Spectrum Sensing: A Distributed Approach for Cognitive Terminals

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***Abstract*— Cognitive Radios is emerging in research laboratories as a promising wireless paradigm, which will integrate benefits of software defined radio with a complete aware communication behavior. To reach this goal many issues remain still open, such as powerful algorithms for sensing the external environment. This paper presents a further step in the direction of allowing cooperative spectrum sensing in peer-to-peer cognitive networks by using distributed detection theory. The approach aims at improving the radio awareness with respect to stand alone scenario as it is shown with theoretical and experimental results.**

***Index Terms*— cognitive radio, spectrum sensing, distributed detection theory, time frequency analysis, mode identification, air interface classification.**

I. Introduction

A. Why spectrum sensing is important

THE growing number of wireless standards is reducing the amount of unlicensed frequencies. However, large part of licensed bands are unused for what concerns a large amount of both time and space: even if a particular range of frequencies is reserved for a standard, at a particular time and at a particular location it could be found free. The Federal Communication Commission (FCC) estimates [1] that the variation of use of licensed spectrum ranges from 15% to 85%, whereas according to Defence Advance Research Projects Agency (DARPA) only the 2% of the spectrum is in use in US at any given moment. It is then clear that the solution to these problems can be found dynamically looking at spectrum as a function of time and space. This is the base of *Cognitive Radios* (CR): the paradigm, defined the first time by J. Mitola [2], [3], foresees devices able not only to adapt themselves to spectrum environment and, in general, to external environments, but also to learn from experience, as a biological cognitive process, how to carry out this adaptation. CRs can change their features in relation to the conditions of the wireless channel, to the traffic status and to the users' requirements. In this process, in order to allow a representation of the external environment as close as possible to real world, a key role is played by *spectrum sensing*. By sensing the spectrum, the terminal collects fundamental data from external environment, in particular from radio channel, and it can carry out the typical adaptation of CR.

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B. What spectrum sensing is

Spectrum Sensing is characterized by the join of a quantitative and qualitative analysis of a reference band through the collection of information in terms of, respectively:

- frequency usage;
- air interface classification at a used frequency.

To evaluate the use of frequencies in a particular band, some parameters have been studied and, among them, energy level and interference temperature [4] result to be the most used; both quantitatively describe with good performance the occupation of a given frequencies band. Whereas, in order to provide a qualitatively description of spectrum, air interfaces[1] classification (also called mode identification) is performed. Thus, mode identification shows which standard is present, providing data about its nature.

C. How spectrum sensing can be implemented

The simpler and older solution to implement radio sensing modules is the radiometer [6], [7]. Its advantage is the low computational load, but it can be insufficient to discriminate the mode when signals are superimposed [8]. Other solutions have been proposed: in [9] it is studied the use of a radial basis function (RBF) for a power spectral density estimation to identify non overlapping air interfaces. In [10] a further two-stepped solution is proposed: a first energy detection to identify a void or occupied carrier, followed by a GSM and UMTS signals classification. Also in this approach no superposition is taken into account. The first procedure for identifying overlapping modes is presented in [11], where time frequency analysis is combined with neural network to classify spread spectrum interfaces. Time frequency analysis have been subsequently proposed also in [4] with a complete and exhaustive analysis of cognitive radios; in that paper a two-stepped procedure, composed by interference temperature estimation and spectrum holes detection, is proposed. Another recent work is [12], which shows a mode identification, based on cyclostationarity detection.[2] Another related work, probably one of the biggest effort in the field of spectrum sensing, is given by the neXt Generation Program (XG Program), funded by DARPA, whose goal is the improvement in assured military communications through the dynamic assignment of allocated

[1]An *air interface* (also called *transmission mode*) can be defined *as the specification of the radio transmission between a transmitter and a receiver. It defines the frequencies or the bandwidth of the radio channels, and the encoding methods used* such as FH-CDMA, DS-CDMA, TDMA, MC-CDMA, etc. [5].

[2]This property was studied in [13] and [14], in the field of signal interception, concluding that signals exhibit correlation between widely separated spectral components because of spectral redundancy caused by periodicity.

spectrum: a key function is given by sensing module. The criteria for declaring a channel occupied are not specified, but it is reported, that the basic notion is to determine if there is a signal (*frequencies usage*) and, if so, which the characteristics of the signal are (*air interfaces classification*). Other projects started in these last years thanks to NSF program NeTS ProWIN (Programmable Wireless Networks). Among different works it is worth mentioning High Performance Cognitive Radio Platform with Integrated Physical and Network Layer Capabilities [15] and Cognitive Radios for Open Access to Spectrum [16]. They mainly deal with hardware issues but (especially in second project) interesting conclusions about spectrum management and frequency agility of cognitive radios are studied, analyzing potential benefits in system capacity and service quality. Also IEEE is working to define cognitive radio and its aspects: it set up a working group to develop the 802.22 Standard for Wireless Regional Area Networks (WRAN). The new project [17], is specifying a cognitive air interface for fixed, point-to-multipoint, wireless regional area networks with opportunistic spectrum access. Spectrum sensing is there based on Power Detection [18] and the standard aims at using unused spectrum in order to provide new and broadband services to final users. All previous solutions are based on single terminal approach, with no cooperation among devices: this paper aims at improving the flexibility and the generality of spectrum sensing by proposing a distributed classification of air interfaces by means of a network of cooperating cognitive terminal. In the state of the art of distributed detection many works can be found, especially for sensor networks, although these theories have not been applied yet to cognitive purpose: recent tutorials on this subject are [19], [20]; studies on decentralized detection with communication constraint are in [21], [22] and others with energy constraint are in [23]; quantization strategies based on training sequences can be found in [24]. The distributed algorithm which this work is based on is the theoretical scheme developed by Varshney in [25], namely the *distributed detection without fusion*.

II. Aim and Structure of the Paper

The aim of this paper is to present a spectrum sensing procedure based on distributed network of cognitive terminals (CT). Time Frequency Analysis is employed as part of a classification framework, where multiple devices cooperate to sense the spectrum and, in particular, to classify overlapping air interfaces. Each device carries out the first two steps of cognitive cycle (observation and analysis) working together other CTs to obtain a more detailed and correct radio scene representation. In order to explain how this objective is reached, it is shown an example in which two air interfaces, Direct Sequence Code Division Multiple Access (DS-CDMA) and Frequency Hopping Code Division Multiple Access (FH-CDMA), are classified by using distributed cooperative terminals. Two cases of study are considered: IEEE WLAN 802.11b and Bluetooth[3]. The paper starts with an analysis of cognitive terminals with their components in case of stand alone (Section III) architecture. Then, the proposed distributed solution is discussed in Section IV, while details are provided in Section V with proposed framework and its sub-parts (Sections VI and VII). Theoretical bases of distributed detection are explained in Sub-Section VII-B. Experimental and theoretical results are reported in Section VIII. Mathematical steps are detailed in Appendix I.

[3]The choice of these two standards stems from two factors: first, they are based on DS-CDMA and FH-CDMA, the chosen modes; second, they transmit on the Industrial Scientific Medical (ISM) Band, an example of unlicensed spectrum, where spectrum sensing and management could be necessary and based on the design of a unique RF conversion stage, as ideally required for an SDR platform [5].

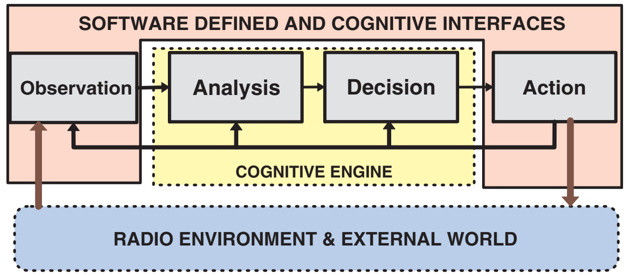

Fig. 1. Stand alone cognitive approach.

III. General Stand Alone Cognitive Architectures

A Cognitive Terminal can be defined as a terminal able to sense the external world, analyze the gathered data, compute them in order to take a decision about which actions have to be carried out to modify its internal and external statuses. These tasks can be summarized in what Mitola calls radio cognitive cycle [3]: during which *...cognitive radio continually observes the environment, orients itself, creates plans, decides, and then acts....*

The vision proposed in this paper is based on a CT implementing the cognitive cycle by using two modules (Fig. 1):

- Software Defined and Cognitive Interfaces (SDCI)
- Cognitive Engine (CE)

Software Defined and Cognitive Interfaces (SDCI) are composed by *observation* and *action* blocks. The observation module is composed by different sensors, which can be classified by using a bio-inspired model for cognitive multisensorial interfaces [26] as *exogenous* or *endogenous* (Fig. 2). Endosensors are devoted to the observation of the internal status of the system.[4] On the contrary, exo-sensors are all devices used to collect data and signals from the external environment.[5]

The other part of SDCI is the *action* block. It gets inputs from decision module and transforms them into real actions. This module is similar to the observation module (Fig. 2), being composed by comparable or, in some case, the same equipments. Another similarity is that also actuators can be classified in endogenous, when aiming at changing internal features, and exogenous when acting in the external world.[6]

[4]Devices belonging to this class are: power consumption sensors, bit error rate computational unit, internal thermal sensors, devices status sensors, and so on.

[5]In this category fall sensors, such as regular and smart antennas, video sensors (working in visible or infrared wave length fields), standard or directional microphones, fingerprints readers, safety-oriented sensors (smoke, gas, fire, etc.), lighting sensors, and so on.

[6]We can list in the first class controllers for SDR platforms (changing carrier frequency, air interface, signal strength, coding, cryptography algorithm and so on), power consumption controllers, Human Machine Interfaces (HMI). In the other class we can list antennas, lights, alarms and speakers.

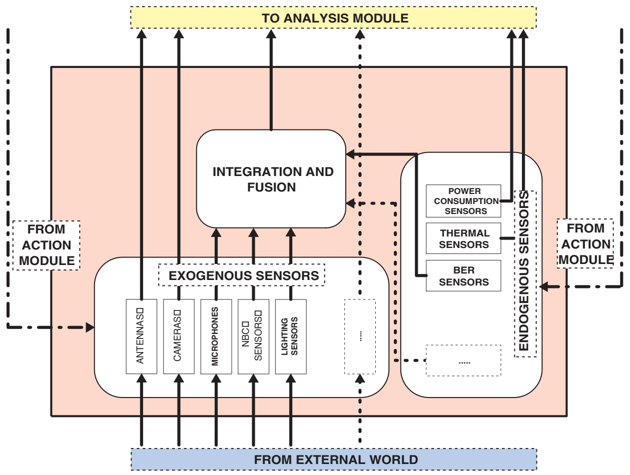

Fig. 2. Observation module.

Raw data and more structured information are processed by *Cognitive Engine*. It is composed by *Analysis* and *Decision* blocks (Fig. 1). The former executes high level data processing functions: it can extract features from signals, reduce and transform the data space, represent them in meta-data format. The steps carried out by this module are represented in Fig. 3 and summarized in what we have called: Features Level Processing (FLP) and Context Level Classification (CLC). At FLP, the CT doesn't provide yet information about external world, but it analyzes, reduces and converts its particular characteristics without knowing which status of external context they can represent.[7] Through CLC, instead, the device relates previous information with experience-based labels representing semantic situations known to the terminal (e.g. presence of a bluetooth source), which represent statuses of external environment.[8] Such a representation is used by the other block, *Decision* block, that selects which actions have to be chosen in order to reach a particular target or to satisfy a particular user's requirement.[9] The decision procedures can be structured in three levels: *strategic* (long term prospectives with general goals and philosophies), *tactical* (medium objectives for supporting strategic decisions), *operational* (low level procedures with high variability and changing). Another classification concerning this module can be done according to the algorithms used to take decisions: rule based engines, expert systems, fuzzy logics, neural networks, non-cooperative and cooperative games are examples of what can be implemented[10].

[7]Procedures which are, for instance, part of this module are the feature extraction and reduction used in this paper.

[8]In this case we can list parametric and non parametric, supervised and non-supervised classification and other classical pattern recognition methods [27].

[9]Target of decision can be: change the internal state with new resources allocation in terms of used memory, communication parameters, sensing and analysis methodology, and so on; change external environment by modifying air interfaces and then the frequencies usage; change the kind of interaction with other users/terminals: typology of messages (text, voice, video, etc), timing and contents of communication.

[10]An interesting analysis has been carried out by Haykin in [4] in the field of Sthocastic Games [28] and [29] for power control algorithms. Other solutions can be found in [30], [31], [32], [33], [34] and [35].

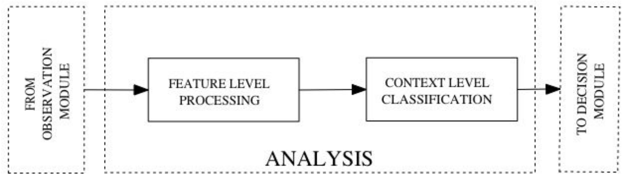

Fig. 3. Analysis module.

IV. Distributed Cognitive Architecture

It can be difficult to figure out how these functionalities can be used and implemented in the same terminal, and a real application is nowadays impossible: the solution is that a network of CTs cooperates sharing information and procedures in order to augment the awareness of the network itself. This is the key idea presented in this work: due to different terminals location and different received waveforms, the gathered pieces of information are various, and their cooperative use can improve radio awareness; in this paper an approach is proposed where cooperative spectrum sensing is carried out by a pair of cognitive terminals according to a distributed processing strategy. The proposed approach allows spectrum sensing by means of a "distributed cooperative consciousness" that terminal share about their cognitive approach to the sensing problem. It is shown how such a shared knowledge can improve global performances of air interface detection with respect to comparable single terminal spectrum sensing approaches.
Modules implemented in the work are *Observation* and *Analysis*, the former belonging to SDCI (Fig. 2) and the latter to CE (Fig. 3). Discussing how the proposed approach affects Decision and Action levels goes beyond the scope of this paper. The novelty consists in the distributed approach to the previous blocks: terminals cooperate in the analysis phase, acting as a wireless sensor network; each radio gathers data about spectrum, and by means of distributed detection theory [25], it estimates the presence of modes and the their type by taking advantage from the presence of the other terminals. The information exchange is based on an a-priori sharing of analysis models giving better results if compared to stand-alone observation and analysis. Details of this approach are described in the following Sections.

V. General and Proposed Framework

The approach is a generalization of the one based on the single terminal air interface detection described in [11]: a network of N cognitive terminals CT_i, with $i = 1, 2, ..., N$, moves in an indoor environment, whose radio map is considered as a-priori known from previous inspection, to observe the 'external world' by analyzing spectrum, searching for radio sources to be localized and identified. Each CT_i is able to extract and analyze information from the external world, and to decide and act in relation to a pre-defined cognitive cycle [2], (Fig. 1 and 4). More precisely, each CT_i captures the observation $O_{i,k,s}$ (where i is the CT, k is the number of radio sources and s is the kind of sensor), processes it and extracts from it a vector of features $\underline{v}(t) = \{v_1, v_2, ..., v_F\}$, which represents $O_{i,k,s}$ in a synthetic form useful to the decision and action

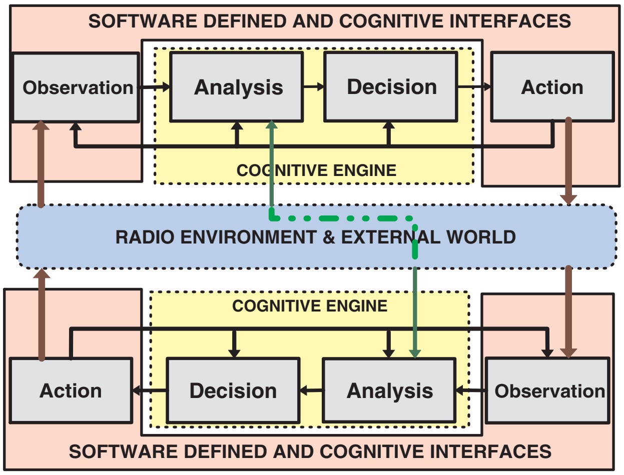

Fig. 4. Distributed cognitive approach.

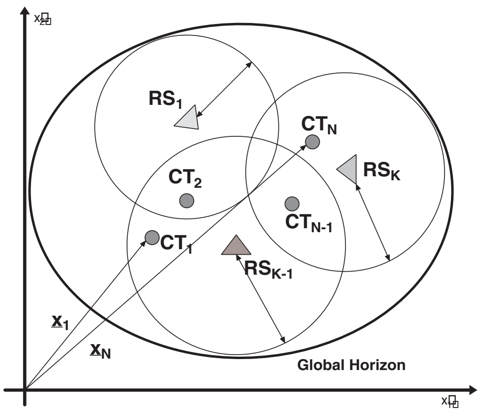

Fig. 5. The general scenario.

procedures. Each device performs a classification $D_i(t)$, based on available observations, by cooperating with other CTs. $D_i(t)$ can be defined as a mapping between a features space V and a classification space D. V is the space of possible values assumed by features extracted by each sensor during the observation. D, according to pattern recognition methods, is basically a label space, where labels identify different regions in the V space associated with different problem solutions. In the general framework the classification is oriented to solve an air interface classification problem combined with the location estimation of sources.

Let's then consider (Fig. 5) that a set of CTs, $\{CT\} = \{CT_i \;:\; i = 1, ..., N\}$, is present within the horizon of a number of radio sources RS_k, $k = 1, ..., K$, where the horizon is the surface, which contains all areas of coverage of RSs. Let's associate with each RS_k a position $\underline{x}_{RS_k}$ in a space $\underline{X}$, and a mode m in a space of possible radio modes corresponding to different air interfaces, let us say, for example M. Let us suppose that each CT_i is associated with a position $\underline{x}_i$ in the space $\underline{X}$, where radio sources are. Finally let's suppose that no null discrete quantized samples of observation $O_{i,k,s}$ are available as effects of radio source RS_k over terminal CT_i. Then, the mode identification, spectrum monitoring and location problem are defined as the capability

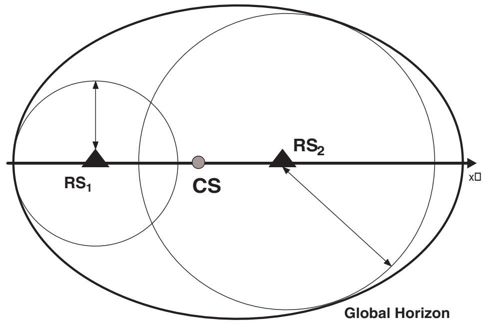

Fig. 6. Example of stand alone scenario.

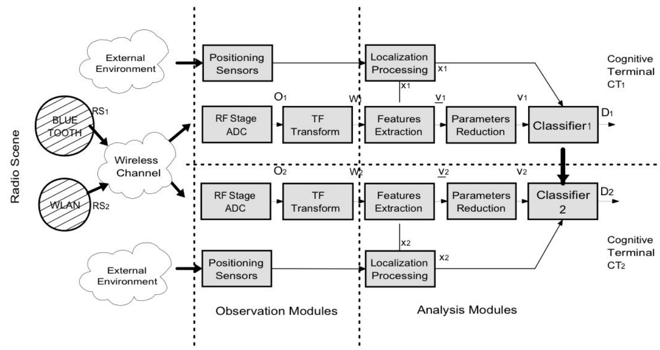

Fig. 7. Logical Architecture of sensing and analysis modules of two Cooperative Terminals.

of CTs to carry out a set of classification $D_i(t)$ about the presence of the transmission mode and the position of a set of Radio Sources RS, which lie in the horizon of CT.

When $dim\{CT\} = 1$, a stand alone scenario is fixed, i.e. a single CT is considered. If $dim\{\underline{X}\} = 1$ and the position of the stand alone CT is fixed, then the *world domain* of the problem is a mono-dimensional space (Fig. 6). A situation with $dim\{CT\} = 1$ and $dim\{\underline{X}\} = 1$ was considered in [11]. The problem with two radio sources was there analyzed with the additional constraint, that $\underline{x}_{RS_1}$ and $\underline{x}_{RS_2}$, i.e. their positions, were fixed. However, even though that problem allows an insight in the complexity due to the overlapping nature of the observations $O_{1,k,s}$ (with k=1,2) in relation to different $\underline{x}_i$ it is by many cases too simple to be able to reflect more direct situations of interest. In particular, in this paper some working hypothesis done in [11] are relaxed, by using $dim\{CT\} > 1$ and, without loosing generality, $dim\{CT\} = 2$. Let us fix $dim(\underline{X}) = 1$ and again $dim(RS) = 2$, where positions of the two sources RS_k are known, and consequently the problem of localization is not present. The mode identification and spectrum monitoring remain the main objective of the study here presented.

Blocks used to solve the problem are part of Observation (Sect. VI) and Analysis (Sect. VII). The proposed logical architecture of these modules is shown in Fig. 7: observation procedures, also called sensing procedures, are performed by directly sampling the received signal and representing it in a bilinear space, the Time Frequency (TF) plane (Sect. VI-A); once TF matrixes, W_1 and W_2, are obtained, the analysis procedures start: from W_i, $i = \{1, 2\}$ the features vector $\underline{v}_i$ is computed (Sect. VII-A) and sent to the classification module

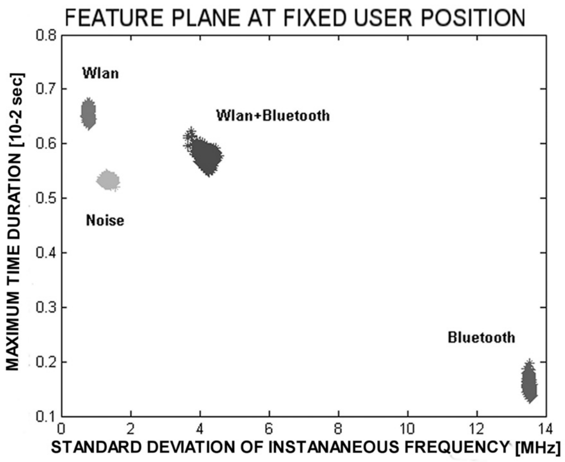

Fig. 8. Feature plane for the four classes at fixed user position.

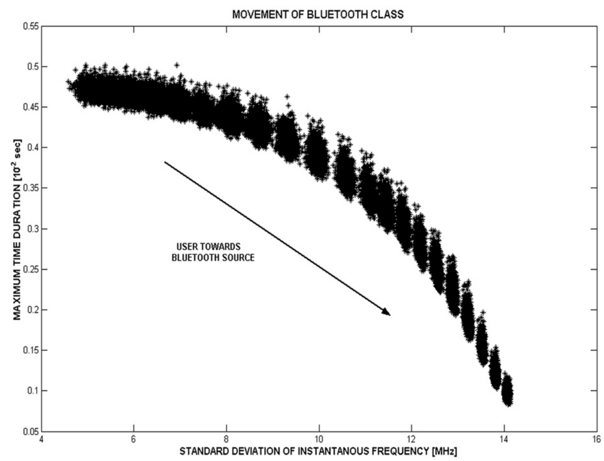

Fig. 9. Feature plane for the Bluetooth class during the movement of user.

(Sect. VII-B), which, by means of a cooperative strategy, extracts the classification D_i.

The observation and analysis modules in a final framework should be composed also by a localization process useful to provide the CT with spatial awareness. The estimated position of CTs, here considered known, is used by spectrum sensing modules to relate gathered data with a particular location.

VI. Observation Procedures

The observation modules are composed by two different channels (Fig. 7): the first one aiming at spectrum sensing and mode identification, and the second one aiming at position estimation. The former will be analyzed in following Sect. VI-A, whereas the latter not being the topic of this work, will not be studied; one can consider the observation modules for this channel as a generic exogenous sensor of either a Radio or Video or other localization systems.

A. Time Frequency Analysis

The observation $O_{i,k,s}$ after Radio Frequency (RF) stage and A/D conversion is processed by a Time Frequency (TF) block. The bilinear nature of the TF transforms provides a methodology to process time-varying and superimposed signals as the ones considered in this work. As TF distribution, the Wigner-Ville transform has been chosen [36]. This transform is the most used in the state of the art, and it has low computational complexity, a good feature for real-time usage[11].

VII. Analysis Procedures

A. Features Extraction and Reduction

The first part of this modules (Feature Extraction) is the same used in [11], and the features are two, namely standard deviation of the instantaneous frequency and maximum time duration of signal.[12]

They are directly computed by Time Frequency transform, $W(t, \omega)$.

It is worth mentioning a significant characteristic of features: as it can be noticed by Fig. 8, when one terminal CT_i is at rest in a given position $\underline{x}_i$, the features plane assumes a given distribution, but when $\underline{x}_i$ changes, i.e. the considered device moves in the environment, also the feature distribution changes. An example of feature movement when CT is approaching to Bluetooth source is reported in Fig. 9. This aspect brings to consider the vector $\underline{v}$ not only a function of time t, $\underline{v}(t)$, but also of position $\underline{x}_i$, then $\underline{v}(t, \underline{x}_i)$. The relation is also shown in Fig. 7, where the observation gathered by positioning sensor is computed by *Localization Processing* module in order to estimate $\underline{x}_i$, input to *Features Extraction* and *Classification* blocks.

Once these two values are computed, it is used the new part of system, consisting in Parameters Reduction and Classification blocks.

1) Karhunen-Loeve method: To simplify the problem, decreasing the dimension of features space, the Karhunen-Loeve (K-L) method [27] has been applied. It is a classical eigenvalue method for linear feature reduction, used in pattern recognition: the optimal weights for features combination are computed on the basis of contribution of features to a reduced pattern classification problem with optimal properties as computed on a training set. It is here applied to the two features, extracted from the observed time-frequency representation, to reduce them to a single one, i.e. a linear combination of them. This step reduces the problem complexity by modeling sources status from multidimensional probability density functions (*pdf*s) to scalar density *pdf*s.

B. Distributed Classification

As reported in Section V, in addition to an advanced signal processing technique, i.e. the Time-Frequency analysis, a distributed classification algorithm is studied to improve the performances of spectrum sensing.

[11]The Wigner-Ville distribution is given by:

$$W(t, \omega) = \frac{1}{2\pi} \int y(t + \frac{\tau}{2}) y^*(t - \frac{\tau}{2}) e^{-j\omega\tau} d\tau \qquad (1)$$

where the superscript * denotes the complex conjugate and integral ranges from $-\infty$ to $+\infty$, and $y(t)$ is the sampled version of the received signal. It is band-limited and contains one of the two superimposed modes (WLAN or Bluetooth) or both.

[12]For more details about considered features and their relation to Time Frequency analysis please refer to [36], [11] and [37].

Different strategies can be designed to implement a cooperative behavior of CTs: in the following, two possible strategies are explained, pointing out the advantages and disadvantages of each one. A first possible way of cooperation is to provide each device with multiple samples of the features vector $\underline{v}(t, \underline{x}_i)$: these samples are used by the device to take its decision, knowing what other terminals are observing. This can be reached by allowing each CT_i to communicate its vector $\underline{v}_i$ to another terminal CT_j, and by defining decision algorithms based on multiple observations.
This approach implies that information on $\underline{v}(t, \underline{x}_i)$ is exchanged as a wireless message: the radio-frequency transmission can overlap to the air interfaces already present in the environment, i.e. it can be interpreted as an interfering signal on the observations $O_{i,k,s}$, changing the nature of observations themselves and of the problem.
Another possibility is that each CT shares the analysis model with all the other devices in an a-priori way. Let's assume that each device knows context analysis maps, i.e. the mapping function $D_i(t)$; this a-priori knowledge is shared in an off-line phase when no detector is immersed in the environment and no one is observing the radio scene. No exchange of information is required and no signal interferes with the present radio scene.[13] This second case finds a theoretical framework in the distributed bayesian detection theory by Varshney [25]. This study foresees the application of this approach with some changes to the considered scenario.
To study and implement the distributed classification behavior, it still remains to define $D_i(t)$. The following steps have been carried out:

1) define the classification problem;
2) decompose each M-ary sub-test into a set of binary tests;
3) identify space-variant sub-tests;
4) define the distributed version of each binary test.

Step 1 - Define the classification problem. Starting from the general framework described in Section V, having two possible modes, M_1 and M_2, and two radio sources, RS_1 and RS_2, the situations to be classified are four, and in particular:

- absence of signal, when all sources (RS_1 and RS_2) are switched off and only environmental Noise ($\{Noise, Noise\}$ class) can be present;
- presence of WLAN signal ($\{Noise, WLAN\}$ class), RS_1 is switched on, and RS_2 is switched off;
- presence of Bluetooth (BT) signal ($\{BT, Noise\}$ class), RS_1 is switched off, and RS_2 is switched on;
- presence of WLAN and Bluetooth signals ($\{BT, WLAN\}$ class), RS_1 and RS_2 are switched on .

Thus, each terminal CT_i, by using the function $D_i(t)$, has to perform a M-ary classification problem by extracting one of the four classes from D space, composed as follows:

$$D = \{\{Noise, Noise\}, \{Noise, WLAN\}, \{BT, Noise\}, \{BT, WLAN\}\}$$

where the first component of each class is the status of RS_1, and the second component is the status of RS_2;*Noise* means the corresponding source is switched off, and it is only present environmental noise. Each pair composing D is modeled with a *probability density function* (*pdf*): in case of $\{BT, WLAN\}$, the *pdf* can be expressed as a Asymmetric Generalized Gaussian (AGG) *pdf* [38] with the form expressed in (2).

[13]This means that the observation y_i of terminal i is due to its position x_i and to the state of radio sources H_k, but not to the observation of the other terminal j, y_i; then it is possible to guarantee the conditional independence of observation y used in Appendix I.

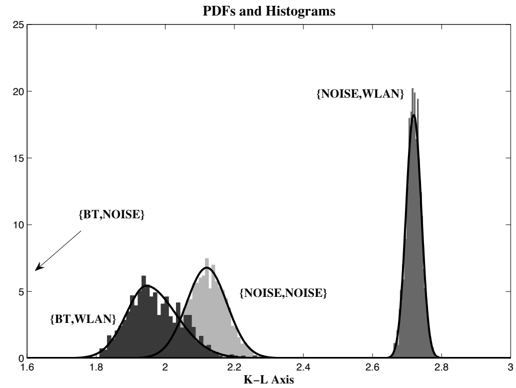

Fig. 10. PDFs and Histograms of classes in the second configuration.

$$p_{agg}(x) = \begin{cases} \frac{c\gamma_a}{\Gamma(1/c)} e^{-\gamma_l^c [-(x-m_x)]^c} & x < m_x \\ \frac{c\gamma_a}{\Gamma(1/c)} e^{-\gamma_r^c [x-m_x]^c} & x > m_x \end{cases} \quad (2)$$

whereas in presence of either $\{Noise, Noise\}$ or $\{Noise, WLAN\}$ or $\{BT, Noise\}$ *pdf*s can be modeled as Generalized Gaussian distributions (GG) [38], whose expression is obtained from (2) setting the equality between the right and left variance.[14]

$$p_{gg}(x) = \frac{c\gamma}{2\Gamma(1/c)} e^{-|\gamma(x-m_x)|^c} \quad (3)$$

Step 2 - Decompose each M-ary sub-test into a set of binary tests. To make the classification process easier, each M-ary problem has been reduced to a set of binary tests, represented in a decision tree as the one reported in Fig. 11.

Step 3 - Identify space-variant sub-tests. According to terminal's position $\underline{x}_i$, it is possible to identify sub-spaces of X where stable decision models can be found in presence of the same set of radio sources configurations. Each decision model can be represented as a decision tree. To better explain this concept let us discuss the example considered in this work: we found that for two RSs case, two regions can be considered sufficient to describe decision problem variability. Let us call such regions X_A and X_B, where $X_A \bigcup X_B = X$ and $X_A \bigcap X_B = 0$. If $\underline{x}_i$ belongs to X_A (the first subspace), features' *pdf*s have the configuration shown in Fig.

[14]For both distributions, (2) and (3), $\Gamma(x)$ is the gamma function and the parameters are: σ^2 the variance, σ_r^2 the right variance, σ_l^2 the left variance, m_x the mean value, β_2 the kurtosis and:

$$c = \sqrt{\frac{5}{\beta_2 - 1.865}} - 0.12 \quad if 1.865 < \beta_2 < 15$$

$$\gamma_a = \frac{1}{\sigma_l + \sigma_r}\left(\frac{\Gamma(3/c)}{\Gamma(1/c)}\right)^{0.5} \quad \gamma_l = \frac{1}{\sigma_l}\left(\frac{\Gamma(3/c)}{\Gamma(1/c)}\right)^{0.5}$$

$$\gamma_r = \frac{1}{\sigma_r}\left(\frac{\Gamma(3/c)}{\Gamma(1/c)}\right)^{0.5} \quad \gamma = \sqrt{\frac{\Gamma(3/c)}{\sigma^2\Gamma(1/c)}}$$

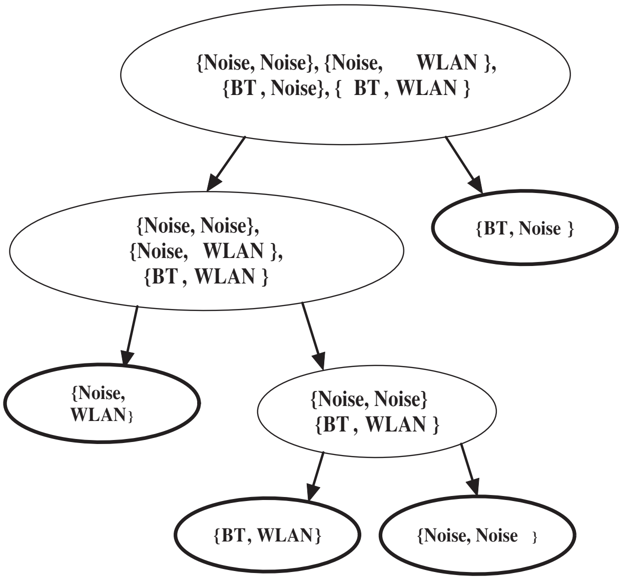

Fig. 11. The binary decision tree DT_A used by each terminal in region X_A.

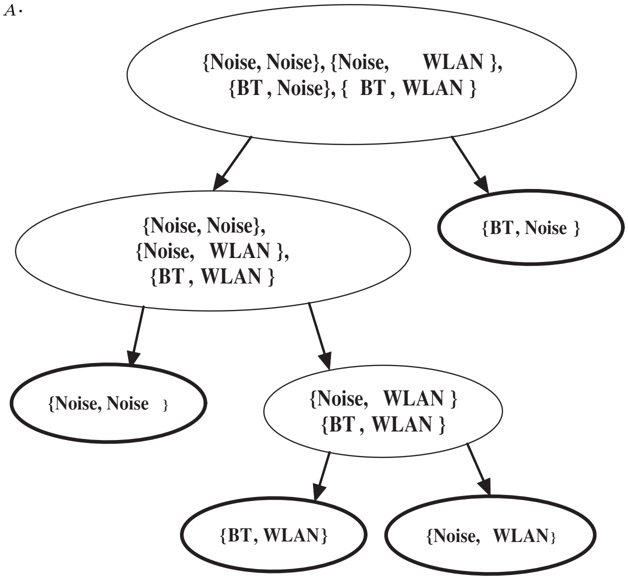

Fig. 12. The binary decision tree DT_B used by each terminal in region X_B.

13, whereas if $\underline{x}_i$ belongs to X_B (the second sub-space) *pdf*s have the configuration represented in Fig. 10. A binary tree is associated to each *pdf*s' configuration: configuration one (Fig. 13) with tree DT_A of Fig. 11, and configuration two (Fig. 10) with tree DT_B of Fig. 12. It is worth mentioning, that the Bluetooth class *pdf* is not plotted in Fig. 13 and 10, because it is very far (in K-L axis) from *pdf*s of other classes; last consideration is reported in binary trees, where the Bluetooth class is the first one which can be classified at the first decision level.[15]

It is now possible to identify the classification as $D_{i,l}(t, x_i)$: $V \rightarrow D$, according to position x_i and related to level l of tree and to terminal i.

[15]The reason is due to the nature of the sources: WLAN has a transmission power higher than Bluetooth, this mean the *region of influence* of the first one is larger. Consequently the *pdf* of $\{BT, WLAN\}$ class is closer to one of $\{Noise, WLAN\}$ class than the one of $\{BT, Noise\}$. In other words, the received signal composed by the two modes is more similar to WLAN air interfaces, and then their *pdf*s closer, for a large region; on the contrary it is very different to Bluetooth signal for the largest part of observation area, and then the *pdf*s are more far.

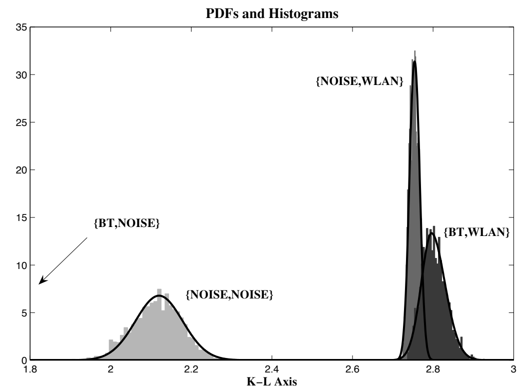

Fig. 13. PDFs and Histograms of classes in the first configuration.

Step 4 - Define the distributed version of each binary test. The aim of this step is to define a distributed approach to the classification problem used for air interface identification. Varshney's distributed detection theory [25] has been applied with some changes in order to improve the performance with respect to classical stand alone procedure.

Let's then consider one of the previous binary tests; let's say the one at level l of decision tree U (with $U \in \{DT_A, DT_B\}$), identified by terminal's position $\underline{x}_i$ (with $\underline{x}_i \in \{X_A, X_B\}$). Two possible hypothesis are present, $H_0^{U,l}$ and $H_1^{U,l}$, for the sake of simplicity here reported as H_0 and H_1, in association with the own a-priori probabilities P_0 and P_1. Being y_1 and y_2 the observations relative to the two terminals, taken at position $\underline{x}_1$ and $\underline{x}_2$, the local classification D_i, (where i denotes which terminal makes the classification), is given by:

$$D_i = \begin{cases} 0 & \text{if } H_0 \text{ is declared present} \\ 1 & \text{if } H_1 \text{ is declared present} \end{cases} \tag{4}$$

The cost assigned to each classification is given by C_{ijk}, $i, j, k = \{0, 1\}$, and it represents the cost of terminal 1 classifying H_i, terminal 2 classifying H_j when H_k is present. The target is to obtain a classification rule, which minimizes the average cost of the classification, starting from [25] and inserting the positions of the two detectors, i.e. $\underline{x}_1$ and $\underline{x}_2$. The following bayesian risk function is used for this purpose:

$$\begin{aligned} \Re =& \sum_{i,j,k} \int_{y_1,y_2} p(D_1, D_2, y_1, y_2, H_k|X) C_{ijk} \\ =& \sum_{i,j,k} \int_{y_1,y_2} P_k C_{ijk} p(D_1, D_2|y_1, y_2, H_k, X) \\ & \cdot p(y_1, y_1|H_k, X) \end{aligned} \tag{5}$$

where the dependance from the distance $X = \{\underline{x}_i, i = 1, 2\}$ is added to [25]. In Appendix I steps to obtain classification rule for each binary distributed test are reported.

Summarizing, the problem has been reduced to a set of cooperative binary detections whose nature depends on: its intrinsic distributed approach, so that the decision of one terminal affects the other device; and terminal's position, which rules the two binary hypothesis and the likelihood function. For a more complete analysis, Table 1 reports previous relations

TABLE I
LIKELIHOOD FUNCTIONS.

	$x_i \in X_A$	$x_i \in X_B$
$j=1$	$\Lambda(y_1) = \frac{\prod_{n=1}^{N} \frac{c_{BT}\gamma_{BT}}{2\Gamma(1/c_{BT})} e^{-\lvert\gamma_{BT}(y_1^n - m_{BT})\rvert^{c_{BT}}}}{\prod_{n=1}^{No} \frac{c_{No}\gamma_{No}}{2\Gamma(1/c_{No})} e^{-\lvert\gamma_{No}(y_1^n - m_{No})\rvert^{c_{No}}}}$	$\Lambda(y_1) = \frac{\prod_{n=1}^{N} \frac{c_{BT}\gamma_{BT}}{2\Gamma(1/c_{BT})} e^{-\lvert\gamma_{BT}(y_1^n - m_{BT})\rvert^{c_{BT}}}}{\prod_{n=1}^{No} \frac{c_{No}\gamma_{No}}{2\Gamma(1/c_{No})} e^{-\lvert\gamma_{No}(y_1^n - m_{No})\rvert^{c_{No}}}}$
$j=2$	$\Lambda(y_1) = \frac{\prod_{n=1}^{N} \frac{c_{WL}\gamma_{WL}}{2\Gamma(1/c_{WL})} e^{-\lvert\gamma_{WL}(y_1^n - m_{WL})\rvert^{c_{WL}}}}{\prod_{n=1}^{N} \frac{c_{WL+BT}\gamma_{WL+BT}}{\Gamma(1/c_{WL+BT})} e^{-\gamma_{r,WL+BT}^{c_{WL+BT}}[y_1^n - m_{WL+BT}]^{c_{WL+BT}}}}$	$\Lambda(y_1) = \frac{\prod_{n=1}^{N} \frac{c_{No}\gamma_{No}}{2\Gamma(1/c_{No})} e^{-\lvert\gamma_{No}(y_1^n - m_{No})\rvert^{c_{No}}}}{\prod_{n=1}^{N} \frac{c_{WL}\gamma_{WL}}{2\Gamma(1/c_{WL})} e^{-\lvert\gamma_{WL}(y_1^n - m_{WL})\rvert^{c_{WL}}}}$
$j=3$	$\Lambda(y_1) = \frac{\prod_{n=1}^{N} \frac{c_{No}\gamma_{No}}{2\Gamma(1/c_{No})} e^{-\lvert\gamma_{No}(y_1^n - m_{No})\rvert^{c_{No}}}}{\prod_{n=1}^{N} \frac{c_{WL+BT}\gamma_{WL+BT}}{\Gamma(1/c_{WL+BT})} e^{-\gamma_{r,WL+BT}^{c_{WL+BT}}[y_1^n - m_{WL+BT}]^{c_{WL+BT}}}}$	$\Lambda(y_1) = \frac{\prod_{n=1}^{N} \frac{c_{WL}\gamma_{WL}}{2\Gamma(1/c_{WL})} e^{-\lvert\gamma_{WL}(y_1^n - m_{WL})\rvert^{c_{WL}}}}{\prod_{n=1}^{N} \frac{c_{WL+BT}\gamma_{WL+BT}}{\Gamma(1/c_{WL+BT})} e^{-\gamma_{r,WL+BT}^{c_{WL+BT}}[y_1^n - m_{WL+BT}]^{c_{WL+BT}}}}$

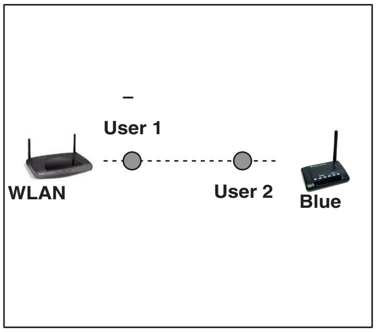

Fig. 14. Considered Indoor scenario.

showing all possible likelihood functions, which have to be implemented. In all formulas, sub-scripts represent the class the parameters refer to, as instance m_{WL+BT} identifies the mean value of $\{BT, WLAN\}$ class. It is here reported the case with $x_i \in X_B$ and $j = 2$, that is the identification of the $\{Noise, WLAN\}$ class; the likelihood function is then simplified getting the following decision rule:

$$\sum_{n=1}^{N} [-|\gamma_j(y_n - m_j)|^{c_j} + |\gamma_{WL}(y_n - m_{WL})|^{c_{WL}}] \tag{6}$$

$$\underset{u_i=0}{\overset{u_i=1}{\gtrless}} \ln\left(\frac{c_k\gamma_{WL}}{2\Gamma(1/c_{WL})}\right) - \ln\left(\frac{c_j\gamma_j}{2\Gamma(1/c_j)}\right) + \ln t_i$$

The decision process can be formally evaluated, always for the same case above described, by computing error probability: once defined the thresholds t_1 and t_2, the error probability of detector 1 of classifying the absence of sources ($\{Noise, Noise\}$ class), when WLAN signal ($\{Noise, WLAN\}$ class) is present, is:

$$P(err\,|WL) = \int_{-\infty}^{t_1} \frac{c_{WL}\gamma_{WL}}{\Gamma(1/c_{WL})} e^{-|\gamma_{WL}(x_1 - m_{WL})|^{c_{WL}}} dx_1 \tag{7}$$

In the following paragraph, the simulation environment, based on previously described assumptions, the theoretical error probability for the moving terminal CT_i and a comparison with a stand alone case are shown.

VIII. RESULTS

The general scenario explained in Section V is implemented by using Matlab/Simulink. Two cognitive terminals, CT_1 and CT_2, are used (Fig. 14) moving around a room of 15×15 meters. The environment, in terms of user's position and map, is considered known by each of the two devices by using whatever Geographical Information System they can implement. The radio scene to be detected can be composed by either one of two possible modes, M_1 or M_2 (DS-CDMA, FH-CDMA), or both or none of them. The two air interfaces, implemented taking into account all parameters defined in the standards [39], [40] except for protocols higher than the physical layer, are transmitted to a wireless channel.[16] Received signals are then translated in IF at 30 MHz with a sample rate of 120 Msample/s to satisfy the Nyquist limit. Then, they are computed by TF block: the Wigner-Ville distribution uses blocks with $N = 512$ samples, obtained through a time window T large enough to contain 10 frequency hops. The time hopping is $625\mu s$. The extraction module stores 10 TF matrices, and it calculates the features as expressed in Section VII-A. Then, the features are reduced with K-L method and sent to classification block.

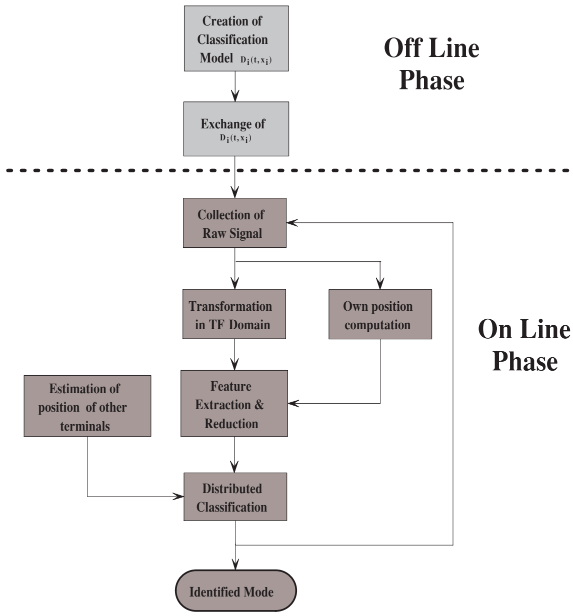

Fig. 15. Flow chart of spectrum sensing algorithm.

[16]The radio channel is modelled as indoor multipath with AWGN. Multipath model is Rice fading with delay spread of 60 ns, and root mean square (rms) delay spread of 30 ns [41]. A path loss term has been inserted: it follows the model proposed in [42].

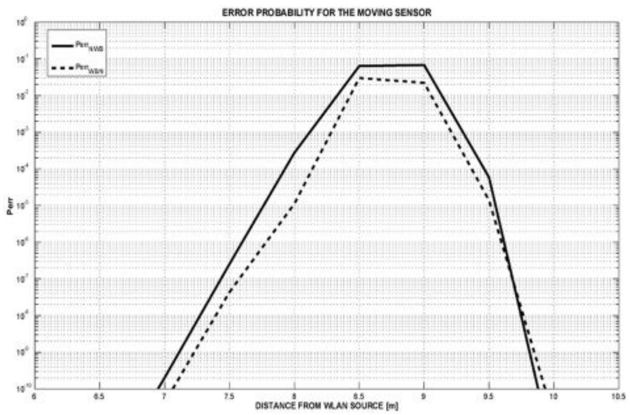

Fig. 16. Error probability of $\{BT, WLAN\}$ and $\{Noise, Noise\}$ classes for the cooperative scenario.

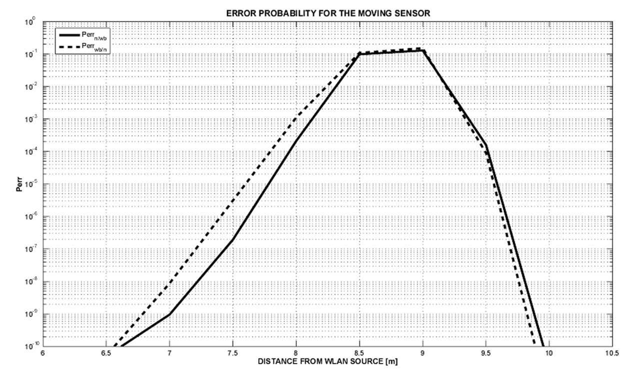

Fig. 17. Error probability of $\{BT, WLAN\}$ and $\{Noise, Noise\}$ classes for the stand alone scenario.

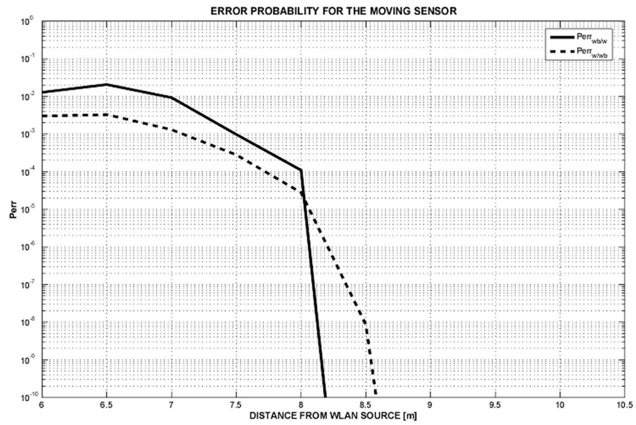

Fig. 18. Error probability of $\{Noise, WLAN\}$ and $\{BT, WLAN\}$ classes for the cooperative scenario.

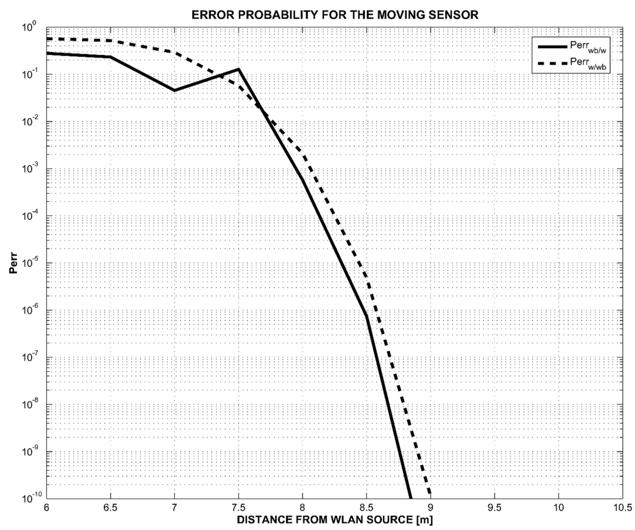

Fig. 19. Error probability of $\{Noise, WLAN\}$ and $\{BT, WLAN\}$ classes for the stand alone scenario.

The CT has to be aware of its position in order to chose the right decision model; in the present work, this quantity is assumed to be known, but on-going researches are dealing with a methodology to relax this constraint applying methods for hidden parameters estimation. The described algorithm is summarized in the flowchart of Fig. 15: it represents steps the system implements in order to obtain the classification of available air interfaces.

To prove the improvement of performances given by the proposed distributed system, in the following figures error probabilities, both for cooperative and stand alone scenarios, are shown. Moreover, in order to validate the simulator, we computed the comparison between Error Probability and Error Rate (Fig. 20 and 21).

In Fig. 16, error probabilities are compared for the pair $\{BT, WLAN\}$ and $\{Noise, Noise\}$, computed in case of one terminal at rest at 8.5 meters from the WLAN source, and the other one moving from 2 up to 12 meters on the line of sight between the two access points; the cost k of the double error is set to 10. Two error probabilities are shown in the Figure: one represents the probability of classifying $\{BT, WLAN\}$ instead of $\{Noise, Noise\}$ when all sources are switched off, and the other one represents the probability of deciding the presence of only Noise while $\{BT, WLAN\}$ is present. In both cases, the error probability increases, reaching a peak at about 8 meters from the WLAN source; this fact is due to an overlap of the two classes which generates ambiguities in the decision process. In Fig. 17, it's possible to see the error probability for the classes $\{BT, WLAN\}$ and $\{Noise, Noise\}$ for the stand alone scenario. It is possible to see a worst performance than in the cooperative scenario, where, for instance, the value of 10^{-10} is maintained within a distance of 7 meters, while, in this case, it's held within 6.5 meters. Moreover, the overall behavior is characterized by an Error Probability higher than the one obtained with distributed detectors.

In Fig. 18, the error probabilities computed for the couple $\{BT, WLAN\}$ and $\{Noise, WLAN\}$ for the following scenario are presented: one detector fixed at 3.5 meters from the WLAN 802.11b source, and the other one moved from 2 up to 12 meters on the line of sight between the two access points; the cost of double error, even in this case, is taken equal to 10. For both cases (classification of $\{Noise, WLAN\}$ when $\{BT, WLAN\}$ is present and viceversa), the maximum ambiguity has been obtained for distances close to the WLAN source, where the classes are strongly overlapped. Also in

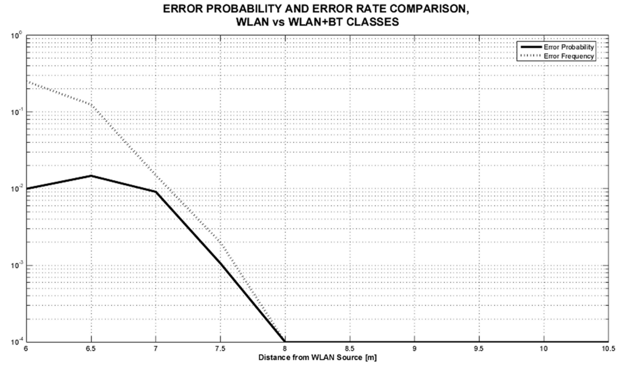

Fig. 20. Error Probability vs Error Rate of $\{Noise, WLAN\}$ and $\{BT, WLAN\}$ classes.

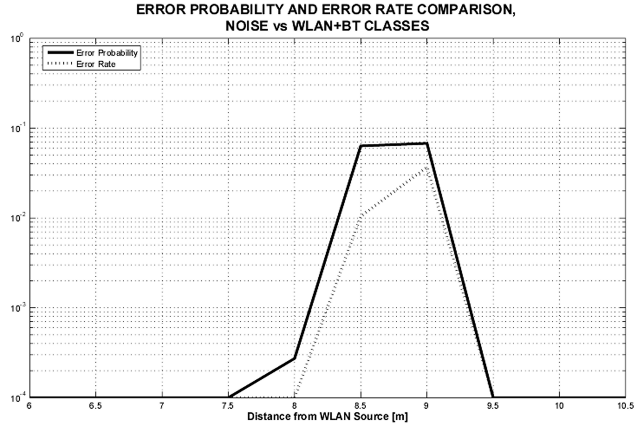

Fig. 21. Error Probability vs Error Rate of $\{Noise, Noise\}$ and $\{BT, WLAN\}$ classes.

this case the system presents good performances, and the closed form of the error probability, (7), allows an objective evaluation, biased by the fitting error and by K-L reduction, of the proposed algorithm. The improvement of cooperative case with respect to stand alone scenario is clear also in this case (Fig. 18 and 19).
Finally in Fig. 20 and 21 the comparison between Error Probability and Error Rate is shown; the first plot shows the error of classifying only WLAN source switched on ($\{Noise, WLAN\}$ class) when both sources are working ($\{BT, WLAN\}$ class), whereas the second one regards the error of identifying $\{Noise, Noise\}$ class when both sources are switched on ($\{BT, WLAN\}$ class). The similarity in behavior of the two curves demonstrates the efficiency of simulator, taking into account that the small difference is due to the non complete accuracy of fitting procedures in the theoretical case, as reported in Sect. VII-A.

IX. Conclusion

The paper deals with a distributed decision approach to solve the problem of spectrum sensing for Cognitive Terminals in a known indoor environment. To prove the proposed algorithm, two air interfaces are classified, namely Frequency Hopping Code Division Multiple Access and Direct Sequence Code Division Multiple Access. Binary and distributed likelihood tests have been computed obtaining closed forms for error probabilities in case of Generalized and Asymmetric Generalized Gaussian probability density functions. Shown results demonstrate good performance of proposed approach. On going researches are centered on the resolution of multiple hypothesis distributed decision test, taking into account new air interfaces such as multi-carrier techniques, and new methodologies for a joint estimation of position and modes.

Acknowledgment

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Appendix I

Being the local classifications D_1 and D_2 independent and based respectively on the local observation y_1 and y_2, and on the positions of terminals $\underline{x}_1$ and $\underline{x}_2$, it's possible to express the risk function as follows:

$$\Re = \sum_{i,j,k} \int_{y_1,y_2} P_k C_{ijk} p(D_1 = i | y_1, \underline{x}_1) \cdot p(D_2 = j | y_2, \underline{x}_2) p(y_1, y_2 | H_k, X) \tag{8}$$

Explicitly summing over i, considering that:

$$p(D_1 = 1 | y_1, \underline{x}_1) = 1 - p(D_1 = 0 | y_1, \underline{x}_1) \tag{9}$$

and ignoring the constant terms with respect to D_1, it's possible to re-write $\Re$:

$$\Re = \int_{y_1} p(D_1 = 0 | y_1, \underline{x}_1) \sum_{j,k} \int_{y_2} P_k p(D_2 = j | y_2, \underline{x}_2) \cdot p(y_1, y_2 | H_k, X)[C_{0jk} - C_{1jk}] \tag{10}$$

It's now possible to derive a classification rule for terminal 1:

$$\sum_{j,k} \int_{y_2} P_k p(D_2 = j | y_2, \underline{x}_2) \cdot p(y_1, y_2 | H_k, X)[C_{0jk} - C_{1jk}] \underset{D_1=0}{\overset{D_1=1}{\gtrless}} 0 \tag{11}$$

Expanding the sum over k, the following formula can be obtained [25]:

$$\sum_{j} \int_{y_2} P_0 p(D_2 = j | y_2, \underline{x}_2) p(y_1, y_2 | H_0, X)[C_{0j0} - C_{1j0}] \underset{D_1=0}{\overset{D_1=1}{\gtrless}} \sum_{j} \int_{y_2} P_1 p(D_2 = j | y_2, \underline{x}_2) p(y_1, y_2 | H_1, X)[C_{1j1} - C_{0j1}] \tag{12}$$

Assuming that the cost of terminal 1, making an error when H_0 is present, is higher than the cost of classifying correctly regardless the classification of terminal 2, i.e. $C_{0j0} < C_{1j0}$, and considering that:

$$p(y_1, y_2|H_k, X) = p(y_2|y_1, H_k, X)p(y_1|H_k, X),\ k = 0, 1 \tag{13}$$

the (12) can be expressed as a likelihood ratio test [25]:

$$\Lambda(y_1) \underset{D_1=0}{\overset{D_1=1}{\gtrless}} \frac{P_0 \sum_j \int_{y_2} p(D_2 = j \,|\, y_2, \underline{x}_2) p(y_2 \,|\, y_1, H_0, X)[C_{1j0} - C_{0j0}]}{P_1 \sum_j \int_{y_2} p(D_2 = j \,|\, y_2, \underline{x}_2) p(y_2 \,|\, y_1, H_1, X)[C_{0j1} - C_{1j1}]} \tag{14}$$

where $\Lambda(y_1)$ is the bayesian likelihood function for detector 1:

$$\Lambda(y_1) = \frac{p(y_1|H_1, \underline{x}_1)}{p(y_1|H_0, \underline{x}_1)} \tag{15}$$

The previous formula (14) shows that the right-hand side is a function not only of the observation for terminal 1, i.e. y_1, but it's possible to note that it is a function of D_2, i.e. the classification rule for terminal 2 too, and this dependance appears under the form of $p(D_2|y_2, \underline{x}_2)$.

As reported in section VII-B, terminals don't transmit anything in the observation band, then the observation y_1 of terminal 1 is due to its position x_1 and to the state of radio sources H_k, but not to the observation of the other terminal 2, y_2. It is then possible to consider the conditional independence of y_1 and y_2 [25], i.e. when

$$p(y_2 \mid y_1, H_k, \underline{x}_1, \underline{x}_2) = p(y_2 \mid H_k, \underline{x}_2) \tag{16}$$

the right-hand side of (14) can be reduced to a threshold given by:

$$t_1 = \frac{P_0 \sum_j \int_{y_2} p(D_2 \,|\, y_2, \underline{x}_2) p(y_2 \,|\, H_0, \underline{x}_2)[C_{1j0} - C_{0j0}]}{P_1 \sum_j \int_{y_2} p(D_2 \,|\, y_2, \underline{x}_2) p(y_2 \,|\, H_1, \underline{x}_2)[C_{0j1} - C_{1j1}]} \tag{17}$$

Noting that

$$p(D_2 = 1|y_2, \underline{x}_2) = 1 - p(D_2 = 0|y_2, \underline{x}_2) \tag{18}$$

it's possible to expand (17) in order to show explicitly that t_1 is a function of $p(D_2 = 0|y_2, \underline{x}_2)$, which represents the classification rule for terminal 2. A similar conclusion can be obtained for the threshold of terminal 2.

The proposed general definition and optimization of the whole system involves the existence of two coupled thresholds and for the setup considered in the present paper, an offline exchange of information consisting in $p(D_i = 0|H_j, \underline{x}_i)$ with $i = \{1, 2\}$ and $j = \{0, 1\}$ is performed.

Let's now consider a special assignment of the costs as follows [25], where the cost value doesn't depend on which terminal makes the error:

$$\begin{gathered} C_{000} = C_{111} = 0 \\ C_{010} = C_{100} = C_{011} = C_{101} = 1 \\ C_{001} = C_{110} = c \end{gathered} \tag{19}$$

The resulting threshold for terminal *1* becomes [25]:

$$t_1 = \frac{(c-1) + (2-c)p(D_2 = 0 \mid H_0, \underline{x}_2)}{1 + (c-2)p(D_2 = 0 \mid H_1, \underline{x}_2)} \tag{20}$$

A similar expression can be used to compute the threshold for terminal *2*. These are, in general, different from the ones computed if each terminal was considered independently.

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