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Detecting low-power primary signals via distributed sensing to support opportunistic spectrum access

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***Abstract*—Cognitive radio operation with opportunistic spectrum access has been proposed to utilize spectrum holes left unused by a primary system owning the spectrum license. The key of cognitive radio operation is the ability to detect weak primary signals and to control the transmission of cognitive users in a way that interference between the two systems is minimized. In this paper we evaluate how a sensor network deployed to provide distributed spectrum sensing can assist cognitive operation. Specifically, we consider sensor networks with regular topology, where a high level of cooperation also means that sensors far from the source of the primary signal are involved in the sensing process. Assuming energy detection and hard-decision combining we derive worst case probabilities of missed detection and false alarm, determine the necessary level of cooperation among the sensors and evaluate how the sensor density and the sensing time affect the performance of distributed sensing.**

I. Introduction

Opportunistic spectrum access allows secondary communication when primary licensed networks do not fully utilize the allocated spectrum [1] [2], or gives opportunity for low-priority communication when the primary system is using an open spectrum band, but its performance should not be negatively affected by the secondary system. The secondary system therefore has to operate in a cognitive way, adapting its transmission parameters in terms of used frequency band and transmission power, such that the interference caused to the primary receivers is below a predefined level [3]. The detection of primary signals is therefore crucial for opportunistic spectrum access. The reliability of signal detection at the secondary transmitter is however limited by attenuation due to path loss, fading and shadowing [4], and distributed sensing, that is the cooperation of several sensing nodes, has been proposed to improve the quality of sensing [5].

Distributed sensing based on measurements conducted by the secondary users performs well, if there is a high number of users in the area of opportunistic access [6] but becomes unreliable if the number of secondary users is small or if their spatial distribution is unbalanced. Therefore, in this paper we investigate the scenario when distributed sensing is performed by a sensor network deployed to assist opportunistic spectrum access as proposed in [7]. We consider the case when the primary and secondary systems operate in similar scale in terms of transmission power, such as the scenarios when the primary system is a cellular communication network or a wireless local area network. We address the challenge of detecting primary signals generated by mobile transmitters at unknown locations. Considering opportunistic access in a single frequency band we study the worst case signal detection performance of the fixed sensor network examining different levels of sensor cooperation.

The remainder of the paper is organized as follows. In Section II we discuss related work on spectrum sensing for opportunistic spectrum access. Section III describes the target networking scenario. We derive analytic expressions on the sensing performance, considering the probability of false alarm and missed detection in section IV and present numerical results in section V. Section VI concludes the paper.

II. Related Work

Previous work in the area of distributed sensing for cognitive operation has mainly been focusing on the problem of cooperative detection of a single, high power primary source, like Digital TV broadcaster. Authors in [5] analyze how cooperative sensing of TV signals reduces the requirements for single sensors in terms of channel detection times and reliability of observations. In [8] and [9] it is concluded that cooperative sensing can provide high reliability spectrum measurements in fading environments, where single sensor performance is not acceptable. In [9] a tradeoff between the level of sensor cooperation and delay overhead is also studied. The signal detection in these papers is based on energy detection schemes though lately more sophisticated techniques have been introduced as well [10]. Experimental results for single and cooperative sensing with energy detection are presented in [11]. Authors in [12] study the performance of cooperative sensing under hard decision combining and OR and AND decision rules, while [13] extends the study to include log-likelihood ratios and weighted hard combining. In [14] distributed sensing over multiple frequency bands is considered. An optimization problem with an efficient sub-optimal solution is defined that maximizes the rate of a

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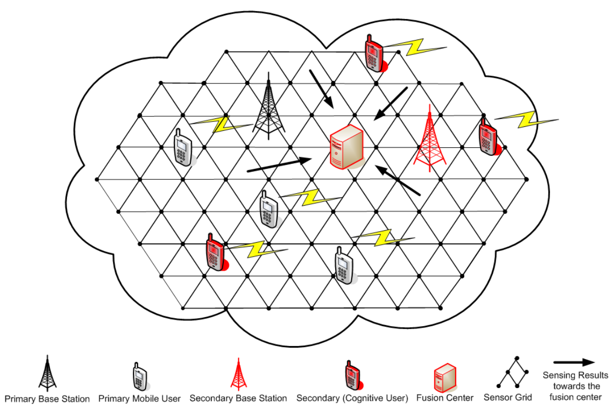

Fig. 1. Detailed description of Sensor Network Architecture. The primary and secondary system coexist, the sensor network is a fixed triangular grid.

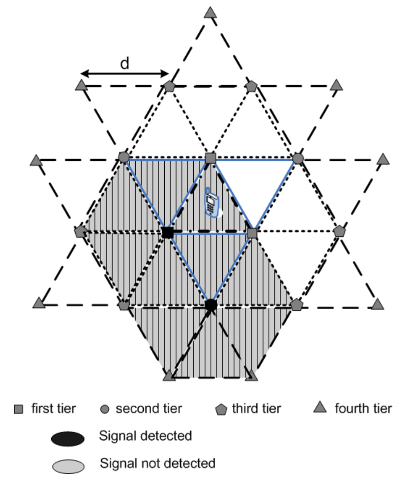

Fig. 2. Construction of sensor tiers in case of a triangular grid. PU lies in the middle point of the central triangle. The shaded part denotes the PT location estimation.

secondary user transmitting in all the available bands. Finally, a scenario similar to the one in our work is considered in [6], as it addresses the case when the secondary system operates on the same spatial scale as the primary one. It assumes collaboration among the secondary nodes and investigates the required node density for reliable signal detection. Based on channel budget calculations it concludes that an unrealistically high density of active secondary users is necessary under realistic values of signal attenuation.

III. System Description and Problem Formulation

Figure 1 depicts the networking scenario addressed in this paper. The primary and secondary nodes - base stations and mobile users - are located in the same area. The sensor network is deployed to provide spectrum availability information assisting the interference management at the secondary users. Interference management is necessary to control the cognitive operation of secondary users, since a secondary signal should not interfere, either at all or beyond a prescribed interference level, with a primary signal at the location of a primary receiver. As the location of primary mobile users is not known, two approaches of interference management are *possible*: a*)* Trying to locate the primary transmitter and then prevent secondary transmitters located in the circular region centered at the primary transmitter's position and with radius equal to the sum of the coverage radii of primary and secondary transmitters from transmitting; *b)* Considering each point where a primary signal is detected, and the region around it as a potential location of a receiver and instructing the secondary transmitter to set its transmit power such that its signal does not reach these regions. In this work we address the problem of locating the primary transmitter and leave the details of interference management for future studies. Since the location of the mobile primary transmitters is not known, the sensor network has to cover the whole area of cognitive operation. We assume that the secondary users and the sensor network operate in a time-slotted manner, and the sensors are slot-synchronized. The sensor network conducts spectrum measurements and reports spectrum availability information at the beginning of a time-slot, secondary users may then transmit until the end of the time-slot. Since primary user transmission is then detected within a time-slot, the duration of the slots has to be selected based on the interference constraints of the primary system. Information provided by the sensors can be collected at a fusion center that decides on the presence and possible location of a transmitter or it can be distributed via gossiping, in which case decisions are made at the secondary users. The way of information distribution and its costs in terms of delay and transmission bandwidth are not considered in this paper. However, to limit the amount of information to be collected, we consider hard decision combining, that is, each sensor shares only its "only noise" or "signal present" decision. We evaluate the OR (occupied if at least one sensor decides for signal present) fusion rule in detail and comment on the AND (occupied if all sensors decide for signal present) operation and the more general k-out-of-n rule. For simplicity we consider energy detection to make local hard decisions at each sensor.

We evaluate the performance of the sensor network in terms of global false alarm probability and global probability of missed detection, defined as the probability that the system decides for the presence of the signal when the signal is not present, and the probability that it decides for a free band when the band is occupied. The probability of missed detection must be bounded at a predefined level in order to keep the interference caused by the cognitive users to the primary system limited, while the probability of false alarm should be as low as possible to increase the throughput of the secondary system.

The critical issue is to determine the set of sensors that should cooperate to achieve a common decision. The existence of an optimal cooperation level can be expected by noticing that beyond a given number, additional sensors that are added to the cooperative decision increase the probability of false alarm, since there are more nodes that can erroneously detect a signal when only noise is present, while they do not decrease the probability of missed detection as they do not receive enough signal power because of their distance from the primary source. Therefore we have to evaluate the sensing performance as a function of the geographical area where sensors cooperate. As shown in Figure 2 the sensor network investigates the existence of a primary transmitter in a specific location by considering the set of sensors around this location. We denote the set of sensors having the same distance from the center of a cell formed by adjacent sensors as *tiers*. In the case of a triangular grid the first tier consists of the three sensors forming the smallest triangle, the second one of the three sensors forming triangles with first tier sensors, and so on. Then, under *m*-tier cooperation and OR decision rule a transmitter is detected within the area of the first tier if any of the *m*-tier sensors detect a signal. Such cooperative decision can be performed centrally at a fusion center or in a distributed way with m-hop gossiping. Note that the granularity of the primary transmitter localization depends on the decision rule, the sensor distance and the level of cooperation. Figure 2 shows with a grey area the possible location of the primary transmitter under OR decision and single-tier cooperation if two neighboring sensors detect the signal.

IV. Distributed Sensing Model

We first describe the primary channel model considered for the performance evaluation of the sensor network. Then we give the analytic model of local and distributed sensing. To define the channel model we have to further specify the considered networking scenario. We consider a urban or dense-urban environment and slowly moving primary users communicating in the 2GHz frequency band. As for the sensor network, we consider neighboring sensor distance in the range of 50-100 meters and sensing time in the range of milliseconds to leave time for the cognitive transmission.

A. Channel model

Let N be the number of sensors that monitor the band of cognitive operation. In this work, for simplicty, we assume a Rayleigh flat-fading channel, so that the equivalent baseband channel between a primary transmitter and sensor l can be written as

$$h_l = \frac{1}{\left(d_l/d_0\right)^{\eta/2}} e^{j\phi_l} \alpha_l \, 10^{\zeta_l/20},$$

where d_l is the distance between transmitter and sensor l, d_0 is a close-in reference, η is the path loss exponent, α_l is a Rayleigh distributed random variable accounting for small-scale fading, with p.d.f. $p\left(\alpha\right) = 2\alpha\, exp\left(-\alpha^2\right)$, ϕ_l is a random phase shift uniformly distributed in the interval $\left[-\frac{\pi}{2}, \frac{\pi}{2}\right]$, whereas ζ_l is a zero mean Gaussian random variable representing the log-normal shadowing.

The correlation distance of the small scale fading is in the order of tens of wavelengths. For carrier frequencies around 2GHz the wavelengths are in the order of 15 cm, hence the random variables α_l, $l = 1, \ldots, N$, are uncorrelated. The correlation distance of the shadowing attenuation depends on the considered propagation scenario. For urban or dense-urban scenarios the correlation distance of the shadowing effects is in the range of 5 and 50 meters [15]. Thus, we can assume that even the variables ζ_l, $l = 1, \ldots, N$, are uncorrelated.

Considering fixed or slowly moving users for the primary network, and allowing other objects, i.e. possible scatterers, to move at a speed of up to 10 m/s, the channel coherence time is in the order of 5 ms. Therefore within a sensing interval we can consider the channel as slowly fading, which means that for a sensing interval we can assume the same realization of α_l at sensor l. To simplify modelling we do not consider channel frequency selectivity, the extension however is straightforward.

B. Distributed spectrum sensing

To perform spectrum sensing in the band of interest, each sensor filters and down-converts to baseband the received signal. At some point, the continuous-time signal is sampled, so that detection can be performed in the digital domain. Let K be the number of samples of the received signal used for the decision making process. Clearly, the number of samples is at least twice the product of the bandwidth of the sensed band and the sensing time.

We denote the "only noise" and the "signal present" hypotheses by $\mathcal{H}_0$ and $\mathcal{H}_1$, respectively. The received baseband discrete time signal at sensor l, under the two hypotheses, can be written as

$$\begin{array}{ll} \mathcal{H}_0 : & r_l\left[k\right] = v_l\left[k\right] \\ \mathcal{H}_1 : & r_l\left[k\right] = h_l s\left[k\right] + v_l\left[k\right] \end{array}, \ \forall l \in \{1, \ldots, N\}$$

where $r_l\left[k\right]$ is the k-th sample, $k = 1, \ldots, K$, h_l is the channel coefficient between the primary transmitter and sensor l, $s\left[k\right]$ is the transmitted signal, and $v_l\left[k\right]$ is an AWGN noise realization with variance σ^2. In this work, for simplicity, we assume that the signal has a constant value, i.e. $s\left[k\right] = s$, $\forall k = 1, \ldots, K$, however the same line of reasoning that we outline in this work can be applied with more realistic signal models.

Assuming energy detection, the local decision test is given by

$$y_l \triangleq \sum_{k=1}^{K} \left|r_l\left[k\right]\right|^2 \underset{\mathcal{H}_0}{\overset{\mathcal{H}_1}{\gtrless}} \gamma_0,$$

where y_l is the energy of the received signal and γ_0 is a local decision threshold. We assume that γ_0 can range from as low as noise energy.

Closed form expressions are well known, see e.g. [16], for the probability density function of this kind of test statistic. In particular the test statistic under $\mathcal{H}_0$ is a chi-square random variable with $2K$ degrees of freedom and mean $K\sigma^2$. That is, omitting index l for simplicity,

$$p_Y\left(y; \mathcal{H}_0\right) = \frac{1}{\sigma^{2K}\Gamma\left(K\right)} y^{K-1} e^{y/\sigma^2}.$$

Under hypothesis $\mathcal{H}_1$, conditioned on the specific realization of the fading random variables α_l and ζ_l, and on the position of the transmitter, the probability density function is a noncentral chi-square with $2K$ degrees of freedom

$$p_Y\left(y; \mathcal{H}_1/\alpha, \zeta\right) \;=\; \frac{1}{\sigma^2}\left(\frac{y}{q^2}\right)^{\frac{(K-1)}{2}} e^{-\frac{\left(q^2+y\right)}{\sigma^2}} I_{K-1}\left(\sqrt{y}\frac{2q}{\sigma^2}\right),$$

where we have used the quantity $q^2 \triangleq P_S K \frac{10^{\zeta_s/10}\alpha_s^2}{(d_l/d_0)^\eta}$, P_S being the transmitted signal power in the considered band, i.e. $P_S = |s|^2$, and $I_K(\cdot)$ is the K-th order Bessel modified function of the first kind.

The *local* false alarm probability $p_{fa} \triangleq Pr\{y > \gamma_0; \mathcal{H}_0\}$ and miss detection probability $p_{md} \triangleq Pr\{y \leq \gamma_0; \mathcal{H}_1\}$, are given by

$$\begin{aligned} p_{fa} &= \int_{\gamma_0}^{+\infty} p_Y(y;\mathcal{H}_0)\, dy \\ p_{md}(d_l) &= \int_0^{\gamma_0}\int_0^{+\infty}\int_{-\infty}^{+\infty} p_Y(y;\mathcal{H}_1/\alpha,\zeta)\, p(\zeta)\, p(\alpha)\, d\zeta d\alpha dy. \end{aligned}$$

Next we derive P_{FA} and P_{MD}, the false alarm and missed detection probabilities after the cooperative decision. Clearly, P_{MD} depends on the position of the transmitter within the first sensor tier. Here we consider the worst case position under OR decision rule, which is the center of the first tier triangle[1]. We consider the same γ_0 value at each sensor and assume that local decisions are independent, based on the channel model given in section IV-A.

We define the set of ordered pairs (n_i, d_i), which corresponds to the i-th cooperative sensor tier: n_i is the number of sensors in the i-th tier, while d_i is the distance between the center of the first tier and the sensors of the i-th tier. This distance is related to the distance d between adjacent sensors in the grid which is a parameter in our problem formulation.

If m is the number of cooperating tiers and $n = \sum_{i=1}^m n_i$ the total number of cooperating sensors, then the *k-out-of-n* rule implies that if at least k out of n sensors have made a positive decision on the existence of a primary source, the cooperative decision adopts this positive decision, otherwise it decides that there has been no primary user active at the corresponding time period, that is,

$$\begin{aligned} &P_{FA} = \\ &= Pr\{at\ least\ k\ sensors\ give\ false\ alarm\} \\ &= 1 - Pr\{less\ than\ k\ sensors\ give\ false\ alarm\} \\ &= 1 - \textstyle\sum_{i=0}^{k-1} \binom{n}{i} (p_{fa})^i (1-p_{fa})^{n-i} \end{aligned} \quad (1)$$

and

$$\begin{aligned} &Pr_{MD} = \\ &= Pr\{at\ least\ n-(k-1)\ sensors\ miss\ detection\} \\ &= \textstyle\sum_{j=(n-k+1)}^{n} Pr\{j\ sensors\ miss\ detection\} \\ &= \textstyle\sum_{j=n-k+1}^{n} (\sum_{k_1=0}^{n_1} \sum_{k_2=0}^{n_2} \cdots \sum_{k_m=0}^{n_m} (\\ &\tbinom{n_1}{k_1} (p_{md}(d_1))^{k_1} (1-p_{md}(d_1))^{n_1-k_1} \ldots \\ &\tbinom{n_m}{k_m} (p_{md}(d_m))^{k_m} (1-p_{md}(d_m))^{n_m-k_m})), \\ &k_1 + k_2 + ..k_m = j. \end{aligned} \quad (2)$$

The OR and the AND decision rules are extreme cases of the general *k-out-of-n* rule, for $k = 1$ and $k = n$, respectively.

[1]The proof is based on basic analytic geometry, it is omitted due to space limitation.

V. Performance Evaluation

TABLE I
PARAMETER VALUES FOR WLAN AND 3GPP LTE CASE STUDY

Case Study	WLAN	3GPP LTE
Signal Bandwidth (W)	20MHz (all channels)	5MHz
Signal Power (P_0)	15dBm	24dBm
Path Loss (η)	4.5	4
Shadowing (μ, σ^2)	0dBm, 10dB	0dBm, 5dB
AWGN Power (σ^2)	-96dBm	-96dBm
Outage Probability	10^{-3}	10^{-6}
Sensing Time	0.25msec	50μsec
Number of Samples (K)	100	20
Sensed Band Size (B_s)	200kHz	200kHz
Signal Power in Sensed Band ($P_0 B_s/W$)	-5dBm	4dBm

In this section of the paper we study the density requirements of the sensor network in two different scenarios regarding the primary systems: WLAN and 3GPP Long Term Evolution (LTE) networks. Both systems use OFDM modulated signals, but with different transmission power, transmission frequencies and interference constraints [17][15]. Table I depicts the values of the system and sensing parameters we use in the numerical analysis, unless otherwise noted. We consider the sensing of 200kHz band within the frequency range of the primary system, to allow cognitive transmission over OFDM sub-bands.

The topology of the sensor network determines the (n_i, d_i) pairs of i-th tier defined in section IV. Considering the triangular grid and the tested location as the center of the first tier (see Figure 2) the (n_i, d_i) pairs are given as:

$$n_i = n_{i-1} + n_{i-2},$$

and

$$d_i = \begin{cases} d\sqrt{\frac{i^2}{4} + \frac{1}{(2\sqrt{3})^2}}, & i = 2k+1, k \in \mathbb{N} \\ d\sqrt{\frac{i^2}{4} + \frac{1}{\sqrt{3}^2}}, & i = 2k, k \in \mathbb{N}^*, \end{cases}$$

that is, d_i grows linearly with i. Replacing these formulas in (1) and (2), we can calculate the performance metrics for the triangular pattern.

In Figure 3, both performance metrics are plotted for a sensor network with a fixed density, considering the WLAN scenario. The curves correspond to different levels of sensor cooperation, expressed in number of tiers that participate in the cooperative decision. Each (P_{FA}, P_{MD}) pair corresponds to a specific value of the detection threshold γ_0. In this case the lowest P_{MD} and P_{FA} values are achieved by the cooperation of five tiers. Figure 4 compares the OR and AND decision rules for the same scenario considering up to three tiers. The OR decision policy outperforms AND by at least one order of magnitude difference in P_{MD} for the same P_{FA}, and P_{MD} is bounded due to the physical limitations on γ_0. The AND decision performs poor in this scenario because the signals

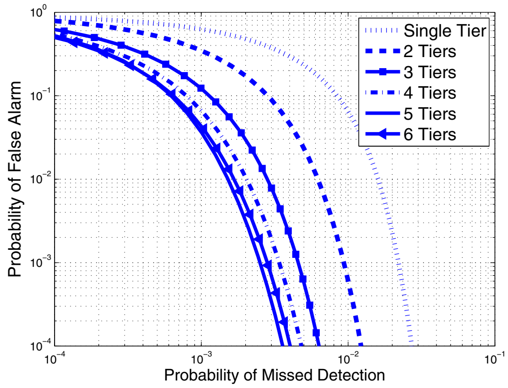

Fig. 3. P_{FA} with respect to P_{MD} for the WLAN case study. $d = 55m$, OR decision rule is applied.

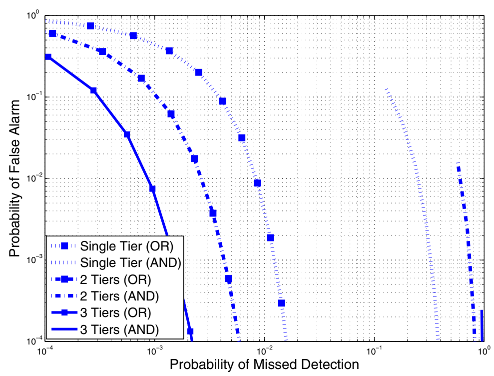

Fig. 4. Comparison between AND and OR decision rules. WLAN case study, $d = 55m$.

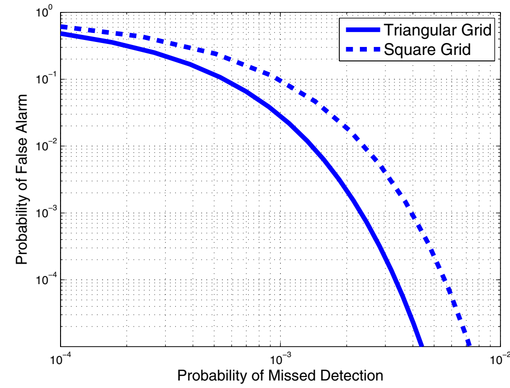

Fig. 5. Best case performance of the triangular and the square grid. WLAN case study, $d = 55m$.

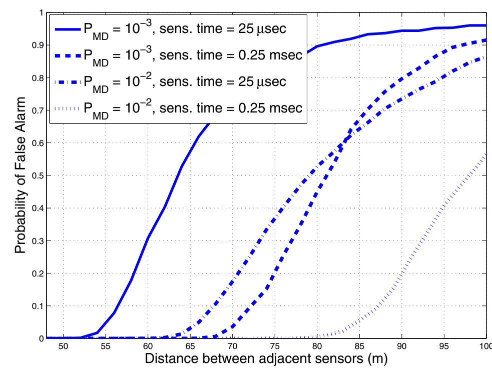

Fig. 6. P_{FA} with respect to network density for different values of sensing time and missed detection probability. OR decision rule.

received by the sensors are very weak and the probability that none of the cooperating sensors misses detection is low even at low γ_0. Increasing sensor density would make the AND decision rule more powerful.

We comment on the effect of the network pattern with Figure 5. The figure compares the performance of the triangular and square grid under optimal level of sensor cooperation. The distance between the adjacent sensors is $\sqrt{\frac{\sqrt{3}}{2}}d$ in the square grid to keep the density equal in the two scenarios. The triangular grid outperforms the square one in this specific case, but general conclusions can not be drawn. We aim at investigating the optimality of the triangular pattern in our future work.

Since the probability of missed detection should be bounded by the allowed outage probability in the primary system, on Figure 6 we evaluate how the false alarm probability changes with the density of the sensor network for various missed detection probability limits and sensing time values. Note that for the secondary users both high false alarm probability and long sensing times decrease throughput. As the figure shows, for all scenarios there is a threshold value of inter-sensor distance d, further increasing d the false alarm probability increases rapidly. The required sensor density seems to be acceptable even with strict constraints on missed detection probability and sensing time.

Figure 7 shows how the sensing time affects the system performance. The marginal gain is large at small sensing times, the probability of false alarm decreases to 0.01 at around 2ms, while further increase of sensing time will not lead to significant performance improvement.

Figures 8 and 9 present the results for the LTE case study with parameters listed in Table I. Opportunistic access of LTE cellular systems requires a very low P_{MD} in the order of 10^{-6}. Furthermore, the sensing time of LTE bands needs to be in the order of microseconds. Figure 8 shows the optimal level of sensor cooperation if the distance of the sensors is d=100m. Again we can see the gain of moving from single tier to multi-tier cooperation schemes. We conclude that the cooperation of four tiers is optimal in this particular case. Figure 9 shows the probability of false alarm as a function of the sensor distance d. We can see that d has to be in the range of 100m. Relaxing the performance requirement in terms of missed detection probability and allowing longer sensing time does not relax the density requirement significantly.

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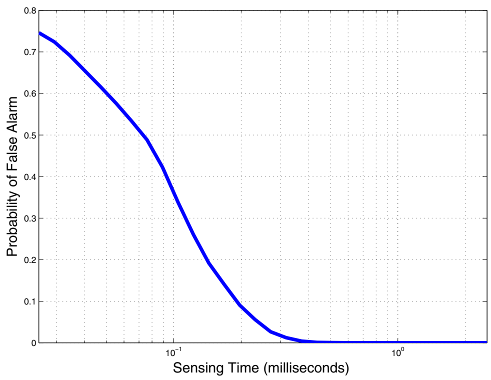

Fig. 7. P_{FA} with respect to sensing time. $P_{MD} = 10^{-3}$, $d = 55m$, OR decision rule.

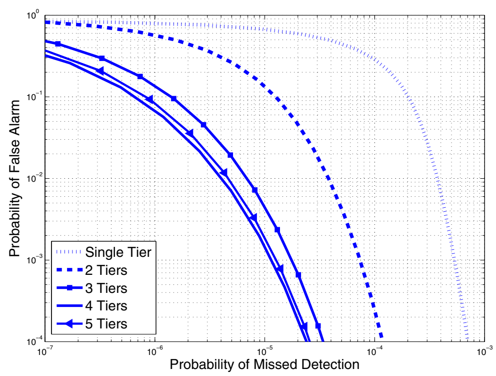

Fig. 8. P_{FA} with respect to P_{MD} for the 3G LTE case study. $d = 100m$, OR decision rule.

VI. Conclusion

In this paper we considered the issue of spectrum sensing to assist opportunistic spectrum access for the case when primary and secondary systems operate on similar scale. We considered the scenario when a dedicated sensor network is deployed to perform the spectrum sensing. We proposed a cooperation model based on sensor tiers and gave an analytic model of the sensing performance that accounts for the increasing distance between the signal source and the sensors as more sensor cooperate. We considered the specific cases when the primary system is a WLAN or a 3GPP LTE network and derived achievable missed detection and false alarm probabilities. We evaluated the sensor network performance as a function of the network density and concluded that the required sensor densities are reasonable and the approach of sensor network assisted opportunistic spectrum access is therefore feasible. Future work will be focusing on the problem of relaxing fixed sensor network density requirements by introducing a hybrid architecture where sensing duty is partially allocated to existing cognitive users.

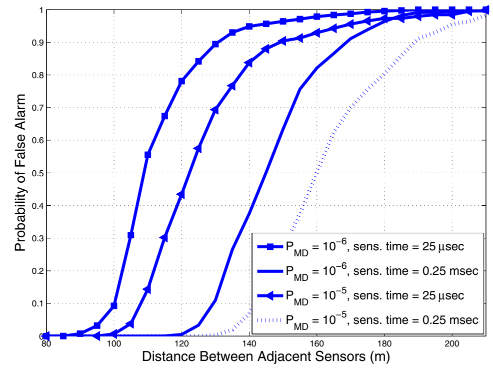

Fig. 9. P_{FA} with respect to network density for different values of sensing time and missed detection probability. LTE case study, OR decision rule.

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