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Energy-Based Spectrum Sensing For Uplink Downlink Identification

Jean-Sébastien Gomez, Wei Chen, Bo Bai, Xin Guo, and Philippe Martins

Abstract—In this paper, an energy-based spectrum sensing algorithm is proposed to address the problem of Uplink (UL)/Downlink (DL) resource block identification in a single cell. This framework aims to provide a general UL/DL identification tool for interference management algorithms in autonomous cells. The proposed algorithm is base on the observation that user terminals can be active from any part of the cell during DL. And on the contrary, a base station is only active at one single position during DL. Because of these two spatial properties, UL/DL identification is made impossible with only one single sensing equipment -or Secondary User Equipment (SUE). A multiple soft-sensing framework is introduced, using path-loss as spatial information provider. Theoretical analysis and simulations show that the proposed algorithm achieve high reliability, with an error probability decreasing exponentially to zero in the number of SUE.

Index Terms—Cognitive radio, 5G mobile communication, Spectral analysis, UL/DL identification, Energy-based spectrum sensing, Resource block.

I. INTRODUCTION

TECHNOLOGIES in 5G networks will aim to introduce more real-time and more dynamic resource allocation strategies to fulfill energy consumption and data traffic needs. Heterogeneous cell architecture implemented in third generation cell networks, have enhanced cell edge user experience, by optimizing local spatial use of spectrum. Research on interference management between micro-cells and macro-cells have brought numerous cooperative and non-cooperative strategies. In this paper, we consider that cooperation between micro and macro-cells is impossible or undesirable due to limited overhead, limited channel capacity, etc. Then, state of the resource blocks (UL or DL) of the macro-cell can be required by the micro-cell to apply the appropriate interference management policy. Spectrum techniques (a core topic in Cognitive Radio) can provide information about the use of the local spectrum environment. In the studied scenario, a micro-cell or Secondary System (SS) cell is placed in a macro-cell or Primary System (PS) cell. A Secondary Base station (SBS) is

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located at the center of the SS. Secondary Users Equipments (SUE) are randomly spread in the SS cell. To optimize the allocation of resource blocks on point-to-point links, the SS has to retrieve some state information about the PS.

Spectrum sensing techniques have been widely explored in CR papers. Classical CR problems found in the literature, are related to active Primary User (PU) detection. Common spectrum sensing techniques are presented in [3] and [4] such as energy-based, cyclostationary and waveform-based frameworks. In early development of CR, single SS equipment sensing has been investigated. Such cognitive equipment would determine itself the availability of the spectrum band. In order to mitigate path-loss, fading and overcoming the hidden primary user issue (i.e. a PU that cannot be detected but will interfere during transmission), sensing results of each SUEs can be combined at a SBS or a super-SUE to get a sensing result. One can distinguish two strategies to merge SUEs information. The first one -called hard-decision process [4]- considers the spectrum sensing output of each SUE (i.e. presence or absence of a PU using the spectrum band) and merge it through an AND, OR, majority voting or n among m law. In [5], hard-decision process has proven to be sub-optimal compared to the second merging strategy (soft-decision process). In this case, raw results are transmitted to a SBS or a super-SUE. SUEs do not have an active role in the computation of the sensing algorithm output. The spectrum sensing algorithm is processed at the SBS or at the super-SUE.

The framework proposed applies soft-decision process to generate a sensing output. However, this paper focuses on Primary User (PU) type differentiation rather than PU detection. Based on the observation of antenna power difference between each type of PU, the PU differentiation problem could be reduced to a trivial PU detection problem. However, because of the spatial characteristics of the two types of PU, such reformulation is made impossible (see next part). In [6], a UL/DL identification framework based on waveform already exists. But to our knowledge, no energy-based spectrum sensing algorithm has been proposed.

As demodulation of the signal is not needed, the choice of energy-based sensing has been made. Only raw value of the energy received by the SUE is required, cutting down equipment complexity and gaining robustness to privacy policies. The main contribution is the use of path-loss as a criterion to differentiate PU types. In the next section, a closer description of PS system will be given and an energy-based spectrum sensing framework will be proposed. On this basis, an algorithm will be given to discriminate the two types of PUs. The optimality of this algorithm will be proven in part

IV. In part V, simulation results will be given for a single cell scenario.

II. SYSTEM DESCRIPTION

In a macro PS cell of radius R , a Primary Base Station (PBS) is placed in the center. Primary User Equipments (PUEs) are uniformly distributed in the cell. SUEs numbered from 1 to N_s , are also randomly distributed in the same cell. The SBS which only computes the output result, is omitted on Figure 1. Sensing is performed in a time-frequency slot, in which either the PBS is active (DL state) or a PUE is active (UL state). R and of the coordinates of the SUEs are known by the SS.

Definition 1. The space engendered by the energy received by each SUEs is called energy space. Each dimension of the energy space represents the energy received by each SUEs.

Let P_k be either P_1 or P_2 , respectively the antenna power of the PBS, or the PUE. The path loss exponent α can take values between 2 and 4. Let D_{SUE_j-PU} be the distance in meters between the active PU and the SUE number j denoted SUE_j . Thermal noise due to the measurement of the SUE is considered as a normal random variable Z_j and of power P_{noise} .

Definition 2. In the energy space, let \mathbf{Et} be a vector where the j^{th} coordinate is the energy received by the SUE_j in a time-frequency slot.

$$Et(j) = \frac{P_k}{D_{SUE_j-PU}^\alpha} + P_{noise}Z_j \quad (1)$$

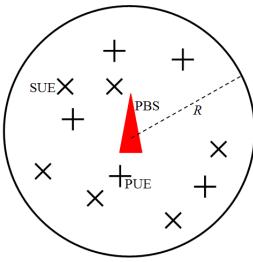


Figure 1. An Example of PS and SS configuration

Two assumptions are made on the PS. The first one states that the antenna power of a PBS is far greater than the antenna power of a PUE.

$$P_2 \gg P_1 \quad (2)$$

The second one states that the PBS is a static source, whereas a PUE can be active from any position of the cell.

Lemma 3. Under the two stated assumptions, the spectrum sensing energy space must be at least of dimension two to ensure UL/DL identification.

Proof: The identification of UL and DL is assumed to be possible in an energy space of dimension one. The following situation: $\alpha = 2$, $P_2 = 100 \cdot P_1$ is considered. A SUE is placed at 1 meter from a PUE and 10 meters from the PBS.

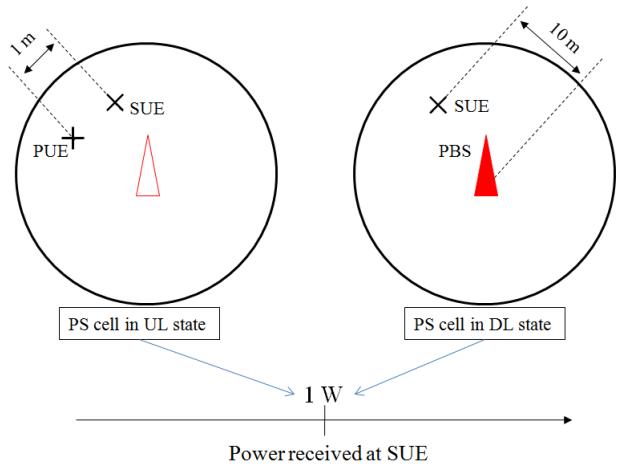


Figure 2. Counterexample. Because of path loss, it is not possible to discriminate the source.

Therefore, the same amount of energy is received by SUE in DL and UL state. Thus identification is not possible. Hence to ensure UL/DL identification, the spectrum sensing energy space must be at least of dimension two. ■

Let (r, θ) and (R_k, θ_k) be respectively the polar coordinates of an active PUE and the SUE number k (SUE_k). Let $\rho_k(r, \theta)$ be the distance between SUE_k and the active PUE. Let N_s be the number of SUEs.

Definition 4. Let f be the mapping between the positions of a PUE of coordinate (r, θ) and the spectrum sensing energy space:

$$f : (r, \theta) \mapsto \begin{pmatrix} \frac{P_1}{\rho_1^\alpha(r, \theta)} \\ \vdots \\ \frac{P_1}{\rho_{N_s}^\alpha(r, \theta)} \end{pmatrix} \quad (3)$$

Let the image of f be defined by:

$$D = \{\mathbf{P} \in \mathbb{R}^{N_s} | \exists (r, \theta) \in [0, R] \times [0, 2\pi], f(r, \theta) = \mathbf{P}\} \quad (4)$$

Definition 5. Let \mathbf{E}_2 be the vector engendered by the PBS in the spectrum sensing energy space:

$$\mathbf{E}_2 = \begin{pmatrix} \frac{P_2}{R_1^\alpha} \\ \vdots \\ \frac{P_2}{R_{N_s}^\alpha} \end{pmatrix} \quad (5)$$

Figure 3 gives an example of the shape of D and relative position of \mathbf{E}_2 in dimension two. In UL state, the vector \mathbf{Et} will appear in D , or at least in the topological neighborhood of the set D . As for DL state, \mathbf{Et} will appear in the neighborhood of \mathbf{E}_2 . Hence, identifying UL or DL state becomes equivalent to separate D and \mathbf{E}_2 . A strategy for finding a frontier between these two subspaces is therefore proposed in the next part.

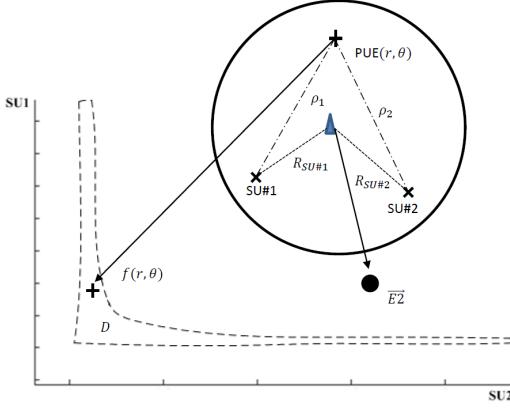


Figure 3. Shape of D and relative position with \mathbf{E}_2

III. SPECTRUM SENSING ALGORITHM

A. Framework

An analytical description of D proves to be complex, especially in high dimensions. A discrete representation is then preferred. Each of chosen point of D (called test vector) is associated with a decision hyperplane.

Definition 6. Let $\{(r_i, \theta_i) | i \in [|1, N|]\}$ be a set of N random positions in the PS cell. Let $S = \{\mathbf{E}_{1i} | i \in [|1, N|]\}$ be a set of test vectors of D . Each component of such vectors are given by:

$$E_{1i}(j) = \frac{P_1}{\rho_j^\alpha(r_i, \theta_i)} \quad (6)$$

The notation $\langle \cdot, \cdot \rangle$ is introduced for the inner product in the energy space. For more clarity, $\mathbf{E}_{1i}\mathbf{E}_2$ represents the vector $\mathbf{E}_2 - \mathbf{E}_{1i}$.

Definition 7. A decision hyperplane \mathcal{H}_i is associated to each element \mathbf{E}_{1i} . \mathcal{H}_i is defined by its normal vector $\mathbf{E}_{1i}\mathbf{E}_2$ and the middle of the segment $[\mathbf{E}_{1i}, \mathbf{E}_2]$

$$\left\{ \mathbf{P} \in \mathbb{R}^{Ns} | \langle \mathbf{P}, \mathbf{E}_{1i}\mathbf{E}_2 \rangle = \left\langle \mathbf{E}_{1i} + \frac{1}{2}\mathbf{E}_{1i}\mathbf{E}_2, \mathbf{E}_{1i}\mathbf{E}_2 \right\rangle \right\} \quad (7)$$

B. Algorithm

The algorithm is performed in two steps. In the first step (figure 4), the vector from S that best matches the direction of the vector \mathbf{E}_t is selected. Let $i0$ be the index of this vector. In the second step (figure 5), the position of \mathbf{E}_t is compared relatively to the position of the hyperplane \mathcal{H}_{i0} . If \mathbf{E}_t is “over” the hyperplane \mathcal{H}_{i0} , then the PS is considered in DL state. Otherwise, the system is considered in UL state.

IV. THEORETICAL ANALYSIS

Assumption 1: The minimum distance between two test vectors in the energy space is bigger than the noise power.

$$P_{noise} \ll \min_{(i,j) \in [|1, N_S|]^2} (\|\mathbf{E}_{1i}\mathbf{E}_{1j}\|) \quad (8)$$

Algorithm 1 Decision algorithm

```

i0 = 1;

/*Step one*/
for i = 2 to Ns
    if  $\langle \mathbf{E}_t, \frac{\mathbf{E}_{1i}}{\|\mathbf{E}_{1i}\|} \rangle \geq \langle \mathbf{E}_t, \frac{\mathbf{E}_{1i0}}{\|\mathbf{E}_{1i0}\|} \rangle$  then
        i0 = i;
    end
end

/*Step two*/
if  $\langle \mathbf{E}_t, \mathbf{E}_{1i0}\mathbf{E}_2 \rangle \geq \langle \mathbf{E}_{1i0} + \frac{1}{2}\mathbf{E}_{1i0}\mathbf{E}_2, \mathbf{E}_{1i0}\mathbf{E}_2 \rangle$  then
    return DL;
else
    return UL;

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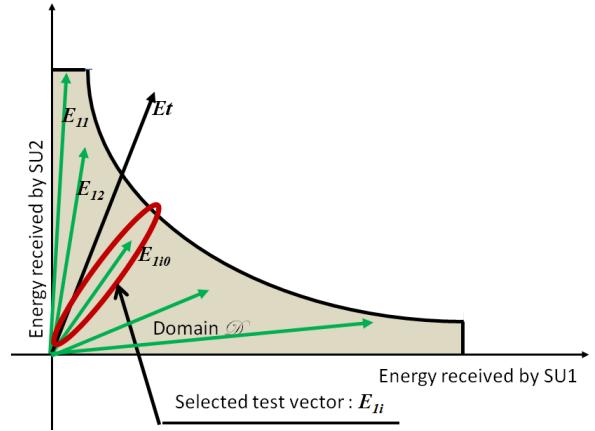


Figure 4. Algorithm step one. The test vector circled in red, is selected.

This situation is encountered for high SNR, big values of N , and low noise power value P_{noise} , or in low SNR, small values of N and high noise power value P_{noise} .

Assumption 2: Let \mathbb{P}_i be the probability of selecting the test vector number i . Regardless of the state of the PS,

$$\mathbb{P}_i = \frac{1}{N} \quad (9)$$

A. Optimality of the algorithm

Theorem 8. The proposed sensing algorithm minimizes the error probability \mathbb{P}_e . \mathbb{P}_e is given by:

$$\mathbb{P}_e = \sum_{i=1}^N \frac{1}{N} \cdot Q \left(\frac{\|\mathbf{E}_{1i}\mathbf{E}_2\|}{2P_{noise}} \right) \quad (10)$$

Proof: Proposition 9 ensures the optimality of step one and proposition 10 ensures the optimality of step two in terms of error probability. Hence, the proposed sensing algorithm minimizes the overall error probability \mathbb{P}_e . ■

Proposition 9. The selected test vector \mathbf{E}_{1i0} is the one minimizing the error probability \mathbb{P}_e .

Proof: Considering assumption 1, the influence of the noise in the selection of the test vector is minimized. Noise is indeed constraint in a sphere of radius P_{noise} , thanks to

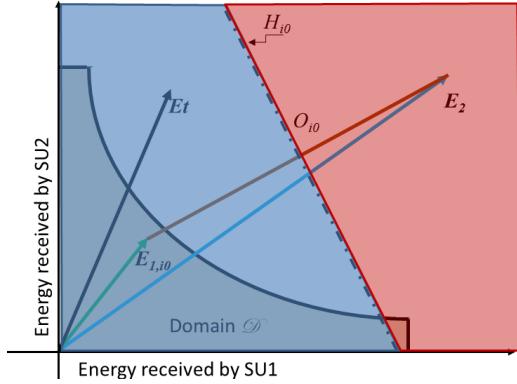


Figure 5. Algorithm step two. If \mathbf{E}_t is in the blue part, then we consider that PS is in UL state. Otherwise we consider that PS is in DL state.

Chebyshev inequality. The deviation angle of the vector \mathbf{E}_t is therefore mainly due to the position of the active PUE in the PS cell rather than noise. The selected test vector $\mathbf{E}_{1,i,0}$ is the one which best matches the spacial configuration of the currently active PUE, introducing the smallest error. ■

Proposition 10. *The position of the hyperplanes \mathcal{H}_i are those minimizing the error probability \mathbb{P}_e .*

Proof: The direction of the hyperplane is already optimal because of assumption 1. A hyperplane \mathcal{H}_i has for normal direction the vector $\mathbf{E}_{1,i}\mathbf{E}_2$. A particular point \mathbf{O}_i of the hyperplane is given by the middle of the segment $[\mathbf{E}_{1,i}\mathbf{E}_2]$. We want to demonstrate that for each i , \mathbf{O}_i is the optimal point on the segment. Let's consider :

$$\mathbf{O}_i : t_i \mapsto \mathbf{E}_{1,i} + t_i \mathbf{E}_{1,i}\mathbf{E}_2 \quad (11)$$

with $t_i \in [0, 1]$. The error probability, when the PS is in UL state and when the PS in in DL state, for the test vector number i , are respectively given by:

$$\mathbb{P}_{DL/UL,i} = Q\left(t_i \frac{\|\mathbf{E}_{1,i}\mathbf{E}_2\|}{P_{noise}}\right) \quad (12)$$

$$\mathbb{P}_{UL/DL,i} = Q\left((1-t_i) \frac{\|\mathbf{E}_{1,i}\mathbf{E}_2\|}{P_{noise}}\right) \quad (13)$$

Considering assumption 2, the probability error \mathbb{P}_e is given using the law of total probability by:

$$\mathbb{P}_e = \mathbb{P}_{DL}\mathbb{P}_i \mathbb{P}_{UL/DL,i} + \mathbb{P}_{UL}\mathbb{P}_i \mathbb{P}_{DL/UL,i} \quad (14)$$

$$\text{Let } C = \frac{\|\mathbf{E}_{1,i}\mathbf{E}_2\|}{P_{noise}}.$$

$$\mathbb{P}_e = \sum_{i=1}^N \frac{1}{2N} \cdot [Q(t_i \cdot C) + Q((1-t_i) \cdot C)] \quad (15)$$

It is clear that \mathbb{P}_e is a convex function for each t_i in $[0, 1]$. Then to find the minimum error probability, it suffices that for each i :

$$\frac{\partial \mathbb{P}_e}{\partial t_i} = 0 \quad (16)$$

A trivial solution of (16) is given for

$$t_i = 0.5 \quad (17)$$

This proves that if \mathbf{O}_i is the middle of the segment $[\mathbf{E}_{1,i}\mathbf{E}_2]$ for all i , \mathbb{P}_e is minimal. ■

B. Influence of the number of SUEs

Theorem 11. *The error probability \mathbb{P}_e is going to zero exponentially as the dimension of the energy space is increasing.*

Proof: As $\|\mathbf{E}_{1,i}\mathbf{E}_2\| \neq 0$, let

$$E_{1,i_m}E_2(j_m) = \min_{i,j, E_{1,i}E_2(j) \neq 0} (E_{1,i}E_2(j)) \quad (18)$$

Using the Chernoff bound of the Q-function in equation (10) we have:

$$\mathbb{P}_e \leq \frac{1}{2} \exp\left(-\frac{Ns \cdot (E_{1,i_m}E_2(j_m))^2}{2P_{noise}^2}\right) \quad (19)$$

Hence the error probability is going down to zero exponentially as the number of SUEs increases. ■

Remark 12. One can notice that the number of test vectors N has no influence on the error probability. In figure 6, the decision region is given by several hyperplanes. However, adding hyperplanes will not influence in a decisive manner the error probability, because the decision volume added by the new hyperplanes is small compared to the sphere of radius P_{noise} .

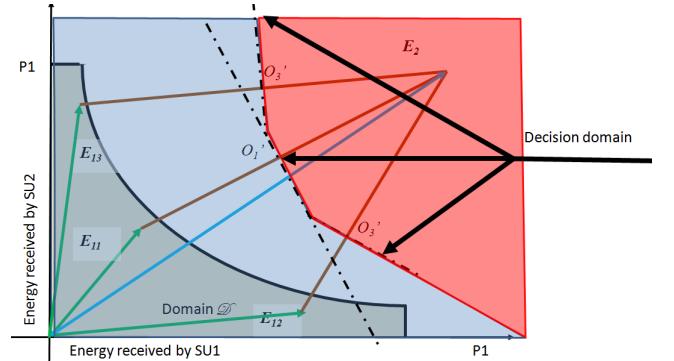


Figure 6. Example of decision domain for 3 test vectors, symbolized by the interface between the red and blue subspace.

C. An analytical approximation for the error probability

As the term $E_{1,i_m}E_2(j_m)$ is difficult to evaluate, an analytical approximation is proposed for the error probability.

Definition 13. Let SNR_{min} , the quantity representing the SNR for a SUE and PUE placed at the edge of the PS cell and diametrically opposed. In this situation, SNR is minimum.

$$SNR_{min} = \frac{P_1}{(2R)^\alpha P_{noise}} \quad (20)$$

$$\mathbb{P}_e \approx Q(2^{\alpha-1}(k-1)SNR_{min}\sqrt{N_s})$$

Proof: Let k be:

$$k = \frac{P_2}{P_1} \quad (21)$$

Hence considering definition 13, equation (10) becomes:

$$\mathbb{P}_e \approx Q(2^{\alpha-1}(k-1)SNR_{min}\sqrt{N_s}) \quad (22)$$

V. SIMULATIONS

This sensing algorithm has been tested on one scenario: single PS cell environment. Simulation parameters are given in table 1. The influence of two parameters of the algorithm

Table I
SIMULATION PARAMETERS

R	1 km
P_1	1 W
P_2	10 W
α	2
SNR_{min}	0.25

is studied: the number of test vectors (N) and the number of SUEs (N_s).

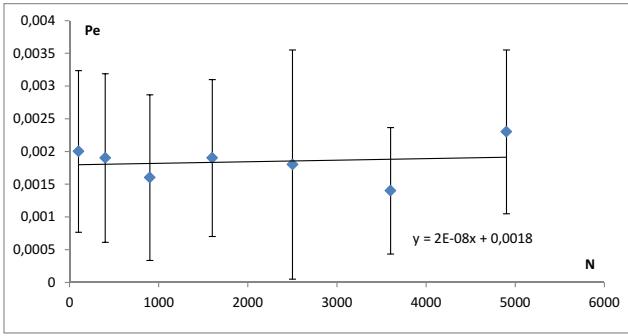


Figure 7. Influence of the number of test vectors on the error probability.
 $N_s = 10$.

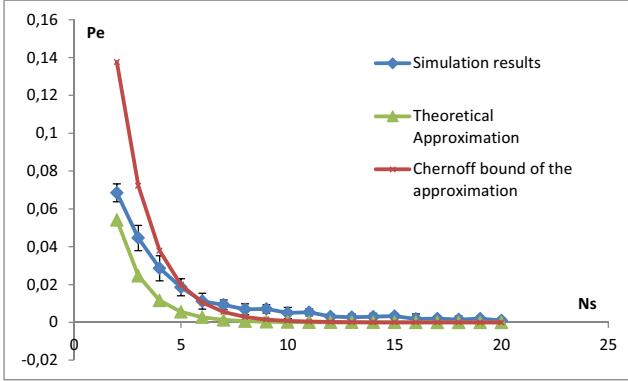


Figure 8. Influence of the number of SUEs on the error probability. In green the theoretical approximation, in blue, the simulation results, in red the Chernoff bound of the approximation. $N = 400$.

In figure 7, no obvious correlation can be observed between the number of test vectors and the evolution of the error probability. This confirms the argument given in remark 12. In figure 8, the more SUEs, the smaller the error probability. The analytical formula given in proposition 14 is an optimistic approximation of the error probability. However both curves shape are alike.

VI. CONCLUSION

In this paper we have introduced an energy-based spectrum sensing algorithm using soft-decision process to identify the

two types of PU. Path-loss ensures that the energy received in UL and DL resource blocks is constraint in the neighborhood of two different subspaces. The proposed decision algorithm is performed in two steps. The first step relies on test vectors to diminish complexity. In the second step, UL/DL identification is done by a simple position comparison of the current received energy vector and the selected decision hyperplane. Simulation results shows that the error probability is going exponentially to zero with the number of SUEs, confirming theoretical analysis.

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