Impact of mobility in cooperative spectrum sensing: theory vs. simulation

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***Abstract*—This work addresses the problem of cooperative spectrum sensing in cognitive radio networks, focusing on the impact of mobility on performance of cooperative sensing. First, a review of the most recent results on cooperative spectrum sensing is provided, resulting in the identification of measurement correlation and frame error rate in the reporting channel as the main parameters influencing the performance of cooperative sensing schemes. Next, the paper discusses the extension of the analysis to the case of mobile sensors, and determines the set of assumptions made in existing literature when taking into account mobility in sensing. The paper moves then to remove some of such assumptions, by presenting simulation results obtained in presence of realistic models for propagation in the considered area, as well as of a realistic mobility model. A comparison between theoretical derivation and simulation results shows that correlation among measurements taken by different sensors and the selected mobility model may significantly affect the sensing performance.**

I. Introduction

Spectrum sensing is a key means of radio environment information acquisition for cognitive radio purposes. It does, however, present a number of challenges affecting its viability in opportunistic secondary spectrum usage scenarios. First, it struggles to achieve the required sensitivity in detecting the presence of a primary signal without being configured in such a way that the probability of falsely detecting such a signal is excessively high [1]. Moreover, spectrum sensing is affected by localized shadowing and fading characteristics, meaning that in reality, complex networks of spectrum sensors placed in different locations are required to reliably detect the presence of the signal [2]. This presents a number of questions, including: How many such sensors are required, in which locations? How do they communicate with the decision making entity? How do you select which sets of information from sensors to use (or which redundant information to neglect)? How do you handle security issues, such as sensors maliciously reporting false information? Such challenges and unknowns have been a large influencing factor in regulatory decisions to remove spectrum sensing as a requirement in the TV white space arena [3], [4]. Nevertheless, regulators are keen to bring concepts such as spectrum sensing back into the fold as soon as they are proven viable and not likely to significantly adversely affect the market potential for pioneering technologies [5]. Spectrum sensing performance particularly in terms of cooperative/collaborative sensing can be improved. Taking advantage of mobility of spectrum sensors is a largely under-investigated means of improvement in performance for sensing. Through mobility, samples may be taken at a range of locations, which in the case of fixed sensors being deployed would very quickly lead to a very large number of sensors being required to achieve a similar performance. Mobile devices with spectrum sensing capabilities embedded can effectively test the spectrum in various locations as the user moves, without the users knowledge, with one sensor therefore being able to act as if it were many tens of even hundreds of stationary sensors. Moreover, in many cases such as TV white space, such is the slowly changing nature of spectrum usage that a single sensor might effectively cover a very large number of locations before it becomes necessary to update the spectrum usage information it has reported.

Moving from the above observations, in this work recent developments in cooperative spectrum sensing and sensing in presence of device mobility are reviewed, and open issues are identified. The work moves then to define a set of scenarios foreseeing multiple sensing devices in presence of mobility, and analyzes sensing performance in such scenarios, in order to compare with results from pre-existing literature.

The paper is organized as follows: Section II analyzes recent works focusing on performance of cooperative sensing schemes; Section III focuses on previous work on sensing in presence of mobility, and identifies the assumptions adopted in deriving performance bounds. Section IV introduces then scenarios foreseeing sensing in presence of mobility that remove some of the above assumptions, and Section V analyzes performance of sensing in presence of mobility in such scenarios. Finally, Section VI draws conclusions.

II. Cooperative sensing in fixed wireless networks

Solutions for cooperative spectrum sensing in networks of terminals in fixed positions have been widely investigated in the past [2], [6], [7], [8], [9]. In this section the relation between communications and sensing performance in such scenario will be discussed. Firstly, transmission delays and latency of the network increase the sensing and processing time and reduce the agility of the system; secondly, transmission errors also have a direct impact on the detection performance by impacting detection and false-alarm probabilities as shown in the following by adopting a simple network model where the reliability of communication is characterised by the frame-error probability (see [10] for additional details; similar results can be found in [11]).

The model foresees a set of N_S terminals connected to a fusion centre through packet-loss channels. The k-th terminal is characterized by its false-alarm and detection probabilities $P_{fa}^{(k)}$ and $P_d^{(k)}$, respectively, and the communication channel between the k-th sensor and the fusion centre is described by a packet-loss channel with frame-error probability $P_e^{(k)}$. The network state is described by a vector of random variables $\mathbf{E} = [E_1, \cdots, E_n]$, with elements $E_k \in \{0, 1\}$. The random variables E_k indicate whether the k-th channel is in error or not, and they are distributed as follows: $Pr\left(E_k = 1\right) = P_e^{(k)}$ and $Pr\left(E_k = 0\right) = 1 - P_e^{(k)}$. The fusion centre is characterized by its false-alarm and detection probabilities $P_{fa}\left(\mathbf{E}\right)$ and $P_d\left(\mathbf{E}\right)$, which are now conditioned on the network-state vector $\mathbf{E}$. The network-state vector indicates in this case which packets are available to the fusion centre for decision making. Based on the model introduced above, general expressions for the average false-alarm and detection probabilities $\overline{P}_{fa}$ and $\overline{P}_d$ can be derived as the expected value of the probabilities $P_{fa}\left(\mathbf{E}\right)$ and $P_d\left(\mathbf{E}\right)$, averaged over all network-state vectors $\mathbf{E}$:

$$\begin{aligned}\overline{P}_{fa} &= E_{\mathbf{E}}\left\{P_{fa}\left(\mathbf{E}\right)\right\} = \\ &= \sum_{s_1,\cdots,s_{N_S}} P_{fa}\left(\mathbf{E} = [e_1, \cdots, e_{N_s}]\right) \prod_{k=1}^{N_S} \Pr\left(E_k = e_k\right)\end{aligned} \tag{1}$$

and

$$\begin{aligned}\overline{P}_d &= E_{\mathbf{E}}\left\{P_d\left(\mathbf{E}\right)\right\} = \\ &= \sum_{s_1,\cdots,s_{N_S}} P_d\left(\mathbf{E} = [e_1, \cdots, e_{N_S}]\right) \prod_{k=1}^{N_S} \Pr\left(E_k = e_k\right).\end{aligned} \tag{2}$$

In order to better illustrate the effect of packet losses in the network on the sensing performance, let us focus on the special case where all channels experience the same frame error probability $P_e^1 = P_e^1 = \cdots = P_e^{N_s} = P_e$. It is furthermore assumed that the fusion centre chooses a conservative decision rule such that whenever no sensing information is available (i.e., $\mathbf{E} = \mathbf{1}$), the fusion centre decides that the sensed spectrum is occupied. It follows immediately that $P_{fa}\left(\mathbf{E}\right) = 1$ and $P_d\left(\mathbf{E}\right) = 1$. Under these assumptions, one gets the following lower bounds on the average false-alarm and detection probabilities:

$$\overline{P}_{fa} = 1 \cdot P_e^{N_S} + \sum_{e \neq 1} P_{fa}\left(\mathbf{E} = \mathbf{e}\right) \prod_{k=1}^{N_S} \Pr\left(E_k = e_k\right) > P_e^{N_S} \tag{3}$$

and

$$\overline{P}_d = 1 \cdot P_e^{N_S} + \sum_{e \neq 1} P_d\left(\mathbf{E} = \mathbf{e}\right) \prod_{k=1}^{N_S} \Pr\left(E_k = e_k\right) > P_e^{N_S}. \tag{4}$$

The first bound on the average false-alarm probability provides interesting insights. The false-alarm probability can be seen as a measure for the effectiveness of the sensing algorithm and the decision making process. That is, the higher the false-alarm probability, the more spectral holes are not detected and the more opportunities are lost. Accordingly, it is typically desired that the false-alarm probability stays below a certain upper bound (see e.g. [12]). As the inequality above indicates, this is only possible if $P_e^{N_S}$ is below the given threshold. One can then use the threshold for the highest acceptable false-alarm probability to define a quality of service constraint for the frame-error probability in the network as follows:

$$P_e < \sqrt[N_S]{P_{fa}^{(Th)}}. \tag{5}$$

As we can see from this inequality, there exists a tradeoff between the frame-error probability P_e in the network and the number of sensors N_S: to meet the false-alarm constraint, one can either increase the reliability of communication on the links while keeping the number of sensors constant, or allow for a higher frame-error probability in the network and compensate for it by increasing the number of sensors. That is, reliability is increased through diversity.

It is interesting to note, however, that an increase in the number of sensors is only beneficial to the performance of cooperative spectrum sensing when the requirement on the false alarm probability is not too close to the lower bound defined as a function of the frame-error probability on the reporting channels. In particular, in [13] it is shown that the average false alarm probability defined above can be approximated as:

$$P_{fa} > P_{fa}^{min} = 1 - (1 - P_e)^{N_s} N_s P_e \tag{6}$$

where, as defined above, P_e is the frame error probability on the reporting channels and N_s is the number of sensors. It is proven in [13] that an increase in N_s may lead to a worse performance in terms of probability of missed detection P_{md} when the requirement on P_{fa} is set very close to the lower bound P_{min} . Such result highlights the key role of the reporting channel on the performance of cooperative spectrum sensing: in the case of a very noisy reporting channel (high P_e), the cognitive network would be forced to operate with a high probability of false alarm in order to guarantee the required probability of detection. Under such conditions even increasing the number of sensors would not help in improving performance. Achieving a low P_e is thus fundamental in order to take full advantage of cooperation in spectrum sensing. Several approaches can be followed in order to meet this goal:

- In [13] it is proposed to take advantage of transmit diversity for the transmissions from sensors to the BS by organizing them in pairs, that create a virtual antenna by means of Space Time Block Coding.
- A subset of devices characterized by a good channel towards the BS can be selected as reflectors of the local sensing decisions, leading to a clustered network, as suggested in [8], [9].

Actual performance of cooperative spectrum sensing is also heavily affected by the presence of correlation between the propagation channel from the primary user and different sensors in the cognitive network. The work in [14] analyses the impact of correlation between measurements and sensing decisions on cooperative sensing performance: the authors show that as the number of sensors increases, the correlation between the measurements increases as well, reducing and eventually nullifying the positive effect of introducing new sensors in the sensing procedure. For a correlation index as low as 0.2, the net effect of increasing the number of sensors is indeed to reduce the sensing performance as a result of an increased probability of missed detection, confirming that efficient cooperative spectrum sensing requires in most cases the selection of a subset of sensors on the basis of a set of criteria aiming at the maximization of sensing performance.

III. Sensing in mobile networks

The results presented in Section II were derived under the assumption of having the sensing nodes in fixed positions. Significantly lower efforts were devoted to the analysis of spectrum sensing in presence of mobility; furthermore, research activities mainly focused on the role of mobility in the sensing performance of a single device. In [15], authors analyze the impact of mobility on sensing performance by determining the potential gain achieved by combining multiple measurements taken at different times by a single mobile device, showing that the gain increases as the speed of the device increases, since spatial diversity is proportional to the distance traveled by the device between two measurements. Next, they analyze the gain achievable by combining measurements taken by multiple mobile devices, and propose a formula for determining the sensing performance, expressed by the probability of missed detection, as a function of the number of devices, the number of measurements taken by each device, and the speed of a device. The results presented in [15] are quite interesting, as they highlight the presence of a trade-off between the number of devices and the number of measurements taken by each device; it should be noted however that such results are derived under very strict hypotheses, that are seldom verified in real world. In particular, the work assumes that: 1) all devices move at the same speed; 2) correlation between measurements taken by a device is only dependent on the speed absolute value, and not on direction of movement; 3) measurements taken by different devices are uncorrelated, irrespectively of their actual positions. Furthermore, issues related to variable connectivity induced by mobility were not taken into account at all in the work. It can be expected that when more realistic assumptions are made, in particular related to partial correlation between measurements, performance could be significantly different, as reported at the end of Section II.

Authors in [16] move from the work in [15], by correcting some of the approximations introduced in it to obtain the expression of the probability of missed detection, providing thus a better estimation of the sensing performance as a function of speed and number of measurements taken by a single device. The work still relies however on some of the hypotheses adopted in [15], in particular the hypothesis of constant movement direction, so that performance only depends on speed absolute value calling for additional efforts for addressing the impact of mobility on sensing under realistic scenarios. Such scenarios are identified in the next section, and analyzed by simulation in Section V.

IV. Scenarios for Spectrum Sensing using Mobile Sensors

Numerous scenarios for secondary sensing using mobile sensors can be envisioned. This paper concentrates on two such scenarios: (i) an infrastructure-based network such as IEEE 802.22 [17] opportunistically using licensed spectrum, and (ii) a peer-to-peer communications scenario opportunistically using spectrum, which might not be licensed spectrum due to the challenges involved or otherwise might require express permission/allowance by the spectrum license owner. Case (i) is relatively simple to envision as there will already be a communication means existing between the mobile devices operating in slave mode and the infrastructure. Moreover, the presence of the infrastructure will lend well to the computation of information by a powerful infrastructure-based decision making taking advantage of information sent by a large number of sensors. Case (ii) is a lot more challenging, and in many situations will involve a far smaller number

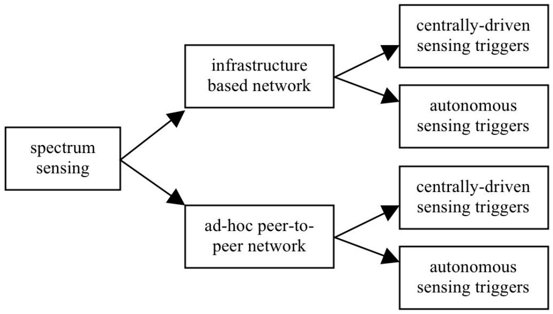

Fig. 1. The considered scenario tree for mobility-based spectrum sensing.

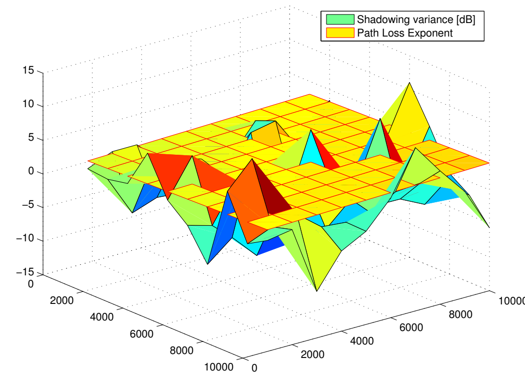

Fig. 2. Values assigned to the propagation parameters (shadowing variance and path loss exponent) within the simulation area.

of sensors and likely a lower allowed transmission power in opportunistic accesses. Although we are not assuming the presence of a database in this paper, cases (i) and (ii) might respectively be seen as somewhat reflective of Mode 2 and Mode 1 devices according to FCC terminology [3]. Another key aspect of the investigated scenarios is the requirement for reporting information on spectrum measurements and the associated frequency of updates of the spectrum availability picture by the central decision making entity. There are two possibilities that can be assumed here: (i) a hard limit on updating of spectrum picture, e.g., once every 24 hours for example as is assumed at least for checking with a geolocation database, and (ii) a best-effort service, where updates to the spectrum availability picture are driven as and when mobile devices are able to send information to the central entity. For the purpose of this paper, it is assumed that for case (i) the central decision making entity polls for sensing to be done, or determines policies that are executed in mobile devices specifying when sensing is done and results are sent. Using such an approach, the central entity might plan ahead, based on known/predicted mobilities of devices, for sensing to be done at certain locations by the devices in order to produce the best possible picture within the given 24-hour sampling period. For case (ii), it is assumed that sensing is automatically done by mobile devices and results sent to the central decision making entity with either a given periodicity, or based on another autonomously-determined trigger (e.g., the device noticing a significant change in power level on a channel thereby knowing that the environment has changed, triggering sensing to take that into account). Based on the above arguments, Figure 1 depicts the scenario tree that is considered in this paper. The analysis based on simulation presented in the next Section focuses on the case of an ad-hoc peer-to-peer network where sensing takes place periodically, e.g. under the input of a centrally-driven trigger.

V. Simulation results

Simulations were carried out to evaluate the performance of sensing algorithm when the measurements are obtained through energy detection at different sensors moving throughout a squared area of 10 km by 10 km. As the degree of correlation among multiple measurements is one of the main factors determining the efficiency of cooperation among sensors, simulations took into account the presence of both spatial and temporal correlation among measurements, thus removing one of the idealistic assumptions identified in Section III. In order to take correlation into account, the simulation area was subdivided in regions characterized by similar propagation conditions, namely the path loss exponent and shadowing attenuation as depicted in Figure 2. The values were selected avoiding sharp variation between adjacent sections, which are hence characterized by a non-null correlation factor.

The licensed user was kept at a fixed position in the center of the area, and transmitted at the constant power of 30 mW, whereas sensors moved according to the Random Waypoint model [18], thus also removing the hypothesis on constant speed and direction adopted in previous works.
Sensing was performed periodically over 200 seconds according to two-phase scheme characterized by a sensing phase of duration equal to $2s$ and an exchange phase of $1s$; in the proposed scheme each device takes samples during the sensing phase with a rate of 10 samples/s, leading to a total number of 200 samples per sensing phase.The device takes then its individual sensing decision, and communicates the decision to the other devices during the subsequent exchange phase. Overall, a combined decision is taken every 3 seconds, leading to $200/3 \approx 66$ combined decisions. During simulations each device moved at a speed of 15 m/s, with a pause time between two movement periods of 0.5 s.
Three fusion rules were considered, namely AND, OR, majority rules, according to which the primary transmitter is considered present only if all sensors (AND), any sensor (OR), or the majority deliver a positive report. Figure 3 shows the variations of the probability to detect the primary transmission as a function of the number of sensors involved in the detection process for the three rules. As expected, the AND rule leads by far to the worst probability of detection. However, this is compensated by a lower probability of false alarm, which comes usually along with a more efficient utilization of the bandwidth. As an example, this could be the optimal option

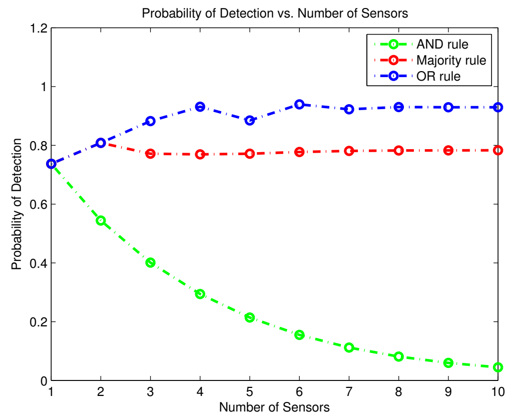

Fig. 3. Probability of detection of primary transmission vs. number of cooperative sensors for different fusion rules (and, or, majority).

for coexisting ad-hoc networks. OR and majority rules present a similar trend; although the probability of detection can be maximized opting for a positive verdict if any sensor reported it, there is again a trade-off to be paid in terms of an increase of the false alarm rate.

The same simulations were also executed considering a fixed sensor network and averaging over multiple runs the assigned random positions: the results were comparable to those represented in Figure 3 in terms of mean value and variance of the probability of detection except for a bigger variance in the case of the AND rule. A possible explanation for this outcome is that both the usage of multiple runs with random positions for the fixed sensors and the adopted mobility model tend to provide uniform measurements over the region. It is left to a following study to assess if a set of sensors moving according to predefined paths are able to improve significantly the achievable performance. It is interesting to note that assuming the same number of devices and sensing decisions, as well as the same propagation characteristics and primary transmission power, the theoretical expression for the probability of missed detection proposed in [15], eq. (13), leads to a probability of detection equal to 1 for 4 or more sensors, highlighting the significant impact of the assumptions identified in Section III on performance evaluation.

VI. Conclusion

This work analyzed the impact of mobility on the performance of cooperative spectrum sensing schemes. The paper first reviewed recent advances on performance evaluation of cooperative sensing schemes in networks of sensors in fixed position, and moved next to the case of mobile sensors, analyzing the assumptions adopted in the few works dealing with such case. The paper then compared the results obtained in such works with those of simulations performed in more realistic conditions, characterized by the presence of correlation between measurements taken by different sensors, and of a more realistic mobility model. The comparison highlights how the assumptions made in the theoretical derivation of performance bounds for cooperative sensing in presence of mobility have a significant impact on the bounds themselves, as shown by the gap between theory and simulation results where such assumptions were partially removed.

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