

Data-Selective Cooperative Spectrum Sensing Based on Imperfect Information Exchange

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Abstract—This paper examines the use of set-membership adaptive filters (SMAF) to distributed detection for spectrum sensing when only imperfect estimates of data statistics are available. The first and second central moments of the energy at each sensor node are calculated as sample averages, and the impact of such estimates on the detection performance is evaluated. The use of SMAF for coefficient update allows significant savings in computational complexity per node and also provides good indication of when sharing data is beneficial. Such features are exploited to propose a cooperative strategy of selected energy estimates. The paper also evaluates the impact of packet loss in the control channel on detection performance. For the simulated scenarios, data selection based on the set-membership approach proved to be a valuable tool for distributed detection in cognitive radio applications due to enhanced robustness, power savings, and increased probability of detection.

I. INTRODUCTION

Efficient utilization of frequency spectrum is of the utmost importance as wireless communications systems become pervasive in our society. Cognitive radio (CR) is one powerful tool for alleviating spectrum shortage, for it allows systems with low priority, also known as secondary users (SUs), to use the frequency band previously allocated to other systems with high priority, also known as primary users (PUs), as long as PUs are idle or not operative. In such scenarios, it may not be realistic to rely on the cooperation of the PUs to inform about spectrum availability, e.g., by broadcasting their transmission schedule. SUs may need to *sense* and *detect* dynamically a window of opportunity to operate. If possible, SUs should cooperate constructively for spectrum sensing (SS) to improve detection probability, thus minimizing interference with PUs.

The challenges for cognitive radio are many. Highly flexible and system-independent CRs have little side information to support their decision. They may need to operate blindly in a time-varying scenario, and to cause minimum disturbance to the wireless environment during decision time. SUs may form a heterogeneous network, each facing a different signal-to-noise ratio (SNR) and severe power constraints. The control channel available for exchanging information may be unreliable, prone to package loss due to interference and collision. Furthermore, if SUs are supposed to cooperate, they need to know when, how, and with whom cooperation is advantageous for performance improvement.

In this paper, we advance previously published results on distributed cooperative spectrum sensing based on energy detection. In our chosen scenario, SUs select when to use and to share information, and face imperfect statistics of possibly corrupted data. In addition to improved robustness to imperfect estimation, the scheme is also economical due to reduced number of operations as well as reduced and savvy utilization of the control channel. The scenario is also more realistic than those considered in previous works, for no a priori statistical information is required.

Distributed detection and its application to cognitive radio are not new research topics (see, e.g., [1]–[4] and the references therein). The goal is well known and involves deciding over two hypothesis, H_0 and H_1 , if the channel is in use or not. Over the years, different schemes have been proposed for establishing a proficuous collaboration among SUs. In general terms, sharing hard decisions requires minimum communication overhead at the expense of a performance penalty when compared with more “soft collaboration” schemes. In [5], the authors proposed a linear combination for distributed detection with very good results even when compared with detectors based on the likelihood-ratio test (LRT). Cattivelli and Sayed [6] proposed an adaptive distributed detection with node cooperation where the detection problem was wisely reformulated as an estimation problem. In [7], the linear combiner was made adaptive using the LMS algorithm, and detection was performed in two steps. In a first step, neighbors share their energy estimates and arrive at a local decision using the adaptive linear (soft) combiner. In a second step, local binary decisions are shared and a local consensus (hard) decision is made. The scheme was further simplified in [8] with the adoption of an approach similar to set-membership adaptive filtering (SMAF). Local computation is reduced, for coefficient updates occur only when input data, including contributions from neighbors, are *jointly informative*. The use of the set-membership normalized LMS (SM-NLMS) algorithm was investigated in [9] with the adoption of a variable error bound for the *constraint set*.

II. PROPOSED SPECTRUM SENSING METHOD

The aim of this section is at both describing the system model employed in this work (Subsection II-A) and proposing a new collaboration algorithm which is able to work when imperfect, yet realistic, information exchanges among SUs occur (Subsection II-B).

A. System Model

Consider a setup in which SUs of a given CR network are able to sense the radio spectrum by computing the energy of their acquired RF signals. The resulting *local* energy estimates depend on many facts, such as presence/absence of PUs, fading and shadowing effects, level of environment interference, just to mention a few. *Collaboration* among SUs is key to achieving a reasonable SS performance under demanding practical conditions. Such collaboration allows SU users to share their energy estimates with other CR nodes, thus enabling the combination of spatially distributed energy estimates. The spatial diversity present in this collaborative strategy is able to enhance the white-space detection capabilities of CR nodes.

Mathematically, assume that H_0 and H_1 stand for the hypotheses “absence of PUs’ signals” and “presence of PUs’ signals”, respectively. In addition, consider that each SU in the

network has a unique ID/index. We shall assume the following model for the signal acquired by the m th SU:

$$x_m(n) = \begin{cases} v_m(n) & \text{if } H_0 \text{ holds} \\ v_m(n) + h_m(n)s_m(n) & \text{if } H_1 \text{ holds} \end{cases}, \quad (1)$$

where $s_m(n) \in \mathbb{R}$ denotes the sum of all PUs' signals at a given discrete-time instant $n \in \mathbb{Z}$ which can be acquired by the m th SU,¹ $h_m(n) \in \mathbb{R}$ denotes the corresponding channel attenuation (assuming to be constant during the measurement window), and $v_m(n) \in \mathbb{R}$ is a local zero-mean additive white Gaussian noise (AWGN) with variance $\sigma_m^2 \in \mathbb{R}_+$.

As mentioned before, local energy estimates can be computed by each CR node by calculating

$$y_m(k) = \sum_{n=0}^{N-1} x_m^2(n+kN), \quad (2)$$

in which a window containing $N \in \mathbb{N}$ acquired samples of $x_m(n)$ is employed in this local computation. Now, if we denote the neighborhood of the m th SU as $\mathcal{N}_m \subset \mathbb{N}$, which is the set of SU IDs that can share energy estimates with node m (we consider that $m \in \mathcal{N}_m$), then a possible (and perhaps the simplest) way of combining those energy estimates is through a linear-in-parameter soft combiner, as follows:

$$y(k) = \sum_{l=1}^{|\mathcal{N}_m|} w_l(k)y_{m_l}(k) = \mathbf{w}^T(k)\mathbf{y}(k), \quad (3)$$

where $|\mathcal{N}_m|$ denotes the number of neighbors of the m th node (including itself), $\mathbf{w}(k) = [w_1(k) \ w_2(k) \ \cdots \ w_{|\mathcal{N}_m|}(k)]^T$ is the parameter vector corresponding to the soft combiner, and $\mathbf{y}(k) = [y_{m_1}(k) \ y_{m_2}(k) \ \cdots \ y_{m_{|\mathcal{N}_m|}}(k)]^T$ represents the vector containing the energy estimates of the SUs in \mathcal{N}_m , i.e., $\{m_1, m_2, \dots, m_{|\mathcal{N}_m|}\} = \mathcal{N}_m$. It is worth mentioning that $y(k)$ depends upon the neighborhood \mathcal{N}_m , but we have omitted such dependence in the notation for the sake of simplicity.

Once we have computed the soft combination of energy estimates, the next step is to perform a detection test considering a local threshold $\gamma_m(k)$ that guarantees a pre-defined probability of false alarm P_f , as follows:

$$y(k) \underset{H_0}{\overset{H_1}{\gtrless}} \gamma_m(k). \quad (4)$$

Given the aforementioned model, there are some questions that must be answered: (i) How one can define the parameter vector $\mathbf{w}(k)$ in (3)? (ii) How one can define the local threshold for the detection test $\gamma_m(k)$ in (4)? We address the first question by using a data-selective adaptation algorithm for the determination of the parameter vector $\mathbf{w}(k)$. Regarding the second question, as the coefficients of $\mathbf{w}(k)$ are iteratively updated, we also redefine the decision threshold $\gamma_m(k)$, as we shall explain soon.

Any adaptive filtering algorithm could be employed in order to compute the weights of the soft combiner. We opted for the set-membership normalized least-mean square (SM-NLMS) algorithm [10] since it enjoys good tracking performance in non-stationary environments, data-selective feature, and computational simplicity. In order to recall the updating equation of the SM-NLMS, let us consider a tolerance

$\bar{\gamma}(k) \in \mathbb{R}_+$ associated with the error $e(k) = r(k) - y(k)$ between a reference signal $r(k) \in \mathbb{R}$ (we shall discuss about it later on) and the output of the adaptive filter. Given this definition, the SM-NLMS updating recursion stems from the solution to the optimization problem:

$$\min \|\mathbf{w}(k+1) - \mathbf{w}(k)\|^2 \quad (5)$$

$$\text{subject to: } r(k) - \mathbf{w}^T(k+1)\mathbf{y}(k) = \bar{\gamma}(k) \text{sign}[e(k)], \quad (6)$$

which is given by

$$\mathbf{w}(k+1) = \mathbf{w}(k) + \delta(k) \frac{\mathbf{y}(k)e(k)}{\mathbf{y}^T(k)\mathbf{y}(k)}, \quad (7)$$

where

$$\delta(k) = \begin{cases} 1 - \frac{\bar{\gamma}(k)}{|e(k)|}, & |e(k)| > \bar{\gamma}(k), \\ 0, & |e(k)| \leq \bar{\gamma}(k). \end{cases} \quad (8)$$

We now have to discuss how one can choose the reference signal $r(k)$ and the error tolerance $\bar{\gamma}(k)$. As the average values of the energy estimates $y_m(k)$ convey information about the presence/absence of PUs' signals, then a practical reference signal could be defined as

$$r(k) = \alpha_r r(k-1) + (1 - \alpha_r) \sum_{l=1}^{|\mathcal{N}_m|} y_{m_l}(k), \quad (9)$$

where $\alpha_r \in [0, 1]$ is a forgetting factor that is usually chosen close to one to preserve memory of previous states. Note that this quantity can be computed locally by each SU. In addition, as the error tolerance $\bar{\gamma}(k)$ can be related to the variance of the error $e(k) = r(k) - \mathbf{w}^T(k)\mathbf{y}(k)$, a practical value is

$$\bar{\gamma}(k) = \alpha_\gamma \bar{\gamma}(k-1) + (1 - \alpha_\gamma) \sqrt{\beta \sigma_e^2(k)}, \quad (10)$$

where $\alpha_\gamma \in [0, 1]$ and $\beta \in \mathbb{R}_+$ is a scalar factor heuristically chosen to guarantee reasonable updating savings. In addition, the sample variance $\sigma_e^2(k)$ is computed based on $e(k)$ in a similar manner as (10).

Regarding the detection threshold, we can compute it as

$$\gamma_m(k) = \boldsymbol{\mu}_0^T(k)\mathbf{w}(k) + Q^{-1}(P_f) \sqrt{\mathbf{w}^T(k)\boldsymbol{\Sigma}_{H_0}(k)\mathbf{w}(k)}, \quad (11)$$

where $\boldsymbol{\mu}_0(k)$ is a vector containing the sample mean of $y_l(k)$, for each $l \in \mathcal{N}_m$, and $\boldsymbol{\Sigma}_{H_0}(k)$ is a diagonal matrix with the sample variances of $y_l(k)$, for $l \in \mathcal{N}_m$ (see [9]). The sample means $\mu_{0,l}(k)$, $l \in \mathcal{N}_m$, can be estimated non-cooperatively at each node following (9) during silence periods in which it is known that hypothesis H_0 holds. Then, $\boldsymbol{\Sigma}_{H_0}(k)$ can be obtained through $\boldsymbol{\mu}_0(k)$.

B. Proposed Collaboration Algorithm

In cooperative networks, SUs usually share data without taking into account the *quality* of that information. In [11], a parameter estimation method with selective cooperation based on the behavior of the SM-NLMS algorithm was presented. In this work, we propose a similar SM-NLMS-based selective cooperation strategy for our detection problem in order to decide if the information of one node is valid for its neighbors or not. We consider that, when a given SU does not update its parameter vector, i.e., when $\delta(k) = 0$ in (8), then it is likely that the energy estimate of that node will not be useful for its neighborhood as well. Thus, that information is not shared until the SM-NLMS updates its coefficients. The selective cooperation method is detailed in Algorithm 1.

¹The PUs' signals can be different across different network nodes.

Algorithm 1 Selective collaborative algorithm for the m th SU.

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1: initialize/update  $\mathbf{y}$ ,  $r$ ,  $\mu_0$ ,  $\Sigma_{H_0}$  and  $\mathbf{w}$ 
2: while silence period is on do
3:   sense the channel with the energy estimator
4:   estimate  $\mu_{0,m}$  and compute the sample variance of  $y_m(k)$ 
5: end while
6: share  $\mu_{0,m}$  and the sample variance
7: if neighbors' statistics were received then
8:   update  $\mu_0$  and  $\Sigma_{H_0}$ 
9: end if
10: compute detection threshold  $\gamma_m$ 
11: while silence period is off do
12:   sense the channel with the energy estimator
13:   update the reference signal  $r$  with the energy estimates  $\mathbf{y}$ 
14:   run SM-NLMS with input  $\mathbf{y}$  and  $r$ 
15:   if  $\mathbf{w}(k+1)$  was updated then
16:     share  $y_m$ 
17:     compute detection threshold  $\gamma_m$ 
18:   end if
19:   if neighbors' energy estimates are received then
20:     update  $\mathbf{y}$ 
21:     compute the reference signal  $r$ 
22:   end if
23:   make the hypothesis decision
24: end while

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III. SYSTEM EVALUATION

In this section, the proposed collaborative framework is assessed by simulation. The analysis is performed from three viewpoints: (i) comparing the performance of the proposed selective-cooperation with its non-selective counterparts using both perfect and imperfect data knowledge; (ii) studying some critical parameters which affect the overall performance such as packet loss (PL) and the choice error threshold $\bar{\gamma}(k)$ employed by the SM-NLMS algorithm; and (iii) evaluating the savings which data-selective strategies yield.

The simulation setup is composed of a CR network with 5 SUs with SNRs = [10.4, 5.1, 9.3, 8.6, 2.6] dB and noise variances $\sigma_m^2 = [0.7, 1.3, 1, 1.8, 0.9]$. The assessment is done at nodes 2, 4, and 5, whose neighborhoods are $\mathcal{N}_2 = \{2, 4\}$, $\mathcal{N}_4 = \{2, 4, 5\}$ and $\mathcal{N}_5 = \{1, 3, 4, 5\}$. We have considered that each node of the CR network obtains uncorrelated energy estimates during $3 \cdot 10^6$ independent realizations. The hypotheses H_0 and H_1 occur with equal probability and each hypothesis is kept invariant during at least 50 realizations. Silence periods are been distributed every 500 iterations. The number of samples of the energy estimator is $N = 20$ for all nodes. The forgetting factor for the noise variance and the reference signal estimation is $\alpha_r = 0.995$ for all nodes.

A PL rate has been defined to analyze the loss of shared information, which consists of the percentage of the energy estimates $y_m(k)$ of one SU that is lost, assuming that information is shared at every single realization. The random events corresponding to PLs from each SU are independent.

A. Cooperation: Selective vs. Non-Selective

Fig. 1 depicts the complementary receiver operating characteristic (C-ROC) for nodes 2, 4, and 5, considering that each node has perfect or imperfect data (i.e., SNRs and noise variances) knowledge, and employing selective and non-selective cooperative SM-NLMS. The parameters of the varying threshold for the SM-NLMS $\bar{\gamma}(k)$ are $\alpha_\gamma = 0.995$ and $\beta = 0.7$, which assures a good trade-off between the number

of updates and the desired probability of false alarm as we will show in the following analyses.

One can observe that the proposed algorithm achieves similar performance as the SM-NLMS with full cooperation and perfect knowledge of data. Moreover, one can see that in some cases our proposal outperforms the ideal case (see nodes 2 and 5). This is due to the fact that cooperation with SUs with bad channel conditions² corrupts the detection performance of those SUs with better channel conditions. Therefore, the selective-cooperation proposal improves the reliability of the detection. Opposite behavior can be observed when a node with bad channel conditions, i.e., with high noise variance, interrupts the cooperation with its neighbors with smaller σ_m^2 .

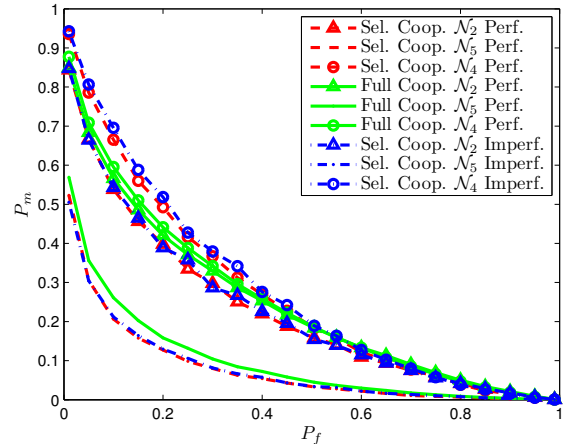


Fig. 1. Probability of miss-detection (P_m) vs. the desired probability of false alarm (P_f), with zero packet loss rate.

Fig. 2 shows the comparison of the Algorithm 1 with an NLMS-based linear combiner with full cooperation among SUs with and without packet loss. The step size of the NLMS has been set to $\mu = 1 \cdot 10^{-4}$. Results show that the proposed algorithm outperforms the NLMS algorithm where neighbors share data every iteration. This behavior is connected with the results shown in Fig. 1 comparing full- and selective-cooperative SM-NLMS. On the other hand, we can see that a loss of data packets of 10% from each node is almost negligible for both algorithms.

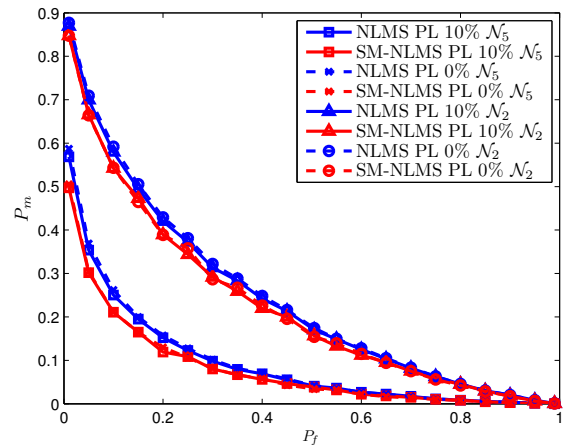


Fig. 2. P_m vs. P_f for NLMS and SM-NLMS.

²Considering the statistics of the energy estimates $y_m(k)$ (see [9]), a higher noise variance leads to a higher variance of $y_m(k)$, which affects negatively the quality of the estimates.

B. Error Tolerance $\bar{\gamma}(k)$ & Packet Loss Rate

In Fig. 3, we present the probability of miss-detection (P_m) and the estimated probability of false alarm (estimated P_f) for different values of the parameter β , which is the critical parameter in (10), and several packet loss rates, given a pre-defined desired $P_f = 0.1$. One can observe that P_m is almost constant for the different values of β . Nevertheless, the actual P_f diverges from the desired P_f when β grows. The difference becomes more important for cooperation with a greater number of neighbors. Therefore, we should take this effect into account in order to choose an appropriate β for $\bar{\gamma}(k)$ at each node.

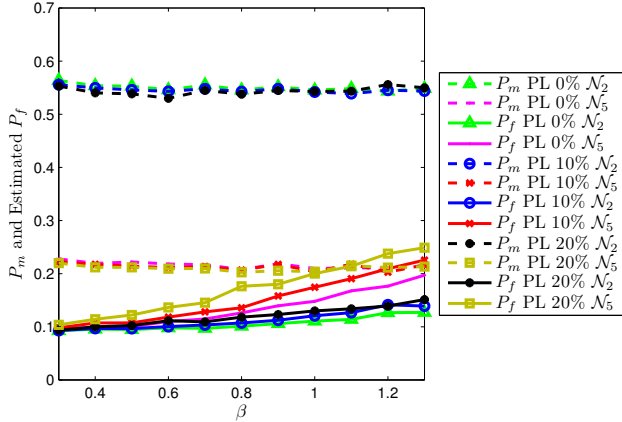


Fig. 3. P_m (dashed) and estimated P_f (solid) for different choices of β in nodes 2 and 5, given a desired $P_f = 0.1$.

It is worth pointing out that, in those nodes with higher SNRs or lower σ_m^2 than its neighbors, a higher packet loss rate can improve the performance in terms of P_m . This effect arises from the loss of information from neighbors with large noise variances, whose non-reliable energy estimates negatively affect the SS process as we also observed in Fig. 1. As a result, a reduced degree of cooperation due to packet loss rate or selective-data information exchange is favourable in those cases.

C. Control-Channel Traffic & Update Savings

In Fig. 4 we can observe the percentage of updates that are performed with the SM-NLMS algorithm for different values of the parameter β and PL rates. On one hand, we can see the expected behavior of data selective algorithms, a looser error tolerance $\bar{\gamma}(k)$ due to a larger β leads to a reduction of the number of updates. On the other hand, results show that a higher PL rate yields a reduction of the number of updates. It is worth noticing that the update reduction implies the same percentage of savings in data transmission through Algorithm 1, which is very desirable since an important portion of the energy of wireless devices is consumed for data transmission. We remark that β must be chosen taking into account the savings and the desired P_f since high values of β diverge from the pre-defined P_f , mainly when many nodes are cooperating. Considering the analyzed case in Subsection III-A, $\beta = 0.7$ implies around 65% of updates and transmission savings maintaining an actual P_f close to its desired value.

IV. CONCLUSION

This paper proposed a new collaboration scheme based on data selection of energy estimates acquired by secondary users in a cognitive radio network. The key feature of the proposal is its inherent robustness to imperfect information exchange between the network nodes. Indeed, the simulation results indicated that the proposed data-selective adaptive soft

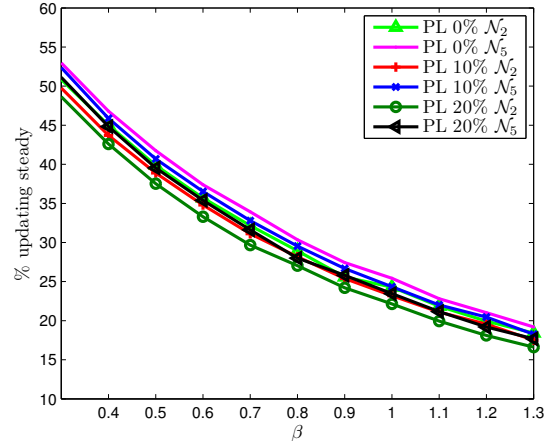


Fig. 4. Percentage of updates of the SM-NLMS algorithm and data sharing transmissions in nodes 2 and 5 for different packet loss.

combiner is almost insensitive to packet loss of around 10%, while yielding significant updating and transmission power savings.

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