Paper

Mobility-Aware, Correlation-Based Node Grouping and Selection for Cooperative Spectrum Sensing

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Abstract—Cooperative spectrum sensing has been proposed as a solution to increase the sensing function accuracy in cognitive radio networks, but the research has, so far, mainly focused on static scenarios, all but neglecting the impact of mobility on spectrum sensing. In this work a novel cooperative spectrum sensing scheme for mobile cognitive networks, based on a correlation-based, mobility-aware node selection algorithm is proposed. Correlation among sensing decisions is used to divide nodes into groups, and mobility is taken into account in the group leaders selection by means of a node selection metric that considers both sensing performance and mobility. Performance of the proposed algorithm is evaluated by computer simulations taking into account mobility and a detailed modeling of temporal and spatial correlation of fading and shadowing components in the channel path loss, going way beyond the performance evaluation carried out in previous works on correlation-based cooperative sensing schemes. Simulation results highlight that the proposed metric leads to a significant increase of the update period required to maintain acceptable sensing performance, and correspondingly to a strong reduction in the overhead caused by the grouping and node selection procedure.

Keywords—cognitive radio, cooperative spectrum sensing, mobility, node grouping, node selection.

1. Introduction

Cognitive radio technology has been proposed as a potential solution to increase efficiency in spectrum utilization as it enables opportunistic temporarily unused frequency bands access once the presence of the so called primary user (PU) is excluded. Spectrum sensing was initially adopted as the solution for determining whether a band is available. However, due to longstanding open research issues in the implementation of reliable sensing solutions, FCC suggested to use databases for detection of PUs presence especially in the so-called spectrum white spaces, whose occupancy is relatively stable [1]. Research on spectrum sensing is still highly encouraged by FCC itself, as sensing can complement and extend the information provided by databases and guarantee reliable and efficient cognitive access in all situations. Under current FCC rules, in fact, databases will only store PUs' locations, thus not guaranteeing effective secondary-to-secondary coexistence. In this context spectrum sensing can provide additional awareness and, as a result, support the construction of dynamic, secondary-aware radio environment maps.

Spectrum sensing can however only be adopted if reliable information can be gathered. Several investigations pointed out that sensing carried out locally by single devices is not accurate enough for safe coexistence between primary and secondary users [2]. Thus, reliable spectrum sensing requires cooperation between nodes. In a widely adopted scenario, also considered in this work, every node in a cognitive network senses the spectrum, and sends information to the fusion centre where a global decision is taken. One can find many papers tackling the problem of optimal decision making in a fusion centre [3]–[6].

In cooperative spectrum sensing the fusion centre combines the decisions from N secondary sensing users (SUs). Assuming the k-out-of-N rule the global false alarm probability Q_f and the global probability of detection Q_d can be obtained as follows [7]:

$$Q_\mathrm{f} = \sum_{i=k}^{N} \binom{N}{i} P_\mathrm{f}^{i} (1-P_\mathrm{f})^{N-i}, \tag{1}$$

$$Q_\mathrm{d} = \sum_{i=k}^{N} \binom{N}{i} P_\mathrm{d}^{i} (1-P_\mathrm{d})^{N-i}, \tag{2}$$

where P_f and P_d are the false alarm and detection probability, respectively, averaged over the statistics of N nodes.

Equations (1) and (2) may simplify in the case of the AND-rule, which is in fact the N-out-of-N rule, and in the case of the OR-rule (known as 1-out-of-N rule). In the latter case the Eqs. (1) and (2) are simplified to:

$$Q_\mathrm{f} = 1 - \prod_{i=1}^{N} (1-P_\mathrm{f}), \tag{3}$$

$$Q_\mathrm{d} = 1 - \prod_{i=1}^{N} (1-P_\mathrm{d}). \tag{4}$$

Under the Constant False Alarm Rate (CFAR) requirement the desired Q_f is set for the whole secondary network. The corresponding value of $P_{\mathrm{f},i}$, assumed identical for every node, can be thus obtained as:

$$P_{\mathrm{f},i} = \; 1 - \sqrt[N]{1-Q_\mathrm{f}} \quad \text{for} \quad i = 1 \ldots N \;. \tag{5}$$

This implies an identical sensing threshold ε for every sensor given by [8]:

$$\varepsilon = [(\mathrm{Q}^{-1}(P_{\mathrm{f},i})/\sqrt{N_{\mathrm{s}}}) + 1]\sigma_{\mathrm{SU}}^2, \quad (6)$$

where N_s is the number of sensing samples per node taken to decision making, $\mathrm{Q}^{-1}(\cdot)$ is the inverse Q-function and σ_{SU}^2 is the noise power at SU.

Cooperative spectrum sensing requires explicit information exchanges between nodes. Minimizing the overhead introduced by such exchanges, so to guarantee energy efficiency and low complexity, is an important aspect to be considered in the design of a cooperative spectrum sensing algorithm. To this aim, selection of nodes subset to take care of sensing has been proposed, in order to limit the number of nodes reporting their sensing results to the fusion centre. This is typically achieved by grouping the nodes according to a given criterion, and selecting a node in each group as representative/leader for that group. The identification of criteria for node grouping and group leader selection is thus a fundamental step in the definition of such sensing algorithm. A detailed analysis of the literature related to node grouping for sensing purposes is presented in Section 2. A solution that received significant interest in the last few years relies on the measure of the correlation between sensing measurements taken by the nodes. Since this is the approach also considered in this work, previous work on this specific topic is discussed in Section 3.

An aspect that was seldom considered in the definition and performance evaluation of cooperative sensing schemes is mobility. There are in fact only a few papers tackling the role and impact of mobility in cooperative spectrum sensing. In [9], the authors present a theoretical analysis confirming that node mobility increases spatial diversity and as a consequence improves the sensing performance. The results presented in that work highlight the trade-off between the number of sensors and the number of measurements taken by each sensor. The authors in [10] base their work on [9] but introduce more accurate assumptions and provide more detailed results. Moreover, the expression for the number of measurement required for a given velocity, detection and false alarm probability is derived. The work in [11] compares results obtained on the basis of the aforementioned works and presents results obtained by simulation under more realistic conditions, showing that relaxation or removal of some of the assumptions taken in previous work has a significant influence on performance. However, the above-mentioned works focused on analyzing the impact of mobility on network performance rather than on proposing an approach towards the design of an optimal CSS scheme in presence of mobility.

In the above context, this work proposes a cooperative sensing scheme aiming at grouping nodes and selecting a leader for each group to be involved in the sensing process. The scheme relies on the measure of correlation in sensing decisions for node grouping, and adopts a mobility and sensing aware metric for the group leaders selection. The concept of node grouping based on correlation is leveraged from [12], and combined with a novel metric for group leader selection that takes into account mobility and sensing performance, so to guarantee adequate sensing performance for extended periods of times. The proposed approach is then compared with previous solutions by computer simulations, implementing accurate models for the mobile radio channel, taking into account spatial and temporal correlation for both fading and shadowing components.

The original contributions introduced in this work can be thus summarized as follows:

- a novel solution for cooperative spectrum sensing taking into account sensing performance and mobility;
- an extensive performance evaluation of correlation-based cooperative spectrum sensing under realistic conditions that foresee accurate modeling for spatial and temporal correlation of channel parameters and take into account the impact of such parameters on sensing performance of nodes;
- the analysis of the node mobility impact on correlation-based cooperative spectrum sensing.

The impact of channel correlation and mobility, in particular, are aspects all but neglected in previous works on correlation-based cooperative spectrum sensing [12].

The paper is organized as follows. In Section 2, previous work on node grouping and selection algorithms in cooperative spectrum sensing is reviewed. In Section 3, correlation-based selection schemes are analyzed in detail. In Section 4, the considered system model is described, while in Section 5 the proposed cooperative spectrum sensing scheme, based on a novel mobility-aware leader selection metric is presented. Simulation results for the analysis of the proposed approach and its comparison with previous work are presented in Section 6, while Section 7 draws conclusions and identifies future research lines.

2. Node Grouping in Cooperative Spectrum Sensing

A large number of cooperating SUs guarantees high global probability PUs detection. However, proper independent nodes selection for cooperation can improve the robustness of cooperative sensing [13], [14]. Moreover, global false alarm probability may be significantly reduced [8]. Node selection reduces also the overhead related to unnecessary sensing information transmission as well as provides significant energy savings.

Several different approaches to node selection have been proposed in the literature, and are briefly reviewed in the following.

2.1. Best-SNR Selection Algorithm

Best-SNR selection algorithms are based on selecting the nodes with the highest signal-to-noise ratio for cooperation [8]. Under the Constant Detection Rate (CDR) requirement, every node maintains a constant local detection probability by adapting the detection threshold on the basis of expected SNR. Hence, the false alarm probability depends on the expected SNR: the higher the SNR, the lower false alarm probability. Therefore, selection of the cooperation nodes with the highest SNR lowers the global false alarm probability in the network (Q_{f}).

Under CFAR requirement, the nodes with the highest SNR have the highest detection probability. Thus, the SUs with the highest SNR should always be chosen for cooperation. However, this requires the nodes to be aware of their own SNR and deliver it to the fusion centre, while the fusion centre has to receive the information from every SU in the network. Variable channel conditions induce SNR variations, that must be dealt with, for example with periodic updates of the estimates of the SNR for each node.

The best-SNR selection approach has been investigated by Peh and Liang in [8]. The authors proved that through selection of a reduced number of nodes significant performance improvement can be obtained. For example, by using only 19 out of 200 nodes for cooperative sensing the Q_{f} decrease from 6.02% to 0.06% under the CDR requirement with OR-rule as well as an Q_{d} increase from 92.04% to 99.88% under the CFAR requirement with AND-rule is achieved.

Another algorithm based on the best-SNR selection has been described in [15]. In this work the secondary user with the highest SNR is chosen in the first iteration. Next, every other node compares its link quality to the fusion centre with its link quality to the formerly selected node and from the formerly selected node to the fusion centre. If a node determines that its own link is less reliable, then it joins the best-SNR node group. Otherwise, the next best-SNR node among ungrouped nodes is selected and then the procedure of comparing links and grouping is repeated until all of the nodes are grouped.

An interesting algorithm relying on best-SNR selection has been proposed in [16]. In this work nodes are classified either as leaders or followers based on the received SNR. Leading nodes have good detection performance and are allowed to sense the PU signal and broadcast their sensing information. Following nodes are considered unreliable due to low SNR, so they do not broadcast their decisions, but rather wait for broadcasted packets from leaders. Thus, only the reliable information is broadcasted. In addition, the information sent by the leaders is rather limited, only consisting in the PU presence information. As a result, the approach proposed in [16] leads to low overhead information. The identification of nodes with highest SNR is however challenging, as it must rely on the presence of the PU during training/measurement periods.

2.2. Best Detection Performance Selection

Algorithms belonging to this family rely on nodes with the highest probability of detection being selected [17]. However, the correct identification of such nodes is an open issue, as algorithms based on best detection performance selection are typically analyzed under the assumption that the PU is always present and thus can identify the best nodes as those that obtain the highest number of the "PU present" positive decisions. These algorithms, similarly to the best-SNR ones seen before, are thus only easily applicable when there are known periods where the PU is always present, allowing to evaluate the probability of detection of the nodes.

2.3. Voting Schemes

The first representative of the voting schemes class is the so-called Confidence Voting [18], in which nodes build reliability-related measures. The idea is to limit unreliable decision transmissions. Every node is obliged to compute a confidence metric. In the hard decision scenario the local and global decisions are collated - in the case of coincidence the confidence metric is incremented, otherwise it is decremented. After the training period, in which the metrics are computed, only the nodes with the highest confidence metrics are allowed to report their decisions to the fusion centre.

The Collision Detection scheme [19] is based on node selection with the highest correctness measure. The measure notifies the number of node's correct decisions when the global false decision is that the PU is not present. The nodes with the highest correctness are selected and involved in cooperative sensing.

The schemes based on voting have the advantage of being applicable in scenarios where there are no periods in which the presence of the PU is known in advance, but they are not without drawbacks. As they rely on the majority opinion, if most of the secondary users faces bad channel conditions, then more confidence goes to unreliable nodes. As a result, the decision obtained in confidence voting may be worse than in a traditional scheme. As a side comment, the voting schemes are not robust enough in the case of malicious SU.

2.4. Other Approaches

A few approaches not falling in the abovementioned families have been proposed in the literature and are briefly discussed below.

A *similarity-based algorithm* has been described in [20]. In this case, the similarity measures for pairs of nodes have to be computed. The similarity measure indicates how well node k can serve as the reporting node for node i [20]. The similarity is determined on the two metrics basis: responsibility and availability. The responsibility is derived for checking how well node k can be a reporting node for node i in comparison with other nodes. The availability coefficient measures appropriateness of being a reporting node to exclude situations when only a small number of nodes is grouped.

Selen *et al.* in [21] proposed a solution for the problem of node selection which does not involve nodes' SNRs nor their performance knowledge. The only required information is the distance from coordinating sensor to the other nodes. The selection is in fact based on such radius information exchanged between nodes. The algorithm finds k sensors within the radius separation under the constraint not to exceed the desired correlation probability between selected nodes.

The sensors may be selected also according to power consumption constraints. The maximum power scheme chooses the set of nodes with the least power consumption in order to guarantee minimal power usage [22]. The maximum lifetime scheme chooses a set which has the longest minimum lifetime. In this algorithm a tiebreaker is also needed to switch between sets of nodes [22].

Najimi *et al.* in the work [23] propose a scheme that combines energy efficiency and sensing performance in node selection. The scheme introduces a cost function that favors nodes with lowest sensing and decision-transmission energy usage among those satisfying the quality of detection constraint. Furthermore, energy efficiency is increased by introducing decision nodes, each acting as collector of sensing results from a set of selected nodes, determining a common decision and sending it to the fusion centre. The scheme requires however full knowledge about nodes signal-to-noise ratios and distances between each node and fusion centre in order to operate, leading to a significant control overhead.

2.5. Correlation-Based Selection

Finally, a few works investigated correlation-based selection schemes. These are based only on node decisions, which are used for finding correlations between nodes. This approach relies on the assumption that finding correlations between sensing nodes and selecting only uncorrelated ones should result in good sensing performance while minimizing transmission overhead associated with reporting the sensing results to the fusion centre. Since the algorithm proposed in this work falls into this category, correlation-based node selection algorithms are analyzed in Section 3.

3. Correlation-Based Node Selection

Correlation-based node selection has been introduced in the aforementioned work [21], where a network consisting of N nodes is considered. All nodes are grouped in an active set at the algorithm beginning, while after selection only X nodes may remain in the active set while the rest is moved to the passive set, that includes all nodes that are not allowed to vote. In order to make a proper selection, the correlation measure is computed for pairs of nodes in the network. Then, the node with the highest summed correlation with the remaining sensors is removed from the active set and moved to passive set. The correlation measure used in [21] is based on the nodes positions and associated positioning uncertainty. An example of correlation measure is the following correlation function (7):

$$R(d) = e^{-ad}, \tag{7}$$

where a is a decay constant related to the environment and d is the distance between sensors.

A distributed correlation-based selection approach was presented in [24], where a node is randomly selected to start the procedure by broadcasting sensing information to the other nodes, in the form of the received signal during the last sensing phase. The remaining nodes listen to this information and estimate their correlation coefficients. Each node compares its coefficient with a correlation threshold, and if it is above the threshold the node does not take part further in the procedure. Nodes that have a correlation coefficient below threshold randomly select a delay and the one that picked the shortest delay transmits its received signal, starting the next iteration of the procedure. The procedure completes when there is no remaining uncorrelated node. Since as part of the procedure all nodes share their received signal, when it is completed each node is capable of taking the same sensing decision according to a soft fusion of the received signals. The work is rather interesting, but the role of noise in the results of the correlation procedure is not completely addressed in the work, as the presence of a denoiser is assumed but its impact is not thoroughly described in the paper.

Pratas *et al.* in the work [25] proposed the Adaptive Counting Rule. In the solution cooperative network of n SUs is considered. The adaptive rule is adopted in the hard-decision fusion scheme. It optimizes the minimal number of SUs declaring the presence of primary signal derived as k. It was shown that optimal value of k depends on the amount of correlation experienced by nodes as well as the number of detectors in the set and their performance. The authors proposed also continuous mechanism of selection optimal k value.

Another correlation-based approach was described in the paper written by Y. Sun *et al.* [12]. In this approach the correlation measure is computed based on the node decisions only. Thus, no additional information, such as position of nodes, is needed. Correlation-based node selection presented in [12] is based on similarity in decision making. The performance evaluation that supports the approach in [12] is however quite preliminary, as it relies on several simplifying assumptions. For example, authors state that sensing information was "generated randomly according to the probability of correct detection between 70 and 90%" [12], implying that the radio channel model was not taken into account in the results. The authors also assume that by putting the value of correlation threshold α to 0.96 the nodes can be divided into 10 groups. This assumption would not hold in general in the real world, as the selected number of nodes resulting from the approach in [12] constantly changes and depends on several parameters, e.g. on actual propagation conditions or nodes positions. Finally, the simulation results in [12] were obtained in a low-correlation scenario for an average signal-to-noise ratio equal to 10 dB, while one would reasonably expect a CSS scheme to be tested in a low SNR regime, where its improvement over local sensing is expected to be most relevant.

Despite the lack of thorough experimental verification, the approach proposed in [12] is appealing, since it inherently takes into account the role of spatial positions of nodes and channel conditions in determining the best set of nodes. A solution inspired by this approach, but also taking into account the role of mobility, is introduced in Section 5, and its performance is evaluated in Section 6.

4. System Model

The model adopted in this work foresees N nodes randomly distributed in a square area of side equal to R meters. Every node is assumed to have the same desired probability of false alarm and therefore the same sensing threshold computed according to Eq. (6).

The generic node moves with a randomly selected direction of movement θ_i and velocity v_i. Angles of movement and velocities are uniformly distributed, with θ taking values between 0 and 2π radians, and velocities v between $v_{\min}$ and $v_{\max}$ m/s. Whenever a node hits the border of the square area it bounces back from it according to a total reflection model, while keeping the same velocity.

The following power attenuation model is assumed for the mobile radio channel between a mobile node and the Primary User:

$$channel|_{dB} = pathloss|_{dB} + fading|_{dB} + shadowing|_{dB}. \tag{8}$$

The path loss depends on carrier frequency f_c and on the distance d between node and PU according to the well-known Friis' formula. The carrier frequency is assumed to be constant for all nodes, while the distance changes in time proportionally to the node velocity. However, it is assumed that during the sensing phase the path loss does not change due to relatively small possible variation of nodes' locations.

Fading coefficients are modelled according to Rayleigh fading channel. Doppler shift is proportional to the node velocity and in the presented model varies according to the following equation:

$$\Delta f = 3 \cdot v_i. \tag{9}$$

In the model every node experiences independent fading channel (as suggested in [26]), resulting in uncorrelated fading between different nodes, but correlated channel coefficients in time for a given node.

As regards shadowing modelling, the decorrelation distance d_{corr} has been set according to Gudmundson model [27] and Min and Shin work [9]. Hence, the square area of side R meters was divided into q smaller (pixel) squares containing different values for shadowing. The values are constant in time for a given location according to [28], so during the observation time the shadowing value for every shadowing centre does not change. The values are randomized with the normal distribution $N \sim (0, \sigma_s)$. However, one can find more sophisticated shadowing models. Kasiri and Cai in the work [29] applied NeSh (Network Shadowing) model taken from the work [30]. The model allows to determine correlation values between links of different users while in Gudmundson case it is possible only for links coming from one node. Since however the scenario considered in this paper focuses on correlation between measurements involving the same primary transmitter, the Gudmundson model was deemed sufficient to the purpose of this work.

In the considered system every node takes M sensing decisions and sends them to the fusion centre, under the assumption that radio coverage between the nodes and fusion centre is always guaranteed. One can reasonably expect that mobility will also significantly impact the topology of the secondary network and thus the radio coverage between nodes and fusion centre. For the sake of simplicity the analysis of such impact is left for future work, while in the present paper the impact of mobility is restricted to the sensing results.

Nodes in the network share a common time reference, and time is organized in frames of duration T_f. The sensing information is gathered and exchanged during a sensing phase of duration T_{se} that takes place at the beginning of each frame. The remaining time in the frame, equal to $T_f - T_{se}$ is dedicated to transmission if the presence of PU is excluded.

The frame duration T_f is also used as the reference period for updating the nodes positions and determining the new values for shadowing. Note that a smaller update period could easily be adopted, but this would have no impact on sensing performance, as sensing is also performed with period T_f and network wide synchronization is assumed.

5. Mobility-Aware Correlation-Based Spectrum Sensing

The proposed sensing scheme organizes network operation in two states: a *training* state, used for node grouping and selection, and an *activity* state, during which nodes selected in the training state perform sensing, and all nodes transmit data packets whenever the network sensing decision excludes the presence of the PU.

While in training state each node takes M signal samples during the sensing phase, with a sampling period $t_s = T_{se}/M$ seconds. The samples are compared with the sensing threshold, with M decisions taken at each sensing node. Each node sends the M decisions to a fusion centre, that uses them to compute the correlation measure. The number of decisions M should be thus large enough in order to allow for a reliable estimation of the correlation between different nodes.

As a result of the selection procedure detailed later in this section, a set of active nodes is determined, and the network switches to the activity state, during which the active nodes perform sensing and report their decisions to the fusion centre, where a network decision on the presence of the PU is taken.

The selection procedure used during the training phase is the following one.

Let's indicate with $S_i(k)$ the k-th decision out of M taken by the i-th node, and define it as follows:

$$S_i(k) = \begin{cases} 1, & \text{when } \mathrm{H}_1 \text{ is declared} \\ -1, & \text{when } \mathrm{H}_0 \text{ is declared} \end{cases}, \tag{10}$$

where H_1 and H_0 are the hypotheses of the presence and the absence of a PU, respectively. Given the decisions taken by two SUs, i and j, the $\gamma_{i,j}$ correlation measure for the two nodes is defined as [12]:

$$\gamma_{i,j} = 1 - \frac{\sum_{k=1}^{M} |S_i(k) - S_j(k)|}{2M}, \tag{11}$$

where $\gamma_{i,j} \in \langle 0, 1 \rangle$. If all decisions for the i-th and j-th nodes are identical $\gamma_{i,j}$ is equal to 1: in general, the higher the number of common decisions, the greater the value of correlation measure.

After computing correlation measures between all pairs of nodes, the Γ matrix of size $N \times N$ is built:

$$\Gamma = \begin{bmatrix} \gamma_{1,1} & \gamma_{1,2} & \cdots & \gamma_{1,N} \\ \gamma_{2,1} & \gamma_{2,2} & \cdots & \gamma_{2,N} \\ \vdots & \vdots & \ddots & \vdots \\ \gamma_{N,1} & \gamma_{N,2} & \cdots & \gamma_{N,N} \end{bmatrix}. \tag{12}$$

It is assumed that correlation coefficients are reciprocal, so Γ is a symmetric matrix. The diagonal elements of matrix are the auto-correlation coefficients. Therefore, Γ can be represented as upper triangular matrix $\widetilde{\Gamma}$ (13):

$$\widetilde{\Gamma} = \begin{bmatrix} 0 & \gamma_{1,2} & \dots & \gamma_{1,N} \\ 0 & 0 & \dots & \gamma_{2,N} \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & 0 \end{bmatrix}. \tag{13}$$

After evaluating the correlation measures for all possible pairs of nodes the grouping procedure is executed. First, the value of a correlation threshold α is defined. Next, $\gamma_{i,j}$ coefficients above α threshold are determined. If more than one γ coefficient is higher than α, then two cases may occur:

- the pairs of correlated nodes are disjoint. In this case nodes are grouped by correlated pairs;
- one node is correlated with more than one node. In this case three or more nodes are grouped together only if all mutual correlation measures are larger than α. Nodes that do not meet this condition are not included in the group.

The procedure is performed repeatedly until there are no further nodes that can be grouped together.

Let's consider a simple example of a network consisting of three nodes: A, B and C. The correlation coefficients and correlation threshold are given as follows: $\gamma_{A,B} = 0.96$, $\gamma_{A,C} = 0.97$ and $\gamma_{B,C} = 0.94$, $\alpha = 0.95$. At first nodes A and B are grouped ($\gamma_{A,B} > \alpha$), then node C becomes a candidate to join group. Although correlation between A and C is sufficiently high, the node C is not allowed to join the group due to a correlation with node B below the required threshold. As a result, a group including nodes A and B is formed, while node C remains ungrouped.

When the grouping procedure is complete, some groups are formed while the rest of nodes remain uncorrelated. Note that the above algorithm, first described in [12], does not require a predetermined number of nodes and groups to be selected as an input parameter. The output number of groups and the total number of selected nodes depend on the correlation environment.

Following the division of nodes into groups, a group leader for each group is selected according to the Leader Suitability (LS) parameter, defined as follows for the generic group member i:

$$LS_i = c_1 P_{\mathrm{d},i} + c_2 e^{\frac{v_i - v_{\min}}{v_i - v_{\max}}}, \tag{14}$$

where c_1 and c_2 are weight coefficients that can be used to adjust the relative importance of the two terms that form the LS parameter. The first term is the detection probability of node i, while the second term models the stability of the node, defined as its ability to stay as long as possible at a given location. The stability coefficient is equal to 1 when v_i is equal to minimal velocity and 0 if $v_i = v_{\max}$. The behavior of the stability parameter is presented in Fig. 1 for $v_{\min} = 1$ m/s, $v_{\max} = 5$ m/s.

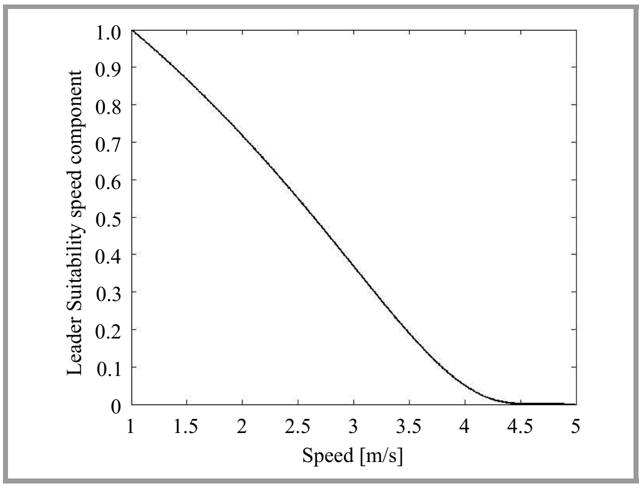

Fig. 1. Behavior of the term related to node velocity used in the Leader Suitability formula.

The goal of the proposed metric is to ensure that selected group leaders are able to guarantee good sensing performance not only at present time, but also in foreseeable future, thanks to their low mobility.

As a result of the selection procedure, the set of active nodes allowed to participate in sensing is determined, and is composed by one group leader from every group and all the uncorrelated nodes. The network switches then to the activity state for a predetermined amount of time, before switching back to the training state for updating the set of active nodes.

6. Simulation Results

The performance of the mobility-aware correlation-based cooperative sensing scheme introduced in Section 5 has been investigated by means of computer simulations carried out in the Matlab environment.

In the simulations a square area of 200 m side was divided into 16 pixels of $d_{\text{corr}} = 50$ m side [9] and $N = 100$ secondary nodes were randomly distributed in the area. The same area was covered by the transmission of a PU. The PU signal was characterized by a carrier frequency of 300 MHz, transmit power of 1 W, and distance to SUs in the range 1.41–1.86 km. In order to observe the benefit of the grouping algorithm, it was assumed that the PU is always present. A complete list of simulation parameters and corresponding values is presented in Table 1.

Table 1
Simulation parameters

Parameter	Description	Value
R	Area Side	200 m
q	Number of pixel squares	16
N	Number of nodes	100
f_c	Carrier frequency	300 MHz
T_{se}	Sensing phase duration	0.1 s
T_f	Frame duration	1 s
t_s	Sample time	0.1 ms
M	Number of samples used for correlation approximation	1000
SNR	Averaged signal-to-noise ratio	2 dB
σ_{SU}	Noise power at SU	3.01e^{-13} W
P_{PU}	PU Signal Power	1 W
d	Distance to Primary User	1.41–1.86 km
d_{corr}	Decorrelation distance	50 m
Q_f	Global probability of false alarm	0.095
P_f	Local probability of false alarm	0.001
θ_i	Direction of movement of nodes	0–2π rad
$v_{\min}$	Minimal velocity of nodes	1 m/s
$v_{\max}$	Maximal velocity of nodes	5-50 m/s
I	Number of iterations	20000
σ_s	Shadowing variance	4.6 dB
Δf	Doppler shift	3–150 Hz
n	Periodic selection time	13 or 18 s
α	Minimal correlation coefficient	0.95

According to Ofcom rules the sensing should be executed at least once a second and occupy no more than 10% of the total frame length [31]. Thus, in the simulations a frame of duration $T_f = 1$ s was divided in $T_{\text{se}} = 0.1$ s and $T_f - T_{\text{se}} = 0.9$ s. During the sensing part every node collected M = 1000 samples, corresponding to a sample time equal to 0.1 ms. The decisions were generated by comparing the power of each sample to a constant sensing threshold.

Such decisions were then provided as an input to the CSS algorithm for group formation and leader selection. As mentioned in Section 5, any fusion rule could be adopted to take the network decision; in the performance evaluation presented in this section an OR fusion rule was adopted.

The CFAR requirement was adopted in the system, with a global probability of false alarm equal to 0.095, implying thus local probabilities of false alarm equal to 0.001, assuming that all nodes participate in the sensing process. Identical P_f and noise power at SUs imply, as a result, constant sensing threshold in every node (see Eq. 6).

All of the simulations were done under the assumption of an average SNR between the PU signal received at an SU and the noise at the same SU equal to 2 dB. The results were averaged over 20,000 iterations, and in each iteration the state of the system was recorded every second for a 70 s observing time.

As already pointed out, mobility is expected to play an important role in sensing performance. As a consequence all simulations were performed in mobility presence.

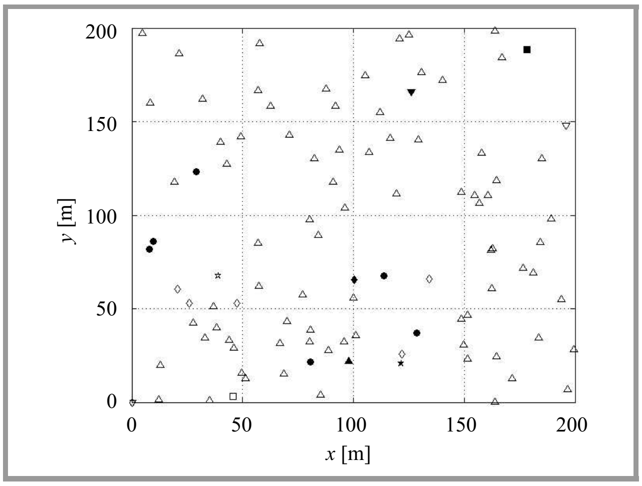

Fig. 2. Exemplary state of the system after node selection procedure.

An example of the state of the system after node grouping and group leaders selection is presented in Fig. 2 (node velocities in the range 1–20 m/s). In the figure different markers correspond to different groups, while filled markers identify the leader of the corresponding group. It shows that from every group, only one node is selected as a group leader except for a group marked by circles. These are uncorrelated nodes – the nodes which are not correlated enough to join another group. Therefore, all of these nodes are allowed to vote. In the situation presented in Fig. 2, 11 nodes out of 100 are selected to vote: 6 uncorrelated nodes and 5 group leaders. In general, it can be observed that in the low-SNR-scenario, the received power is often below the sensing threshold, due to strong shadowing and/or fading. Thus, in such scenario many nodes with bad channel conditions take the decision that the PU is not present. As a result, these nodes are associated to the same, large, group. Therefore, only a few groups are eventually formed. This effect may prove a significant advantage of correlation-based sensing when AND or majority rules are adopted, as it significantly reduces the impact of individual missed detections by grouping all nodes likely to generate such missed detections in a single group. This result was not observed in previous works on correlation-based sensing, most probably due to the lack of detailed modeling for channel correlation.

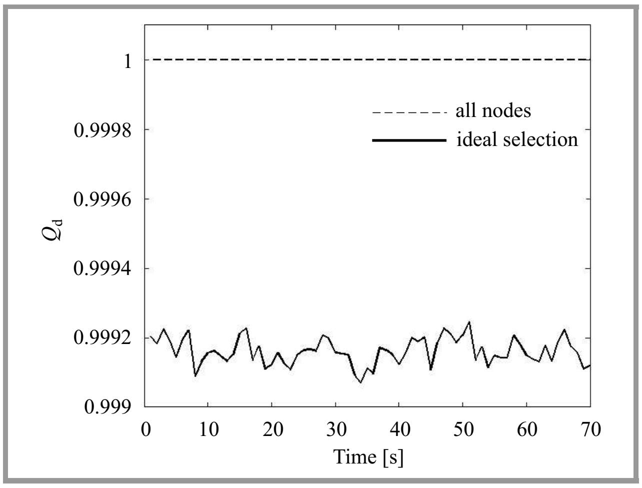

Fig. 3. Q_{d} for N nodes and selected one.

Results also highlighted that the number of selected nodes influences the value of Q_{d}. In general, the lower the number of selected nodes, the smaller Q_{d}, with actual value depending on average SNR, as expected from the adoption of an OR decision rule. Figure 3 shows the loss in global probability of detection Q_{d} due to the reduction of the number of group leaders. The upper curve is the Q_{d} when all nodes in the system are allowed to send their decisions to fusion centre. The second case, referred to as *optimal selection*, corresponds to executing the grouping procedure at the beginning of each sensing phase, so at every second. The Q_{d} for all nodes is equal to 1, while for the optimally selected set of nodes it is around 0.9992. So, the smaller number selection of nodes introduces a penalty in terms of the global detection probability slight reduction, mainly as a selected fusion rule result. On the other hand, the global probability of false alarm was also significantly reduced, which is a strong advantage from the point of secondary network view. In fact, as under the CFAR requirement the local probability of false alarm for every node is kept constant, the global probability of false alarm depends on the actual number of nodes taking part in decision making process. Figure 4 shows the relation between Q_{f} and the number of active nodes. One can see that e.g. selection of 10 out of 100 nodes lowers the Q_{f} from 0.095 to 0.01. This implies that for the SNR used in experiments, the proper node grouping causes barely visible fall of Q_{d} and sensible fall of Q_{f}.

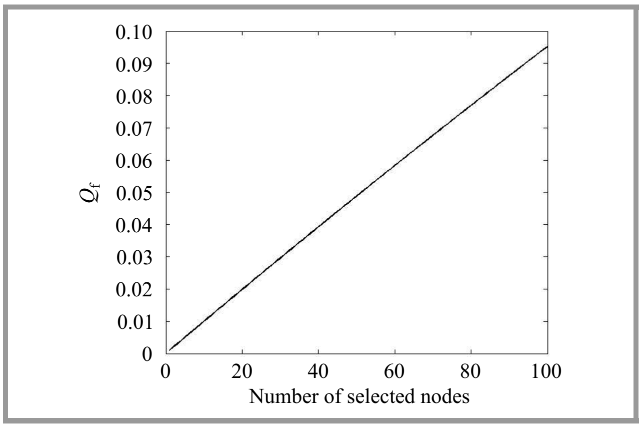

Fig. 4. Q_{f} in the function of number of selected nodes.

The above results prove that correlation-based node grouping can improve performance under realistic channel conditions and go beyond the results in [12] since, as already discussed in Section 3, in that work performance evaluation of the correlation based solution was limited to a scenario with randomly generated local detection probabilities with no connection to relative positions and channel correlation responses between secondary nodes.

The analysis focused next on the impact of the new leader selection metric. Three strategies for the group leader selection were investigated, corresponding to three coefficient sets for the metric. The first strategy selected the node with the highest local probability of detection to act as a group leader (corresponding to weight coefficients for Eq. (14): $c_1 = 1$, $c_2 = 0$), as proposed in [12], referred to in the following as $\max P_d$ strategy. The second strategy aimed to select the group leader on the basis of both the local P_{d} and the stability coefficient ($c_1 = 0.5$, $c_2 = 0.5$), and is referred to as the *mixed* strategy. Finally, the third strategy, $\max ST$, only rewards stability ($c_1 = 0$, $c_2 = 1$).

The results for $\max P_d$, $\max ST$ and mixed strategies are shown in Figures 5, 6 and 7, respectively. In every figure one can find three plots: the top curve is the *optimal selection* update strategy previously defined; the bottom curve corresponds to an update strategy named *starting selection* in which the grouping and selection procedure is executed only once, in the first second of simulation. Finally, the middle plot corresponds to the *periodic selection* update strategy, in which grouping is carried out every n seconds where n is selected so to keep the 0.95 threshold.

One can see that when adopting the optimal selection update strategy, the best result is guaranteed by the $\max P_d$ strategy. In the mixed strategy Q_{d} value is slightly lower while the $\max ST$ strategy leads to the worst result (see Table 2). The optimal selection values (Table 2) are matched exactly by the starting selection at the beginning of each simulation, and by the periodic selection immediately after each update.

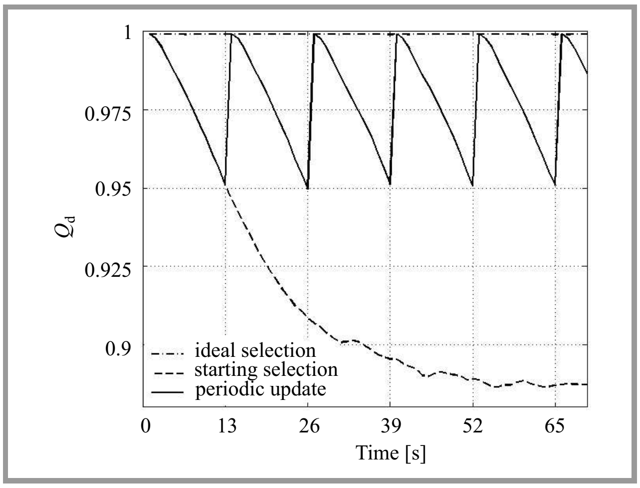

Fig. 5. Q_d vs. time for $\max P_d$ strategy, $n = 13$ s.

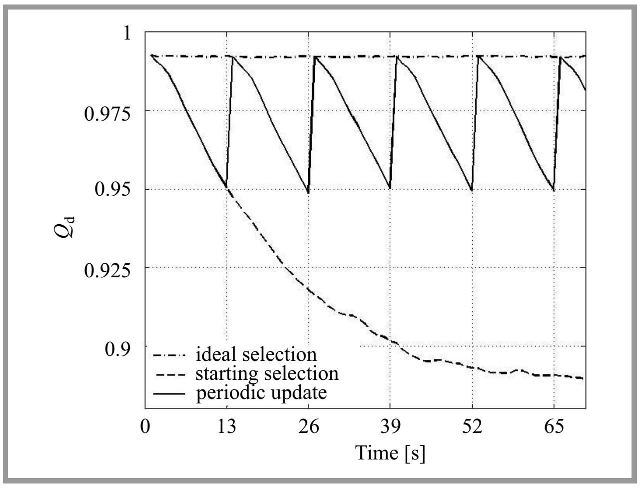

Fig. 6. Q_d vs. time for $\max ST$ strategy, $n = 13$ s.

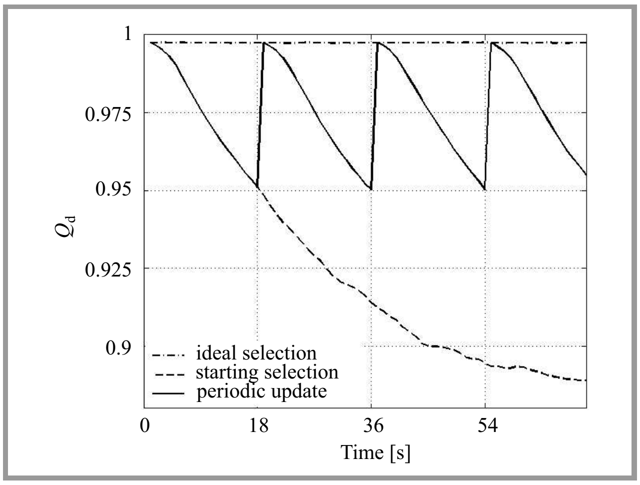

Fig. 7. Q_d vs. time for mixed strategy, $n = 18$ s.

Maximum Q_d values are doubtless relevant for evaluating the performance of grouping and selection algorithms, but the stability of received measures is important as well. Figure 8 presents results for the starting selection update

Table 2
Q_d values for optimal selection

Leader selection method	Q_d value
$\max P_d$	0.9992
mixed	0.9975
$\max ST$	0.9925

strategy for the three leader selection strategies introduced above. One can see that in the $\max P_d$ strategy, which guarantees the highest Q_d value for optimal selection, the Q_d value decreases quickly in time, while for the stability-involved strategies the slope is significantly less steep. The least steep slope and the highest values of Q_d after two seconds were obtained for the strategy involving both stability and P_d in the selection of the group leader.

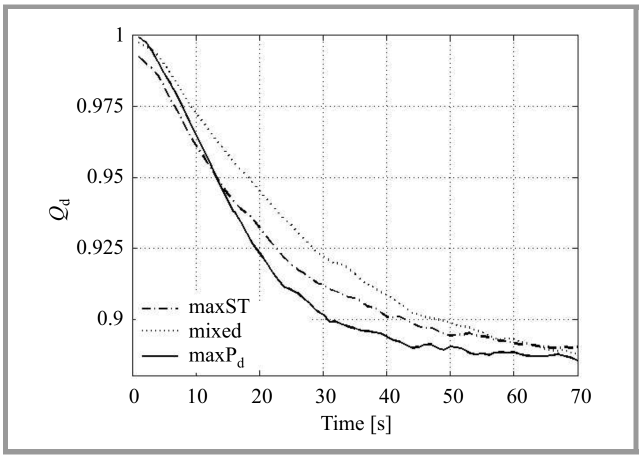

Fig. 8. Q_d for starting selection for terminal velocities from 1 to 5 m/s.

Figure 8 shows that the global detection probability might be acceptable not only immediately after the leader selection, but also some time after the grouping and selection procedure. Since grouping and leader selection require significant information exchanges between nodes and thus introduce significant overhead in the network, one might want to perform such procedure as seldom as possible while guaranteeing the desired detection probability.

The beneficial effect of taking into account stability in group leader selection can be observed by comparing the periodic selection curves in Figs. 5, 6 and 7, that show results assuming a minimum acceptable Q_d equal to 0.95. One can in fact observe that the periodic update time differs in the three cases, with the *mixed* strategy requiring an update only every $n = 18$ s, while the other strategies require an update at most every $n = 13$ s. The combination of node's P_d and stability introduced in the proposed leader selection strategy guarantees thus an increase of the minimum update time from 13 to 18 s corresponding to 38% gain. The price paid to get such an improvement is a slightly lower Q_d value in the very first seconds after each selection procedure. Although further studies are required to quantify the overall impact of the two phenomena on overall performance in the secondary network (e.g. in terms of throughput), the results strongly suggest that the proposed strategy may provide a significant advantage.

The trend of Q_d as a function of time strongly depends on the mobility of SUs. In Fig. 9 one can observe results for nodes velocities in the range of 1–20 m/s. The results in Figs. 8 and 9 show that the floor value in the starting selection update strategy is significantly higher in the $v_{max} = 20$ m/s case. Min and Shin in [9] pointed out that the sensing scheduling gain rises proportionally as node's velocity increases. One could thus predict that wider range of nodes velocities lowers correlation between nodes and thus improves global sensing results.

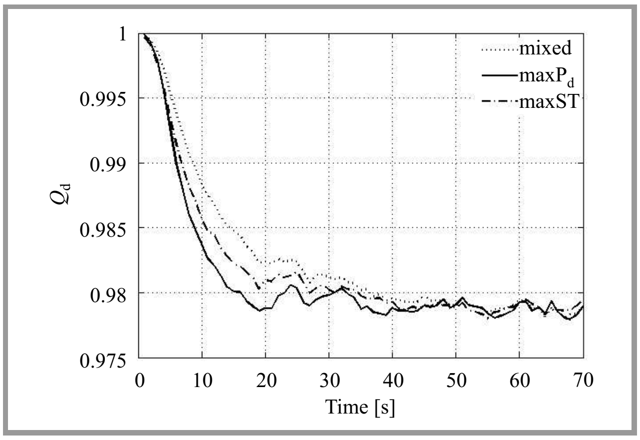

Fig. 9. Q_d for starting selection for terminal velocities from 1 to 20 m/s.

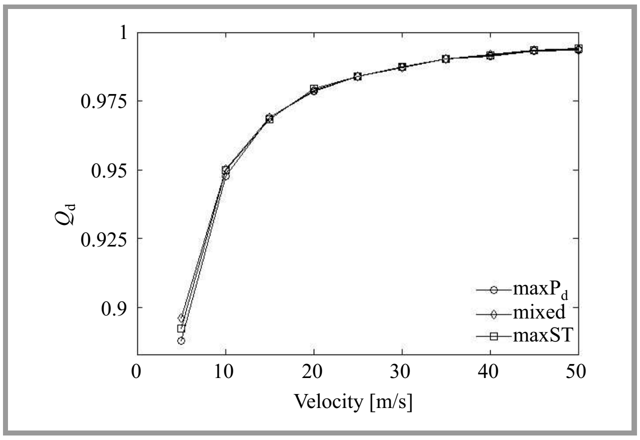

Fig. 10. Floor value of Q_d vs. maximum node velocity for three leader selection strategies.

In order to verify this assumption, the floor value of global detection probability was evaluated as a SU maximum velocity v_{max} function, with minimum velocity v_{min} set at 1 m/s (Fig. 10). One can see that the higher the node's maximum velocity, the higher floor value of Q_d. This is determined by correlation between the sensors. In low-velocity scenarios, decisions of nodes are highly correlated so there are a few large nodes groups. Therefore, only a few nodes are selected and allowed to vote. In a high-velocity

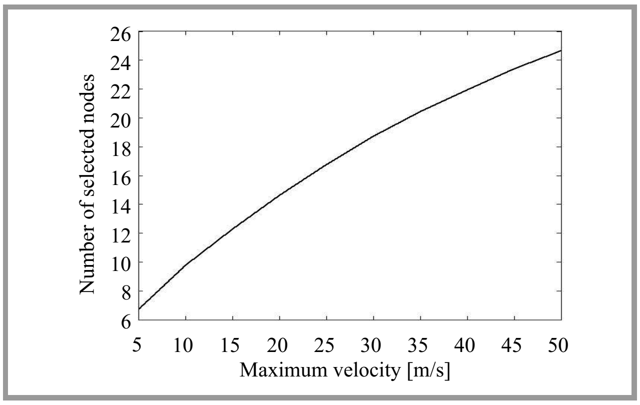

Fig. 11. Number of active nodes vs. maximum node velocity.

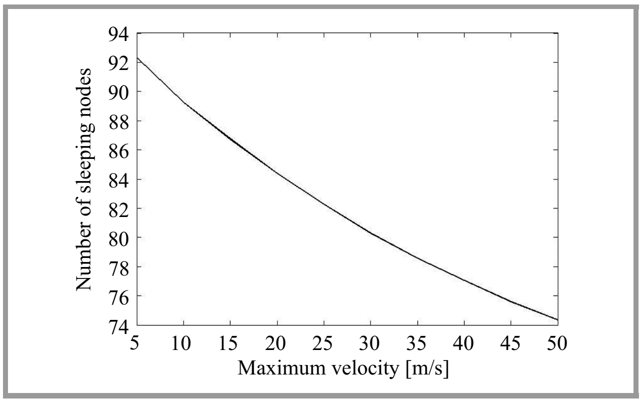

Fig. 12. Number of sleeping nodes vs. maximum node velocity.

scenario the correlation between nodes' decisions is small. As a result, there are more nodes groups and more uncorrelated nodes. The higher the number of active nodes and the higher the average velocity, the higher the probability that one or a few nodes experience reliable channel conditions. This is confirmed by Fig. 11, showing the number of active nodes: the higher the nodes mobility, the higher active nodes number. Moreover, the active nodes higher number provide lower overhead reduction. In Fig. 12 one can observe the percentage of sleeping nodes which were not selected by the procedure. These nodes may sleep and thus lower the overhead information exchange as well as reduce energy consumption. For high-correlated scenario the reduction in the number of updates and the corresponding overhead is the most significant. Even in the low-correlated scenario, the reduction of active nodes number is however still prominent (75% for $v_{max} = 50$ m/s) thus justifying the adoption of a grouping and selection procedure even at relatively high speeds.

7. Conclusion and Future Work

In this work a novel correlation-based node grouping and selection algorithms has been proposed, that takes into account both sensing performance and mobility of secondary nodes by introducing a leader selection metric that combines node's P_d and its stability. The performance of the proposed algorithm was evaluated and compared with previous work by computer simulations.

Simulation results show that by including stability in the group leader selection criteria correlation-based sensing can operate for longer time periods with acceptable performance before an update is needed. In particular, the proposed scheme led to a 38% decrease in the number of updates while guaranteeing a network detection probability above the required 0.95 threshold, at the price of a slight reduction in the maximum value of the same probability. It was also proven that the proposed selection procedure guarantees the involvement of only 9% vs. 25% of nodes in high vs. low-correlated scenario, respectively, achieving in both cases a strong overhead reduction and energy consumption by allowing most of the nodes to enter a power saving mode.

The proposed algorithm requires the availability of information about the nodes velocities. It should be noted however that this information can be derived by means of outdoor (GPS) and indoor positioning systems based on technologies like Wi-Fi or RFID. Furthermore, the algorithm can equally operate on relative comparison between the nodes mobility, rather than on their absolute speed. This relative information can be obtained by monitoring the rate of topological change observed by a node (e.g. average number of neighbors varied per second). One could thus argue that this assumption is overall more realistic than the one of knowing exactly the local detection probability of each node, shared by the algorithm proposed in this work with most of the solutions for cooperative spectrum sensing previously proposed in the literature.

Future avenues for further research include the determination of the optimum balance between the nodes' detection probability and stability so to maximize the global detection probability and at the same time maximize the interval between two grouping procedure updates. In addition, the proposed scheme is currently being implemented in a network simulator to better determine its impact on both primary receivers and secondary network throughput.

Acknowledgements

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References

[1] FCC, "In the matter of unlicensed operation in the tv broadcast bands. Second memorandum opinion and order", 2010 [Online]. Available: http://fjallfoss.fcc.gov/edocs_public/attachmatch/FCC-10-174A1_Rcd.pdf (accessed: 04/12/2013).

[2] A. Ghasemi and E. Sousa, "Collaborative spectrum sensing for opportunistic access in fading environments", in *Proc. 1st IEEE Int. Symp. New Front. Dynam. Spect. Access Netw. DySPAN 2005*, Baltimore, USA, 2005, pp. 131–136.

[3] S. Maleki, S. Chepuri, and G. Leus, "Optimal hard fusion strategies for cognitive radio networks", in *Proc. IEEE Wirel. Commun.Netw. Conf. WCNC 2011*, Cancun, Mexico, 2011, pp. 1926–1931, 2011.

[4] J. Unnikrishnan and V. Veeravalli, "Cooperative sensing for primary detection in cognitive radio", *IEEE J. Selec. Topics Sig. Proces.*, vol. 2, pp. 18–27, 2008.

[5] W. Zhang, R. Mallik, and K. Ben Letaief, "Cooperative spectrum sensing optimization in cognitive radio networks", in *Proc. IEEE Int. Conf. Commun. ICC 2008*, Beijing, China, 2008, pp. 3411–3415.

[6] D. Horgan and C. Murphy, "Voting rule optimisation for double threshold energy detector-based cognitive radio networks", in *Proc. 4th Int. Conf. Sig. Proces. Commun. Sys. ICSPC 2010*, Gold Coast, Australia, 2010, pp. 1–8.

[7] W. Zhang, R. Mallik, and K. Letaief, "Optimization of cooperative spectrum sensing with energy detection in cognitive radio networks", *IEEE Trans. Wirel. Commun.*, vol. 8, no. 12, pp. 5761–5766, 2009.

[8] E. Peh and Y.-C. Liang, "Optimization for cooperative sensing in cognitive radio networks", in *Proc. IEEE Wirel. Commun. Netw. Conf. WCNC 2007*, Hong Kong, 2007, pp. 27–32.

[9] A. W. Min and K. G. Shin, "Impact of mobility on spectrum sensing in cognitive radio networks", in *Proc. ACM Worksh. Cognit. Radio Netw.*, Beijing, China, 2009, pp. 13–18.

[10] K. Arshad and K. Moessner, "Mobility driven energy detection based spectrum sensing framework of a cognitive radio", in *Proc. 2nd UK-India-IDRC Int. Worksh. Cognit. Wirel. Sys. UKIWCWS 2010*, Delhi, India, 2010, pp. 1–5.

[11] L. De Nardis *et al.*, "Impact of mobility in cooperative spectrum sensing: Theory vs. simulation", in *Proc. Int. Symp. Wirel. Commun. Sys. ISWCS 2012*, Paris, France, 2012, pp. 416–420.

[12] Y. Sun, H. Hu, F. Liu, H. Yi, and X. Wang, "Selection of sensing nodes in cognitive radio system based on correlation of sensing information", in *Proc. 4th Int. Conf. Wirel. Commun. Netw. Mob. Comput. WiCOM 2008*, Dalian, China, 2008, pp. 1 –6.

[13] S. Mishra, A. Sahai, and R. Brodersen, "Cooperative sensing among cognitive radios", in *Proc. IEEE Int. Conf. Commun. ICC 2006*, Istanbul, Turkey, 2006, vol. 4, pp. 1658–1663.

[14] D. Godarzi, K. Arshad, Y. Ko, and K. Moessner, "Selecting users in energy-efficient collaborative spectrum sensing", in *Proc. IEEE Wirel. Commun. Netw. Conf. WCNC 2012*, Paris, France, 2012, pp. 1029–1033.

[15] Y. Wang, C. Feng, Z. Zeng, and C. Guo, "A robust and energy efficient cooperative spectrum sensing scheme in cognitive radio networks", in *Proc. 11th Int. Conf. Adv. Commun. Technol. ICACT 2009*, Gangwon-Do, Sth. Korea, 2009, vol. 1, pp. 640–645.

[16] A. Baharlouei and B. Jabbari, "A stackelberg game spectrum sensing scheme in cooperative cognitive radio networks", in *Proc. IEEE Wirel. Commun. Netw. Conf. WCNC 2012*, Paris, France, 2012, pp. 2215–2219.

[17] J. Lehtomaki, J. Vartiainen, Z. Khan, and T. Braysy, "Selection of cognitive radios for cooperative sensing", in *Proc. 3rd Int. Symp. Appl. Sci. Biomed. Commun. Technol. ISABEL2010*, Rome, Italy, 2010, pp. 1–5.

[18] C.-H. Lee and W. Wolf, "Energy efficient techniques for cooperative spectrum sensing in cognitive radios", in *Proc. 5th IEEE Consumer Commun. Netw. Conf. CCNC 2008*, Las Vegas, NV, USA, 2008, pp. 968 –972.

[19] Z. Khan, J. Lehtomaki, K. Umebayashi, and J. Vartiainen, "On the selection of the best detection performance sensors for cognitive radio networks", *IEEE Sig. Proces. Lett.*, vol. 17, pp. 359–362, 2010.

[20] O. Ureten, K. Baddour, and T. Willink, "Distributed selection of sensing nodes in cognitive radio networks", in *Proc. 7th Int. Symp. Wirel. Commun. Sys. ISWCS 2010*, York, UK, 2010, pp. 1056–1060.

[21] Y. Selen, H. Tullberg, and J. Kronander, "Sensor selection for cooperative spectrum sensing", in *Proc. 3rd IEEE Int. Symp. New Front. Dynam. Spect. Access Netw. DySPAN 2008*, Chicago, IL, USA, 2008, pp. 1–11.

[22] M. Perillo and W. Heinzelman, "Optimal sensor management under energy and reliability constraints", in *Proc. IEEE Wirel. Commun. Netw. WCNC 2003*, New Orleans, LU, USA, 2003, vol. 3, pp. 1621–1626.

[23] M. Najimi, A. Ebrahimzadeh, S. Andargoli, and A. Fallahi, "A novel sensing nodes and decision node selection method for energy efficiency of cooperative spectrum sensing in cognitive sensor networks", *IEEE Sensors J.*, vol. 13, no. 5, pp. 1610–1621, 2013.

[24] A. Cacciapuoti, I. Akyildiz, and L. Paura, "Correlation-aware user selection for cooperative spectrum sensing in cognitive radio ad hoc networks", *IEEE J. Selec. Areas Commun.*, vol. 30, no. 2, pp. 297–306, 2012.

[25] N. Pratas, N. Marchetti, N. Prasad, A. Rodrigues, and R. Prasad, "Adaptive counting rule for cooperative spectrum sensing under correlated environments", *Wirel. Personal Commun.*, vol. 64, no. 1, pp. 93–106, 2012.

[26] C. Oestges *et al.*, "Experimental characterization and modeling of outdoor-to-indoor and indoor-to-indoor distributed channels", *IEEE Trans. Veh. Technol.*, vol. 59, no. 5, pp. 2253–2265, 2010.

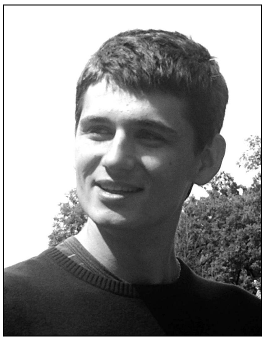
[27] M. Gudmundson, "Correlation model for shadow fading in mobile radio systems", *Electron. Lett.*, vol. 27, no. 23, pp. 2145–2146, 1991.

[28] S. R. Saunders, *Antennas and propagation for wireless communication systems*. Wiley , 1999.

[29] B. Kasiri and J. Cai, "Effects of correlated shadowing on soft decision fusion in cooperative spectrum sensing", in *Proc. IEEE Conf. Comp. Commun. Worksh. INFOCOM 2010*, San Diego, CA, USA, 2010, pp. 1–6.

[30] N. Patwari and P. Agrawal, "Effects of correlated shadowing: Connectivity, localization, and rf tomography", in *Proc. Int. Conf. Inform. Proces. Sensor Netw. IPSN 2008*, St. Louis, MI, USA, 2008, pp. 82–93.

[31] Ofcom, "Digital dividend: cognitive access. statement on license-exempting cognitive devices using interleaved spectrum", 2009 [Online]. Available: http://stakeholders.ofcom.org.uk/binaries/consultations/cognitive/statement/statement.pdf (accessed: 04/12/2013).



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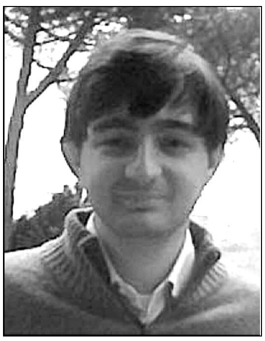

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