectrum sensing networks and proposes an algorithm for topology design which improves significantly detection performance. In a recently proposed two-step distributed scheme, redundancy occurs when some nodes contribute more than once for the consensus decision, leading to correlation and consequently degrading performance in the same way as correlated shadowing. To eliminate this type of correlation, we employ two different topologies, primary and complementary, one for each cooperation step. Topology design is accomplished in a distributed manner by stating criteria for user selection. Results show that the proposed double-topology scheme suppresses redundancy and offers similar performance when compared to the case of independent node contributions.

Index Terms— Cognitive radio, spectrum sensing, distributed detection, user selection, redundancy

1. INTRODUCTION

Cognitive radio (CR) is the enabling technology for dynamic spectrum management. Improving spectrum efficiency through cognition is achieved by letting secondary users (SUs) to opportunistically access the transmission channel when primary users (PUs), who detain the ownership of the radio resources, are disconnected [1]. To reliably detect frequency holes for communication and avoid interference, each SU employs *spectrum sensing* and, based on the sensed data, decides if a PU is present or not in a given frequency band.

A vast literature on the spectrum sensing has demonstrated that *cooperative* networks notably improve the overall detection performance [2, 3]. In these networks, some SUs (or nodes) share information among themselves to render a joint and more reliable decision about the PU activity, due to exploitation of spatial diversity. Cooperation can be done in a *centralized* manner, in which a fusion center collects all the individual sensing data, fuses them and makes the decision. Alternatively, in a *distributed* strategy, the nodes can be divided in neighborhoods (e.g., defined by the transmission radius) and information sharing is performed directly, and only, among nodes within the same neighborhood.

Despite the type of network considered – centralized or distributed –, one key issue in cooperative spectrum sensing is *user selection*: how to properly choose which nodes will cooperate in the network [3]. Prior work in this field was triggered by different motivations. Since many cooperating users incur system overhead and energy consumption, the authors in [4] fix probabilities of false alarm and detection and find optimal numbers of nodes that still meet the targeted values. Results show that best performance is not necessarily achieved by cooperating all the nodes, but only those with the highest signal-to-noise ratio (SNR). In [5], different clustering methods for distributed networks are proposed to delimit cooperation footprints and meet the bandwidth and power requirements set in each cluster. Techniques to identify and remove malfunctioning or malicious nodes from cooperation are proposed in [6, 7]. The deleterious effect of *correlation due to shadowing* [2], which occurs when cooperating nodes experience similar shadowing effects, has also been addressed through user selection. Three methods in [8] consider different degrees of knowledge about user position to select only independent nodes separated by a "decorrelation distance", which is estimated from a correlation measure. In [9], a distributed selection algorithm monitors iteratively the spatial correlation among users without requiring any position information.

Recent work [10] proposes a strategy for distributed spectrum sensing in which information sharing is performed in two steps (soft and hard combining). This simple strategy performs better than centralized schemes and represents an alternative to most distributed solutions in the literature, which usually require several iterations among nodes for a joint decision. However, such two-step strategy may introduce another type of correlation, *correlation due to redundancy*, which occurs when some neighbors contribute more than once for decision. Redundancy appears directly and indirectly in these networks: *direct redundant* neighbors of a node include itself and those linked to it in both steps; *indirect redundant* neighbors are not directly connected to the node but contribute to two or more neighborhoods linked to it in both steps. These two classes of neighbors induce correlation in the consensus decision, degrading the sensing performance in the same way as when fusing correlated information due to shadowing. Moreover, different levels of correlation due to redundancy experienced by each node may lead to large performance variation across them.

In order to eliminate direct and indirect redundancies, we address the correlation due to redundancy as a user-selection problem in this paper. In addition to the two-step cooperation aforementioned, we propose to use two different topologies – *primary* and *complementary* –, one for each step: soft and hard. Proper design of such primary and complementary topologies is ensured by stating some criteria for node selection. Advantages of using this new strategy include more uniform detection performance among all users, increased number of nodes participating in the consensus decision and, most importantly, complete suppression of redundancy.

The performance of the proposed double-topology scheme is evaluated through simulations in a cognitive network with nodes under uncorrelated and correlated shadowing, and comparisons with the single-topology strategy in [10] are made. Results, presented in terms of complementary receiver operating characteristics (C-ROC), show a considerable improvement in detection performance when correlation due to redundancy is mitigated from the network.

This work was supported, in part, by the Academy of Finland, Center of Excellence Smart Radios and Wireless Research at the Aalto University, and by CNPq and FAPERJ, Brazil.

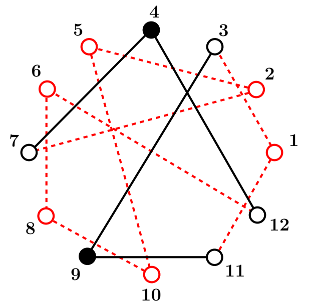

Fig. 1. Primary topology for the soft combining step. Primary neighborhoods $\mathcal{N}_{4,1}$ and $\mathcal{N}_{9,1}$ are highlighted.

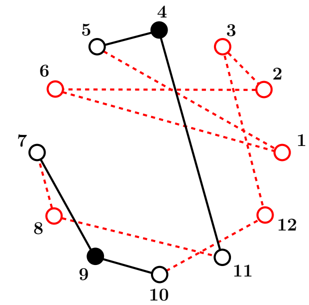

Fig. 2. Complementary topology for the hard combining step. Complementary neighborhoods $\mathcal{N}_{4,2}$ and $\mathcal{N}_{9,2}$ are highlighted.

2. CORRELATION DUE TO REDUNDANCY

The proposed strategy for distributed cooperation in [10] considers a cognitive network composed of M spatially distributed secondary users. During a sensing interval, each node, say Node k, employs energy detection [11] and senses the environment under hypothesis $\mathcal{H}_0$ (absence of primary signal) or hypothesis $\mathcal{H}_1$ (presence of primary signal). To achieve a local consensus decision, Node k shares its sensing data with a fixed neighborhood, $\mathcal{N}_k$, defined as the set of nodes, including itself, linked to it, within a transmission radius [12]. Information sharing with the neighbors in $\mathcal{N}_k$ holds during the entire detection process, which is divided in soft and hard combining steps.

In the *soft combining step*, direct soft information (e.g., energy estimates) from neighbors is fused. For this purpose, linear combination [13] is usually adopted in which the test statistic is obtained after a weighted average of individual sensing data. Considering neighborhood $\mathcal{N}_k$ with node degree $|\mathcal{N}_k|$, the local test statistic at Node k is produced by

$$T(\mathbf{y}_k) = \sum_{i\,\in\,\mathcal{N}_k} w_i y_i = \mathbf{w}_k^{\mathrm{T}}\mathbf{y}_k \mathop{\gtrless}_{u_k=0(\mathcal{H}_0)}^{u_k=1(\mathcal{H}_1)} \gamma_k, \tag{1}$$

where $\mathbf{w}_k = [w_1, w_2, \ldots, w_{|\mathcal{N}_k|}]^{\mathrm{T}}$ and $\mathbf{y}_k = [y_1, y_2, \ldots, y_{|\mathcal{N}_k|}]^{\mathrm{T}}$ contain the respective weights and energy estimates in $\mathcal{N}_k$. The test $T(\mathbf{y}_k)$ is then compared to a local threshold γ_k to yield a local binary decision, u_k. Existing techniques for obtaining the weight vector $\mathbf{w}_k$ and the threshold γ_k should be used in this step. The authors in [13, 14] find optimal parameters for linear combination by treating it as an optimization problem. In [10], we employ a simple adaptive combiner with *online* decision using the LMS algorithm [15], offering performance close to that of the optimal linear combiner. A variation of such LMS combiner, featuring selective updating and reduced processing, was published in [16].

In the *hard combining step*, local binary decisions from neighbors are fused in order to render local consensus decisions. Conventional voting rule (m-out-of-$|\mathcal{N}_k|$) [2] should be employed at each node: considering the particular case $m = 1$ (OR-fusion rule), used in [10], Node k decides that $\mathcal{H}_1$ holds if at least one of the $|\mathcal{N}_k|$ neighbors has suggested $\mathcal{H}_1$. Thus, the final detection performance at Node k after this second step can be measured by

$$P_{f,k,2} = 1 - P(\mathbf{u}_k = [0, 0, \ldots, 0]|\mathcal{H}_0), \tag{2a}$$
$$P_{d,k,2} = 1 - P(\mathbf{u}_k = [0, 0, \ldots, 0]|\mathcal{H}_1), \tag{2b}$$

where $\mathbf{u}_k \in \{0, 1\}^{|\mathcal{N}_k|}$ are the local binary decisions of $\mathcal{N}_k$, taken during the first step.

The inconvenience of a fixed network topology for the two-step cooperation process comes from the fact that local binary decisions of neighbors acquire correlation after soft combining. To better explain this effect, we first denote $\mathcal{N}_{S,k}$ as the set of *direct* and *indirect* neighbors that contribute to the consensus decision of Node k in the single-topology strategy. Let us consider the neighborhoods of Nodes 9 and 4, $\mathcal{N}_9 = \{3, 9, 11\}$ and $\mathcal{N}_4 = \{4, 7, 12\}$, highlighted in Fig. 1. The binary decision of Node 9, u_9, is correlated with the binary decision of Node 3, u_3, because both carry the sensing influence (energy estimate) of each other. The same occurs between binary decisions u_9 and u_{11}. Moreover, the binary decisions of Nodes 3 and 11, u_3 and u_{11}, also acquire correlation as they carry the same sensing influence of Node 9 and also that of Node 1, which is linked to both simultaneously. If $\mathcal{N}_9$ is kept the same for hard combining, the consensus decision taken by Node 9 after fusing u_3, u_9 and u_{11} will carry the sensing influence of the set of direct and indirect neighbors $\mathcal{N}_{S,9} = \{1, 3, 9, 11\}$, where Nodes 3, 9 and 11 are direct *redundant* neighbors, and Node 1 is an indirect *redundant* neighbor. Fusion of such correlated data in the second step will degrade the detection performance at Node 9 in the same way as if the source of correlation were shadowing. Similarly, one can observe the set of direct and indirect neighbors of Node 4 employing single-topology, $\mathcal{N}_{S,4} = \{2, 4, 6, 7, 12\}$, where indirect neighbors 2 and 6 are non-redundant, but direct neighbors 4, 7 and 12 are redundant and will induce correlation in the consensus decision of Node 4.

To properly evaluate the final probabilities $P_{f,k,2}$ and $P_{d,k,2}$ at Node k in (2) by taking into account the correlation, the Bahadur-Lazarsfeld expansion must be used [17]. A more general expression for $P(\mathbf{u}_k|\mathcal{H}_h)$ in (2),

$$P\left(\mathbf{u}_k|\mathcal{H}_h\right) = \prod_{i,j,l,\ldots\,\in\,\mathcal{N}_k} P\left(u_i|\mathcal{H}_h\right)\Bigg[1 + \sum_{i<j} \rho_{ij}^h z_i^h z_j^h + \sum_{i<j<l} \rho_{ijl}^h z_i^h z_j^h z_l^h + \ldots + \rho_{12\ldots|\mathcal{N}_k|}^h z_1^h z_2^h \ldots z_{|\mathcal{N}_k|}^h\Bigg], \tag{3}$$

is given as a function of the correlation coefficients, ρ^h, of the neighbors' binary decisions conditioned on hypothesis $\mathcal{H}_h$, $h \in \{0, 1\}$ [17]. In its turn, z_i^h correspond to the binary random variable u_i normalized conditioned on $\mathcal{H}_h$. More details about the Bahadur-Lazarsfeld expansion can be found in [17, 10].

We emphasize that both sources of correlation – shadowing and redundancy – account for the correlation coefficients in (3). This suggests that existing hard combining methods to deal with correlation due to shadowing, such as the optimal fusion rule in [17] or the suboptimal linear-quadratic detector in [18], would perform better than the voting rule also for the correlation due to redundancy. Nevertheless, in this work, we keep the simplicity of the voting rule and show that redundancy can be eliminated through user selection.

Table 1. Sequential algorithm for topology design ($T = 1, 2$).

```
initialize N_{k,T} ← {k}
for iteration n
  for Node k, not yet chosen at iterat. n
    (1) Node k calls any i ∈ C_{k,T}[n], not yet chosen at iterat. n
    (2) Node i checks: if k ∉ C_{i,T}[n], back to (1). Else,
    (3) Node k receives C_{i,T}[0]:
          N_{k,T} ← N_{k,T} ∪ {i}
          C_{k,T}[n+1] ← C_{k,T}[n] ∩ C_{i,T}[0]
        Node i receives C_{k,T}[0]:
          N_{i,T} ← N_{i,T} ∪ {k}
          C_{i,T}[n+1] ← C_{i,T}[n] ∩ C_{k,T}[0]
  end
end
```

3. DOUBLE-TOPOLOGY SCHEME

To address the problem of redundancy, we employ two different distributed topologies, called *primary* and *complementary*, one for each cooperation step. According to this strategy, Node k performs soft combining within a *primary neighborhood*, $\mathcal{N}_{k,1}$, and then switch to another *complementary neighborhood*, $\mathcal{N}_{k,2}$, for hard combining. The complementary topology is directly related to the primary topology, and both can be generated by the network in a distributed manner, according to the guidelines presented in the following.

3.1. Primary Topology

For the primary topology design, each node first selects its possible primary neighbors. Up to this point, any criterion for user selection can be adopted. For example, in the context of correlated shadowing, each node may recur to those algorithms for estimation of spatial correlation in [8, 9]. In this paper, we consider, for simplicity, that spatially adjacent nodes are more likely to suffer from correlated shadowing and thereby should be avoided in the same primary neighborhood. Using this criterion, and assuming that node indexing corresponds to node position, we define the initial *primary candidate set* of Node k (set of candidates to take part in $\mathcal{N}_{k,1}$) as

$$\mathcal{C}_{k,1}[0] = \{i : 1 < |i-k| < M-1\}\,. \tag{4}$$

Following, the cognitive network runs the sequential algorithm presented in Table 1 to generate the primary topology in a distributed manner: at each iteration n, Node k calls any of the candidates i in $\mathcal{C}_{k,1}[n]$; upon Node i checking that Node k is also a candidate in $\mathcal{C}_{i,1}[n]$, both include each other in their primary neighborhoods. Node k then updates its primary candidate set $\mathcal{C}_{k,1}[n+1]$ with the received $\mathcal{C}_{i,1}[0]$. The same is done by Node i with its primary candidate set $\mathcal{C}_{i,1}[n+1]$ and the received $\mathcal{C}_{k,1}[0]$. The iterative process continues until either any candidate set becomes empty or the desired node degree (equal for all neighborhoods) is reached. The primary topology of Fig. 1 was generated using such algorithm, with desired uniform node degree set to $|\mathcal{N}_{k,1}| = 3$. Note that every primary neighborhood satisfies the criterion stated in (4).

3.2. Complementary Topology

For the complementary topology design, we consider possible complementary neighbors of Node k the nodes whose primary neighbors do not coincide with any primary neighbor of Node k. The initial *complementary candidate set* of Node k is, therefore, given by

$$\mathcal{C}_{k,2}[0] = \{i : \mathcal{N}_{i,1} \cap \mathcal{N}_{k,1} = \varnothing\}\,. \tag{5}$$

The distributed sequential algorithm in Table 1 is used to form the complementary topology. Fig. 2 shows a possible complementary topology associated to the primary topology of Fig. 1, with desired uniform node degree also set to $|\mathcal{N}_{k,2}| = 3$. Note, with the help of Fig. 1, that every complementary neighborhood satisfies the criterion stated in (5).

3.3. Suppression of Redundancy

To illustrate the benefits of the proposed double-topology scheme, let $\mathcal{N}_{D,k}$ be the set of direct and indirect neighbors that contribute to the consensus decision of Node k using a double-topology. Further, consider the complementary neighborhoods of Nodes 9 and 4, $\mathcal{N}_{9,2} = \{7, 9, 10\}$ and $\mathcal{N}_{4,2} = \{4, 5, 11\}$, highlighted in Fig. 2. In the second step, Node 9 fuses the binary decisions u_7, u_9 and u_{10}, which in turn carry the sensing influence of nodes from their respective primary neighborhoods: u_7 from $\mathcal{N}_{7,1} = \{2, 4, 7\}$, u_9 from $\mathcal{N}_{9,1} = \{3, 9, 11\}$ and u_{10} from $\mathcal{N}_{10,1} = \{5, 8, 10\}$ (see Fig. 1). The consensus decision produced by Node 9 thus carries the sensing influence of a set of direct and indirect *non-redundant* neighbors, $\mathcal{N}_{D,9} = \{2, 3, 4, 5, 7, 8, 9, 10, 11\}$. Similarly, one can observe that Node 4 also receives the sensing influence of a set of direct and indirect *non-redundant* neighbors, $\mathcal{N}_{D,4} = \{1, 2, 4, 5, 7, 9, 10, 11, 12\}$. The proposed double-topology scheme, using the criterion in (5), suppresses redundancy from the network, at least up to a single hop.

If the nodes are also free of correlated shadowing, all correlation coefficients in (3) become zero. This reduces the final probabilities at Node k after hard combining within $\mathcal{N}_{k,2}$ in (2) to the expressions for OR-fusion with independent neighbors' local decisions [4],

$$P_{f,k,2} = 1 - \prod_{i\,\in\,\mathcal{N}_{k,2}} (1 - P_{f,i,1}), \tag{6a}$$

$$P_{d,k,2} = 1 - \prod_{i\,\in\,\mathcal{N}_{k,2}} (1 - P_{d,i,1}), \tag{6b}$$

by noting that $P\left(u_i = 0|\mathcal{H}_0\right) = (1 - P_{f,i,1})$ and $P\left(u_i = 0|\mathcal{H}_1\right) = (1 - P_{d,i,1})$; and $P_{f,i,1}$ and $P_{d,i,1}$ are the probabilities at each Node $i \in \mathcal{N}_{k,2}$ after soft combining within $\mathcal{N}_{i,1}$, both defined in [10].

Another advantage of this proposed strategy is that more users contribute for decision. For the consensus decision of Node 9, for example, the number of participating nodes increases from $|\mathcal{N}_{S,9}| = 4$ (with single-topology) to $|\mathcal{N}_{D,9}| = 9$ (with double-topology); for Node 4, this number increases from $|\mathcal{N}_{S,4}| = 5$ to $|\mathcal{N}_{D,4}| = 9$. Note that such improvement is obtained without increasing the number of connections per node, which could lead to more system overhead.

4. RESULTS AND DISCUSSION

In this section, we evaluate the performance of the proposed double-topology strategy for distributed spectrum sensing in cognitive networks. For the simulations, each Node k produces 10^6 energy estimates under equal occurrence of $\mathcal{H}_0$ and $\mathcal{H}_1$, according to the Gaussian statistical model for y_k proposed in [13]. In order to see the effects of correlation, all nodes experience the same SNR in their estimates, 0 dB. We consider the two different scenarios wherein nodes suffer from uncorrelated and correlated shadowing. To simulate the correlated case, we use $E[(y_i - \mu_{i,h})(y_j - \mu_{j,h})] = 0.5$, where i and j are index of spatially adjacent nodes, and $\mu_{i,h}$ and $\mu_{j,h}$ are, respectively, the means of the random variables y_i and y_j under hypothesis $\mathcal{H}_h$, both defined in [13]. Results are measured with single detection, distributed two-step single-topology cooperation proposed in [10], and the two-step double-topology scheme proposed

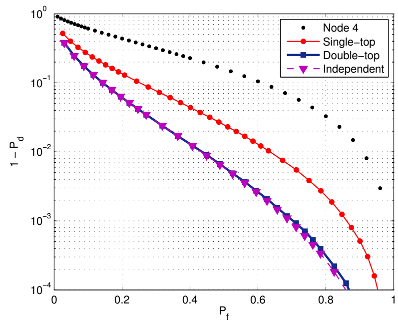

Fig. 3. C-ROC performance at Node 4 employing single detection and distributed two-step cooperation with single and double-topology: uncorrelated shadowing.

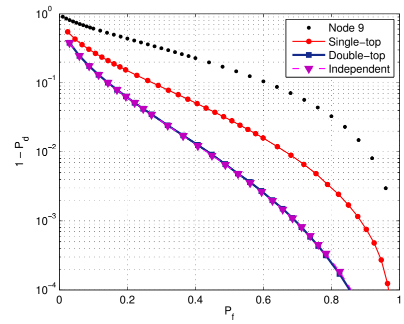

Fig. 5. C-ROC performance at Node 9 employing single detection and distributed two-step cooperation with single and double-topology: uncorrelated shadowing.

in the previous section. For the single-topology simulation, the primary topology of Fig. 1 is fixed for both soft and hard combining steps; for the double-topology simulation, the network switches to the complementary topology of Fig. 2 in the hard combining step.

Figs. 3 and 5 show, respectively, the resulting C-ROC curves of Nodes 4 and 9 for the case of uncorrelated shadowing. With single-topology, we see that the performance degradation is slightly higher in Node 9 as it suffers from correlation due to both direct and indirect redundancies. On the other hand, the curves obtained with double-topology match the optimal curves for independent neighbors' contributions, confirming the redundancy mitigation capability of the proposed scheme. Final detection performance observed with double-topology is the same for all nodes, as expected with equal SNR. Nevertheless, we emphasize that using double-topology suppresses redundancy and promotes increased node participation in the consensus decisions. Moreover, if the number of connections per node is uniform, the amount of participating nodes is equal for every consensus decision (in this case, 9 out of 12 nodes). Such features help to make detection performance more uniform over the network even in scenarios of different SNR, in contrast to the disparate results of Nodes 4 and 9 in [10], by a single-topology without proper topology design.

Finally, Figs. 4 and 6 plot the respective C-ROC curves of Nodes 4 and 9 corresponding to the correlated shadowing simulation. Note that the proposed double-topology scheme still outperforms the single-topology approach. However, both strategies are now suffering from correlation. In the example of Node 9, single-topology suffers only from correlation due to redundancy (note that $\mathcal{N}_{S,9}$ contain only non-adjacent nodes), whereas double-topology suffers only from correlation due to shadowing ($\mathcal{N}_{D,9}$ contain some adjacent nodes). This is because the criterion for complementary user selection stated in (5) only deals with redundancy, not with shadowing. Despite this fact, one can introduce more criteria in (5) to avoid selection of complementary adjacent neighbors, thus eliminating both effects (redundancy and shadowing) and matching again the performance of the optimal independent C-ROC curves.

5. CONCLUSION

This paper proposed the use of a two-step double-topology cooperation scheme for distributed spectrum sensing networks. With this new strategy, each node performs soft combining within a primary neighborhood and hard combining within a complementary neighborhood. The main purpose is to avoid the degrading effect of correlation when direct and indirect redundant neighbors contribute to the consensus decision. We proposed criteria for determining primary and complementary neighbor candidates and a simple sequential algorithm for topology design in order to generate both configurations in a distributed manner. Results showed that the proposed double-topology scheme mitigates correlation due to redundancy from the network, thus offering superior performance when compared to single-topology approaches and leading, in the absence of correlated shadowing, to results equivalent to that for independent neighbors' contributions.

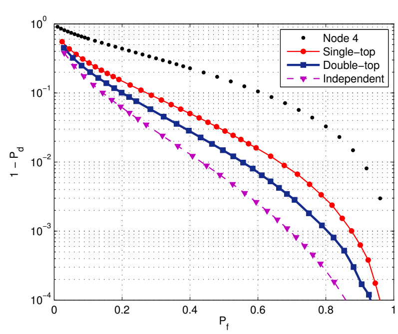

Fig. 4. C-ROC performance at Node 4 employing single detection and distributed two-step cooperation with single and double-topology: correlated shadowing.

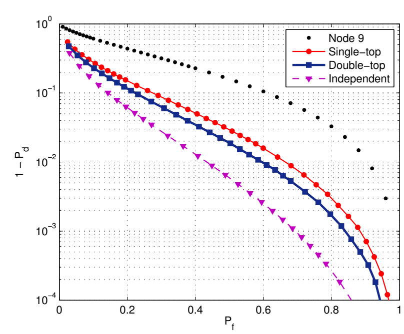

Fig. 6. C-ROC performance at Node 9 employing single detection and distributed two-step cooperation with single and double-topology: correlated shadowing.

6. REFERENCES

[1] S. Haykin, "Cognitive radio: Brain empowered wireless communications," *IEEE J. Sel. Areas Commun.*, vol. 23, pp. 201–219, Feb. 2005.

[2] A. Ghasemi and E. S. Sousa, "Opportunistic spectrum access in fading channels through collaborative sensing," *Journal of Communications*, vol. 2, pp. 71–82, Mar. 2007.

[3] I. F. Akyildiz, B. F. Lo, and R. Balakrishnan, "Cooperative spectrum sensing in cognitive radio networks: A survey," *Physical Communication*, vol. 4, pp. 40–62, Mar. 2011.

[4] E. Peh and Y.-C. Liang, "Optimization for cooperative sensing in cognitive radio networks," in *IEEE Wireless Communications and Networking Conf.*, Mar. 2007.

[5] A. C. Malady and C. R. C. M. da Silva, "Clustering methods for distributed spectrum sensing in cognitive radio systems," in *IEEE Military Communications Conf.*, Nov. 2008.

[6] R. Chen, J.-M. Park, and K. Bian, "Robust distributed spectrum sensing in cognitive radio networks," in *IEEE Conf. Computer Communications*, Apr. 2008.

[7] P. Kaligineedi, M. Khabbazian, and V. K. Bhargava, "Malicious user detection in a cognitive radio cooperative sensing system," *IEEE Trans. Wireless Commun.*, vol. 9, pp. 2488–2497, Aug. 2010.

[8] Y. Selen, H. Tullberg, and J. Kronander, "Sensor selection for cooperative spectrum sensing," in *IEEE Symp. New Frontiers in Dynamic Spectrum Access Networks*, Oct. 2008.

[9] A. S. Cacciapuoti, I. F. Akyildiz, and L. Paura, "Correlation-aware user selection for cooperative spectrum sensing in cognitive radio ad hoc networks," *IEEE J. Sel. Areas Commun.*, vol. 30, pp. 297–306, Feb. 2012.

[10] F. C. R. Junior, M. L. R. de Campos, and S. Werner, "Distributed cooperative spectrum sensing with adaptive combining," in *IEEE Int. Conf. Acoustics, Speech, and Signal Processing*, Mar. 2012.

[11] J. Ma and Y. Li, "Soft combination and detection for cooperative spectrum sensing in cognitive radio networks," in *IEEE Global Telecommunications Conf.*, Nov. 2007.

[12] F. S. Cattivelli and A. H. Sayed, "Distributed detection over adaptive networks using diffusion adaptation," *IEEE Trans. Signal Process.*, vol. 59, pp. 1917–1932, May 2011.

[13] Z. Quan, S. Cui, and A. Sayed, "Optimal linear cooperation for spectrum sensing in cognitive radio networks," *IEEE J. Sel. Topics Signal Process.*, vol. 2, pp. 28–40, Feb. 2008.

[14] Z. Quan, W.-K. Ma, S. Cui, and A. Sayed, "Optimal linear fusion for distributed spectrum sensing via semidefinite programming," in *IEEE Int. Conf. Acoustics, Speech, and Signal Processing*, May 2009.

[15] P. S. R. Diniz, *Adaptive Filtering: Algorithms and Practical Implementation*. Kluwer, 2008.

[16] F. C. R. Junior, M. L. R. de Campos, and S. Werner, "Distributed cooperative spectrum sensing with selective updating," in *European Signal Processing Conf.*, Aug. 2012.

[17] M. Kam, Q. Zhu, and W. S. Gray, "Optimal data fusion of correlated local decisions in multiple sensor detection systems," *IEEE Trans. Aerosp. Electron. Syst.*, vol. 28, pp. 916–920, Jul. 1992.

[18] J. Unnikrishnan and V. V. Veeravalli, "Cooperative sensing for primary detection in cognitive radio," *IEEE J. Sel. Topics Signal Process.*, vol. 2, pp. 18–27, Feb. 2008.