A distributed wireless sensor network for radio scene analysis

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Abstract

In this paper a distributed approach to radio scene analysis is considered. A Wireless Sensor Network, composed by Software Defined and Cognitive terminals, is used to classify air interfaces present in the radio scene. Two modes, namely Frequency Hopping Code Division Multiple Access and Direct Sequence Code Division Multiple Access, are identified employing a signal processing technique, Time Frequency analysis, and a distributed decision theory. Advantages given by distributed detection are used to improve the performance of Mode Identification module. Results in terms of error probability are obtained by modelling the probability density function of considered features as Asymmetric Generalized and Generalized Gaussian functions.

Keywords: Wireless Sensor Network, Cognitive Radio, Distributed Detection, Radio Scene Analysis, Mode Identification, Wireless LAN, Bluetooth

1 Introduction

In the last years the scientific community, under the pressure of the military world (and not only), is concentrating big and multidisciplinary efforts on the study of sensor networks (SN), and in particular of wireless sensor networks (WSN). A SN is a group of nodes able to sense the external world and exchange the gathered information; if the medium of the communication flow is wireless, the network is called WSN. Thousands of applications can be mentioned for WSN, and four main possible fields of use can be identified: military, environmental, health and domestic [1], [2].

The military field is the most demanding and then, best performances can be found in these applications: forces, equipment and ammunition monitoring, battlefield surveillance, target identification and also enemy spying, damages evaluation, nuclear, biologic and chemical (NBC) attack detection [3] are some of the possible uses.

In the environmental application the WSN are very useful, because (usually) the variables to be monitored are spread in large areas, which, many times, are not studied for their inaccessibility; in this case, the absence of infrastructure is overcome by the modularity of WSN allowing the user to cover with high flexibility the monitored area. Some examples can be found in [4], [5], [6], [7], [8].

The third application field is the medical world, where WSNs are essentially used to monitor the health status of the patient. Particular interest is devoted to embedded sensors, directly inserted in the body,

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which compose a network with external nodes for a continuous control of the subject. Examples can be found in [9] and [10].

The last but not less important field is the building automation. In this case, the aim is to join heterogeneous systems present in a building to create a fully-interconnected network of devices. Many applications of this kind can be found in smart spaces, domotic, video surveillance [11] and [12].

In many of the previous mentioned applications and architectures, a common part is present and fundamental for each target: the availability to exchange information by using wireless links. The advantage consists in avoiding a fixed infrastructure, but the drawback is that a radio link is usually time-varying and very noisy. The first solution is to build a network with performances, pre-defined in respect to the worst case, but this means an inefficient use of resources, such as the spectrum. Thus, nowadays the challenge is to project networks and devices able to adapt themselves to the external environment, and in particular to the radio resources (spectrum, standard, mode, etc): this paradigm is reflected by the so-called Software Defined and Cognitive Radio approach [13], [14] and [15]. The Software Defined and Cognitive Radio brings to the definition of a completely adaptable physical layer, where the communication features can change in relation to the conditions of the wireless channel, to the traffic status and to the users' requirements.

2 The Problem of Radio Scene Analysis

In order to reach such fully-reconfigurable devices and networks, many issues are still open, such as powerful algorithms and procedures to understand the external 'radio-scene' [15]; among them, one of the main important topics is Mode Identification and Spectrum Monitoring (MISM) [16], [17] and [18]. MISM is the process through which a base station or a terminal understands the radio-scene by classifying the available transmission modes and the *spectrum holes* in the channel. A *transmission mode* (also called *air interfaces*[13]) 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. [13] . A *spectrum hole* is, as defined in [19], *a band of frequencies assigned to a primary user, but, at a particular time and specific geographic location, the band is not being utilized by that user.* By using MISM, a cognitive terminal should be able to recognize the spectrum holes and the available modes in order to improve the efficiency of spectrum use and of radio resources in general. To implement the framework of a MISM module, this work proposes the use of a Wireless Sensor Network composed by Software Defined and Cognitive radio devices.

3 Solutions for Radio Scene Analysis

In the state of the art some proposals can be found to implement radio sensing modules. The simpler and older solution is the use of the so called radiometer [20]: the idea is to scan spectrum by extracting energy in each sub-band identifying the presence of signals. The advantage of this approach is the very low computational load, but the drawback is that, when signals temporally overlap on the same band, energy detection can be insufficient to discriminate the mode. Moreover, the pieces of information provided by energy detection cannot be enough to take further steps, for example, in the direction of modulation recognition. Another work [16] presents the use of a radial basis function (RBF) neural network for a power spectral density estimation to identify the communication standard. No superposition of signals is considered, and different radio frequency stages are employed. In [18] a further integrated solution is proposed by means of two steps sensing module: a first energy detection to identify a void or occupied carrier; a following Radio Access Technologies (air interface) classification to detect GSM and UMTS signals. Also in this approach no superposition of modes is taken into account and, moreover, the solution is studied for a stand alone sensor. The first procedure for sensing and identification of overlapping modes is presented in [17], where a time frequency analysis is combined with neural network to classify spread spectrum interfaces, such as frequency hopping and direct sequence. The use of time frequency methods allows the study in time and frequency plane of spectrum in order to evaluate the so-called 'white spaces' (or spectrum holes) also in time domain and, moreover, to discriminate two air interfaces using the same band. Approaches for spectrum sensing, based on time frequency analysis, have been subsequently proposed also in [15] with a complete and exhaustive analysis of cognitive radios; in that paper, the Author proposes a two steps-procedure composed by interference temperature estimation and spectrum holes detection. Another recent work is [21], which shows an air interface classification (that is mode identification), based on cyclostationarity detection. The feature of cyclostationarity is used like signature of superimposed modes: each signal provides this property with different frequencies and for different values of time lag and, by using binary hypothesis testing, it is classified. Another related work, and 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 goals are the improvement in assured military communications through the dynamic assignment of allocated spectrum. In the Request for Comments (RFC) of the Program [22], a key function is given by sensing module, which has to sample the channel in order to determine occupancy. 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, what the characteristics of the signal are (*air interfaces classification*).

The paper starts with the vision of cognitive wireless sensors (Next Section), whereas in Section 5 the entire proposed framework is described. In Sections 6 and 7 procedures are explained with a deep analysis of distributed detection (Subsect. 7.2). Results and conclusion are shown in Sections 8 and 9.

4 Cognitive Wireless Sensors Network Vision

The vision proposed in this work joins two different research fields: Sensor Network and Cognitive Radios. The problem of radio scene analysis, typical of Software Defined and Cognitive Radios [15], [18], [23], is tackled starting from the solution proposed in [17] to arrive at proposing the use of Distributed Detection, typical of Sensor Network [24], [25] and [26] , by considering cognitive terminal as cognitive sensor node. Through this approach, advantages of cooperative strategies and sensor network provide, as will be shown in Section 8, a better performance in terms of correct detection, which can not be reached, for stand alone sensor, with its own procedure. Each device/sensor works together with other terminals to obtain data about wireless channel, more detailed and correct than in the stand alone scenario. To explain how this objective is reached, examples of 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. The choice of these two standards stems from three factors: first, they are based on DS-CDMA and FH-CDMA, the chosen modes; second, they use the same bandwidth (Industrial Scientific Medical (ISM) Band) allowing the design of a unique RF conversion stage, as ideally required for an SDR platform [13]; third, the growing interest in them on the market for their wireless connectivity, especially for communications in coexistent environment.

5 General Framework and Proposed Method

The approach is a generalization of the one proposed in [17] to a multiple cooperative scenario. A number N of cognitive sensors (CS) CS_i, with $i = 1, 2, ..., N$, move in an indoor environment to observe the 'external world' by analyzing spectrum, searching for radio sources to be localized and identified. Each CS_i is able to extract pieces of information from the external world, analyze them, decide and act in relation to a pre-defined cognitive cycle [14]. More precisely, each SS captures the observation $O_i(t)$, processes it and extracts from it a vector of features $\underline{v}(t) = \{v_1, v_2, ..., v_F\}$, which represents O_i in a synthetic form useful to the decision and action procedures. Each device performs a classification $C_i(t)$ based on available observations and cooperative strategies. The classification can be defined as a mapping between a features space V and a classification space C. V is the space of possible values assumed by features extracted by each sensor during the observation. C, 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 a MISM problem combined with the location estimation of sources.

The mode identification and spectrum monitoring (MISM) and location problem is defined as follows: let's consider (Fig. 1) that a set of CSs, $\{CS\} = \{CS_i : i = 1, ..., N\}$ 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 the 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, for example M. Let us suppose that each CS_i is associated with a position $\underline{x}_i$ in the space $\underline{X}$, where radio sources are. Finally let's presume that no null discrete quantized observations $O_{ik}(t)$, at each time t, for each sensor CS_i, are available as effects of radio source RS_k over sensor CS_i, i.e. the sensibility of each sensor CS_i is such, that it can detect the presence of each radio source RS_k if only that radio source is present, supposing that all radio sources in RS space lie in the horizon of each sensor in CS. Then, the mode identification, together with spectrum monitoring and location problem, is defined as the capability of the set CS of cognitive sensors to carry out a set of classification $C_i(t)$ about the presence of the transmission mode and the position of a set of Radio Sources RS which lie in the horizon of S.

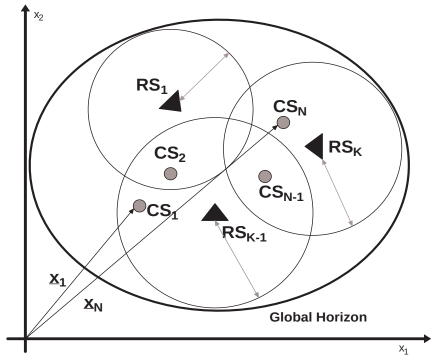


Figure 1: The general framework.

When $dim\{CS\} = 1$, a stand alone scenario is fixed, i.e. a single smart sensor is considered. If $dim(\underline{X}) = 1$, and the position of the stand alone CS, CS_1, are fixed, then a mono-dimensional space and horizon are considered as the *world domain* of the problem (Fig. 2). A situation with $CS = 1$ and $dim(\underline{X}) = 1$ was considered in [17], where a feature vector $\underline{v}_1(t, x_1)$ based on time-frequency analysis of the observed spectrum, $O_1(t, x_1)$ with CS_1 at position x_1, was analyzed. A problem with $dim(RS) = 2$, i.e. with two radio sources, was there analyzed with the additional constraint that $\underline{x}_{RS_1}$ and $\underline{x}_{RS_2}$, i.e. the positions of the radio sources, were fixed. However, even though that problem allows an insight in the complexity, due to the overlapping nature of the observations $O_i(t, \underline{x}_i)$ in relation to different $\underline{x}_i$ (where the overlapping effects of sources can give rise to difficult pattern recognition problems), it is by many cases too simple to reflect more direct situations of interest. In particular, in this paper some working hypothesis done in [17] are relaxed by using $dim\{CS\} > 1$ and, without loosing generality, $dim\{CS\} = 2$, where $\{CS\} = \{CS_1, CS_2\}$ is composed by a set of two smart sensors. Let us fix $dim(\underline{X}) = 1$ and again $dim(RS) = 2$, where positions of the two sources RS_k are known: in this case the problem of localization is not present, whereas the mode identification remains the main objective of the study.

The two cognitive sensors, CS_1 and CS_2, are composed by different blocks (Fig. 3), which can be grouped in *Sensing Modules* and in *Analysis Modules*. The sensing procedures are performed by

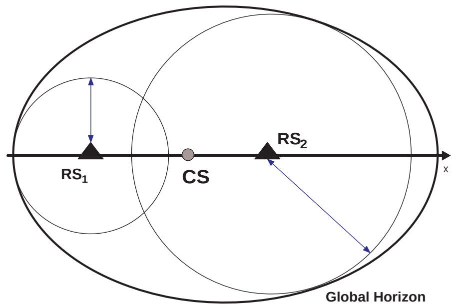


Figure 2: Example of stand alone scenario.

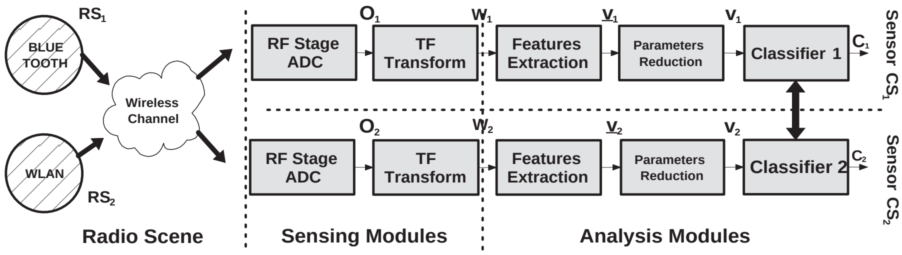


Figure 3: Logical Architecture of two Cooperative Sensors.

directly sampling the received signal and representing it in a bilinear space, the Time Frequency (TF) plane (see Section 6.1); 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 (see Section 7.1) and sent to the classification module (Section 7.2), which, by means of a cooperative strategy, extracts the classification $C_i(t)$. As the classification $C_i(t)$ is taken by these two cognitive sensors, we have to assess the nature of cooperation between the WSN. In particular, each CS CS_i could cooperate in different ways with the other CSs, CS_j, $j = 1, 2$, to take $C_i(t)$ which, in this case, as $M = 2$ and $dim\{RS\} = 2$, are $RS^M = 2^2 = 4$ (see Sec. 7.2).

6 Sensing Procedures

6.1 Time Frequency Analysis

The observation $O_i(t)$ 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 [27]. 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. The Wigner-Ville distribution is given by:

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

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

7 Analysis Procedures

7.1 Features Extraction and Reduction

From Wigner-Ville transform, it is possible to extract TF features of the received signal observed on a time window T. The same two features, used in [17] with one sensor, are here considered:

- Feature 1: standard deviation of the instantaneous frequency.
- Feature 2: maximum time duration of signal.

To obtain the first feature from a given TF distribution, the first conditional moment is computed as:

$$< \omega >_t = \frac{1}{P(t)} \int \omega W(t,\omega) d\omega \tag{2}$$

where $P(t)$ is the time distribution (time marginal), and the integral ranges go from $+\infty$ to $-\infty$. In our case $W(t,\omega)$ is the Wigner-Ville distribution of the received signal. $< \omega >_t$ is the average of frequency at a particular time t, and it is considered as the instantaneous frequency ω_i [27]. The standard deviation of ω_i is:

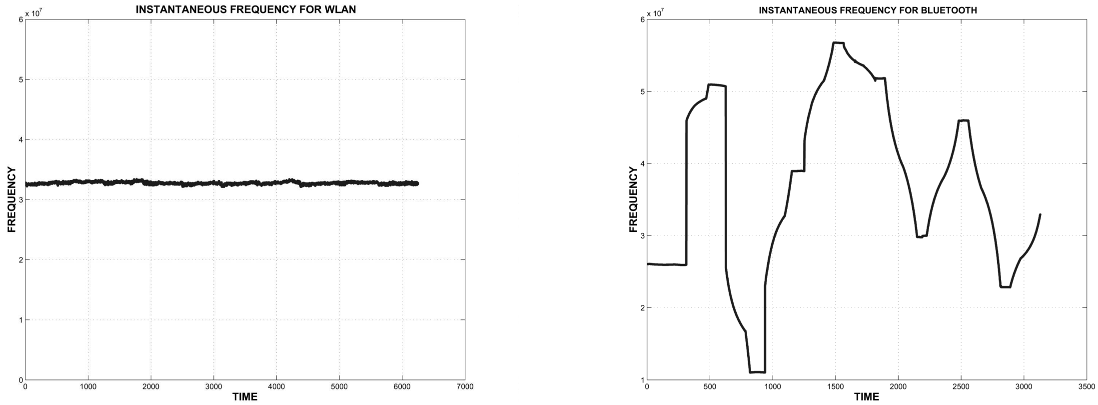
$$std(\omega_i) = \frac{1}{T} \sum (\omega_i - \bar{\omega_i})^2 \tag{3}$$

where $\bar{\omega_i}$ is the mean value of ω_i computed on the time window T. From Fig. 4 you can see that it is reasonable to obtain a low value of $std(\omega_i)$ when the first conditional moment is quite constant as in the case of DS (IEEE 802.11b), while it assumes high values in the case of FH (Bluetooth). The second feature is obtained on the basis of the following considerations: in case of DS, frequency components are continuous in time for a duration that depends on the length of the time observation window T used to compute the distribution. Instead, for FH signal, a discontinuity in time can be observed due to the presence of different frequency hops. Therefore, it is possible to obtain an empirical discriminating feature based on the time duration of the signal. To obtain such data, the following operations are performed:

1. From the chosen transform, a binary TF matrix $W_{bin}(t,\omega)$ is obtained 'binarizing' $W(t,\omega)$ through a threshold to eliminate noise. The values of this matrix represent presence (element equals to 1) or absence (element equals to 0) of signal at a given time t and at a given frequency f.

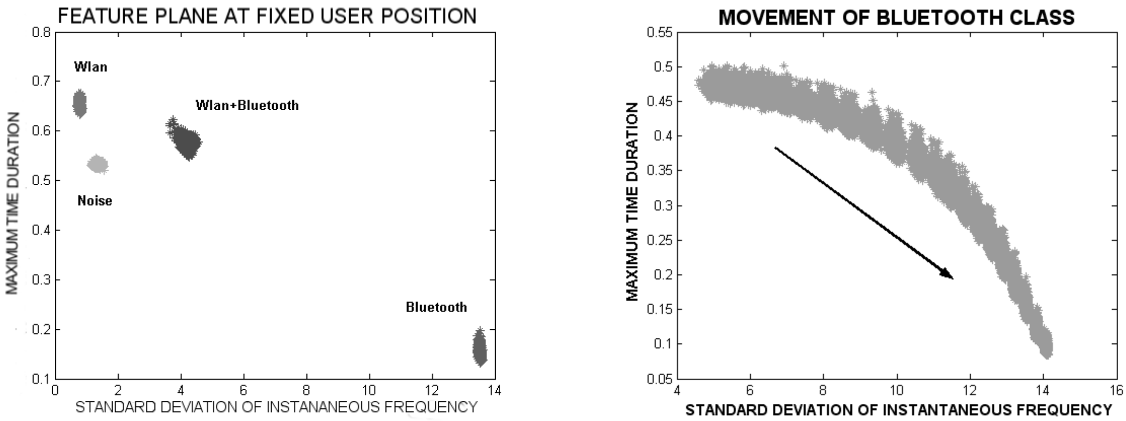
2. The threshold has been chosen in an empirical way. After a trial and test procedure, its value has been chosen as the mean value of the TF matrix;

3. Once $W_{bin}(t,\omega)$ has been obtained, the elements of each row, i.e. for each frequency, are summed up obtaining $T(\omega)$, standing for the length in time of the component in relation to frequency.



(a) (b)

Figure 4: Instantaneous frequency for the two signals, WLAN (a) and Bluetooth (b).



(a) (b)

Figure 5: Feature plane for the four class at fixed user position (a) and for the bluetooth class during the movement of one sensor (b).

The feature used for the classification has been chosen as the maximum value T_M in such set, namely:

$$T_M = max(T(\omega)) \tag{4}$$

where

$$T(\omega) = \sum_t W_{bin}(t, \omega) \tag{5}$$

in which the summation is done over the entire length of the window, where the distribution is computed.

At the end of the feature computation, a vector $\underline{v}$ is obtained:

$$\underline{v} = \{v_1, v_2\} = \{std(\omega_i), T_M\} \tag{6}$$

To simplify the problem decreasing the dimension of features space, the Karhunen-Loeve (K-L) method [28] has been performed. It computes a linear transformation, identified by the matrix $A[n \times m]$, in order to reduce the dimension of features space from n dimensions to m, with $m < n$. Once a new feature, linear combination of the ones proposed in formulas (3) and (4) is obtained from K-L, simpler probability density functions (*pdf*) can be computed. In the case of WLAN, Bluetooth and Noise class the *pdf* can be expressed as a Asymmetric Generalized Gaussian (AGG) [29] with the form expressed in (7).

$$p_{agg}(x) = \begin{cases} \frac{c\gamma_a}{\Gamma(1/c)} e^{-\gamma_l^c[-(x-m_x)]^c} & x < m_x \\ \frac{c\gamma_a}{\Gamma(1/c)} e^{-\gamma_r^c[x-m_x]^c} & x > m_x \end{cases} \tag{7}$$

where

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

$$\gamma_r = \frac{1}{\sigma_r} (\frac{\Gamma(3/c)}{\Gamma(1/c)})^{0.5}$$

In case of WLAN+Bluetooth signal, the *pdf* can be modelled as a Generalized Gaussian distribution (GG) [29], whose expression is obtained from (7) setting the equality between the right and left variance.

$$p_{gg}(x) = \frac{c\gamma}{2\Gamma(1/c)} e^{-|\gamma(x-m_x)|^c} \tag{8}$$

where

$$\gamma = \sqrt{\frac{\Gamma(3/c)}{\sigma^2 \Gamma(1/c)}}$$

where for both distribution, (7) and (8), $\Gamma(x)$ 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:

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

Once *pdf*s of feature are modelled the detection process can be carried out. In the following Subsection the steps to reach distributed classification modules are explained.
It is worth mentioning another characteristic of features: as it can be noticed by Fig. 5.a, when one sensor S_i is at rest in a given position $\underline{x}_i$, the features plane assumes that representation, but when $\underline{x}_i$ changes, i.e. the considered sensor moves in the environment, then also the features change their value. An example of feature movement, when the sensor moves away from WLAN source, is reported in Fig. 5.b. This observation brings to consider the vector $\underline{v}$ not only as a function of time t, $\underline{v}(t)$, but also of position $\underline{x}_i$, then $\underline{v}(t, \underline{x}_i)$.

7.2 Distributed Classification

As reported in Section 5, in addition to an advanced signal processing technique, i.e. the Time-Frequency analysis (Sect. 6.1), to improve the performances of the MISM module, a distributed classification algorithm is studied.

Different strategies can be designed to implement a cooperative behaviour of Cognitive Sensors: 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 sensor with multiple samples of the features vector $\underline{v}_i(t)$ at a given time t_0: these samples are used by the sensor to take its decision knowing what the other sensors are observing. This can be reached by allowing each sensor CS_i to communicate its vector $\underline{v}_i$ to another sensor CS_g, and by defining decision algorithms using multiple observations.

As $\underline{v}_i(t) = \underline{v}_i(t, \underline{x}_i)$, i.e the feature vector is a function of the position of the sensor too, the relative position of all the sensors must be known as well to allow the correct alignment of the observed patterns in the pattern space. Therefore, $C_i(t)$ is a mapping function defined as $\{\underline{v}_i(t, \underline{x}_i)\} \rightarrow C \equiv M_1 \times M_2$. This approach implies that information on $\{\underline{v}_i(t, \underline{x}_i), i = 1, 2\}$ is exchanged as a wireless message: the radio-frequency transmission can be overlapped to the air interfaces already present in the environment, i.e. it can be interpreted as an interfering signal on the observations $O_i(t, \underline{x}_i)$, changing the nature of observations themselves and of the problem.

Another possibility is that each element of the set of sensors shares the decision model with all the others in an a-priori way. Let's assume that each sensor knows its decision behaviour, i.e. the mapping function $C_i(t)$; this a-priori knowledge is shared in an off-line phase, i.e. no detector is immersed in the environment and no one is observing the radio scene. The exchanged information requires a significantly lower bandwidth than the previous cooperative strategy, and no signal interferes with the present radio scene. As the feature vector is a function of the position of the sensor, the classification behaviour depends on the position of the node: the exchanged information can hence be coded as a probabilistic distribution of the features in the space, let us call it "features map". This second case finds a theoretical framework in the distributed bayesian detection by Varshney [24]. This study foresees the application of this approach with some changes to the considered scenario.

To study and implement the detection problem, it still remains to be defined which values the classification $C_i(t)$ can assume: starting from the general framework described in Section 5, given 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 class) can be present;
- presence of WLAN signal (WLAN class), RS_1 is switched on, and RS_2 is switched off;
- presence of Bluetooth signal (Bluetooth (BT) class), RS_1 is switched off, and RS_2 is switched on;
- presence of WLAN and Bluetooth signals (WLAN+Bluetooth class), RS_1 and RS_2 are switched on .

Thus, each sensor CS_i, by using the classification function $C_i(t)$, has to extract one of the four classes from C space, composed as follows:

C={{Noise, Noise},{Noise, WLAN},{BT, Noise},{BT, WLAN}}

where the first component of each class is the status of RS_1 and the second one of RS_2, and *Noise* means the corresponding source is switched off, and the only environmental noise is present. To simplify the classification process, it's possible to reduce the problem to a binary classification test. In fact, given the position of each detector, it's possible to classify the air interface by solving a set of binary problems. The distribution of the probability density functions of the features on the K-L axis shows that only two classes are partially overlapped, and they can generate ambiguities for each sub-problem.

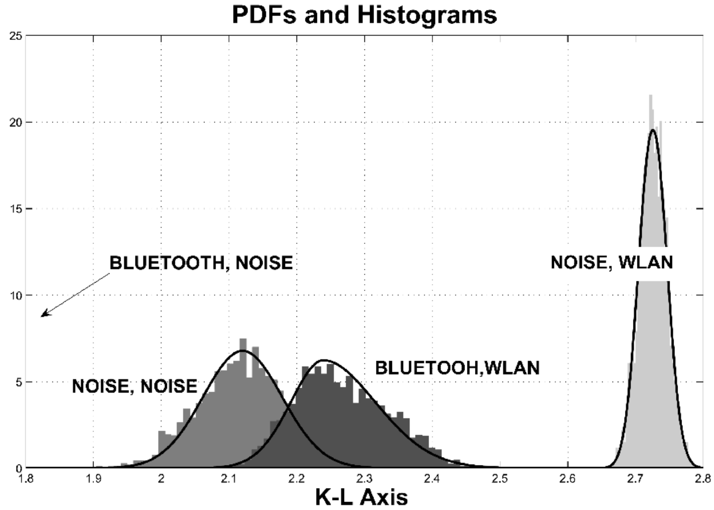


Figure 6: PDFs and Histograms of classes in the first configuration.

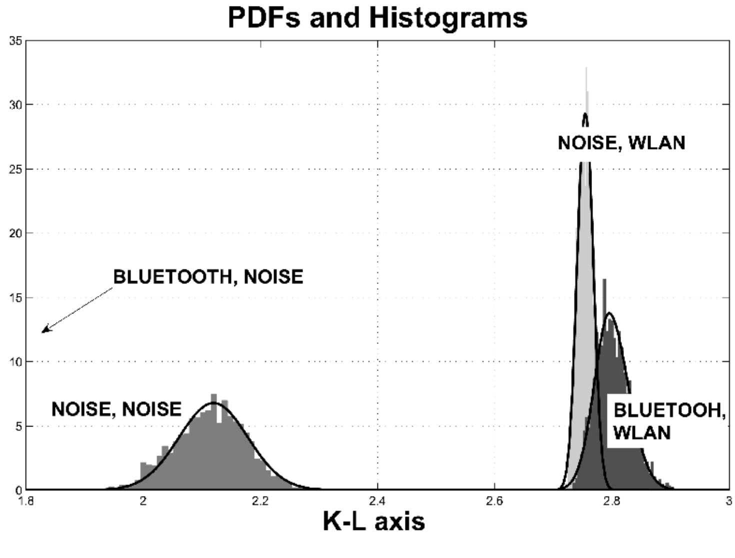


Figure 7: PDFs and Histograms of classes in the second configuration.

Hence, by studying *pdf*s' positions in feature space after the K-L reduction, it is possible to build two binary trees. In particular, in Figure 6 histograms and relative *pdf*s are plotted together showing the first configuration, which generates the first binary tree, Figure 8. Whereas, in Figure 7, the second

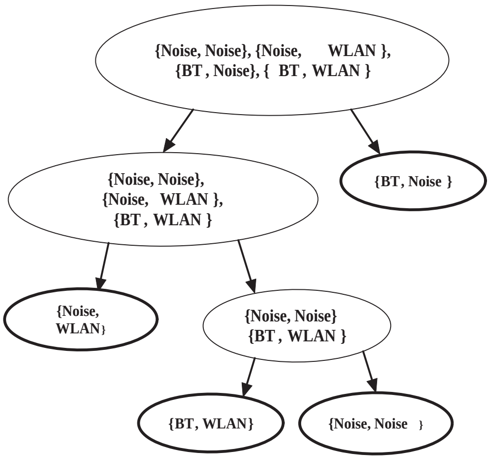


Figure 8: The first binary decision tree used by each sensor.

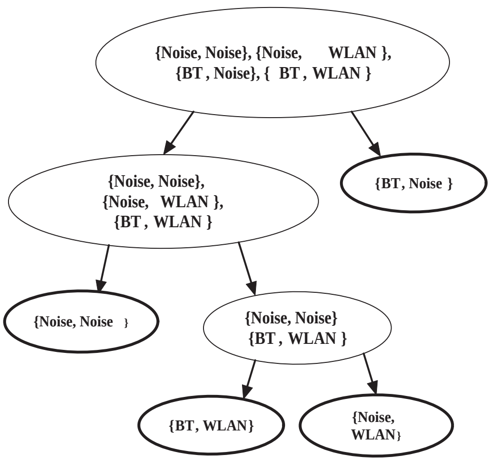


Figure 9: The second binary decision tree used by each sensor.

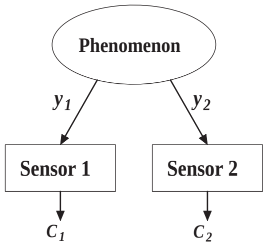


Figure 10: Parallel decision performed by two sensors of a binary phenomenon.

situation is represented, and the relative tree is in Figure 9. It is worth mentioning (as already stated) that the movement of the class is given by the sensor's movement and, moreover, that the Bluetooth class *pdf* is not plotted in Figures 6 and 7, because it is very far (in K-L axis) from the *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.

Let's then consider a binary phenomena, i.e. two possible hypothesis are present, H_0 and H_1, in association with the own a-priori probabilities P_0 and P_1, which represent a possible couple of the previously described classes. Being y_1 and y_2 the observations relative to the two sensors, taken at the correspondent distance $\underline{x}_1$ and $\underline{x}_2$, the local classification C_i, with $i = \{1, 2\}$ (where i denotes which sensor makes the classification), is given by:

$$C_i = \begin{cases} 0 & \text{if } H_0 \text{ is declared present} \\ 1 & \text{if } H_1 \text{ is declared present} \end{cases} \tag{9}$$

The local classification C_i is based on the local observation y_i, at a given position $\underline{x}_i$, if no communication link is present between the two sensors. The cost assigned to each case of classification is given by C_{ijk}, $i, j, k = \{0, 1\}$, and it represents the cost of sensor 1 classifying H_i, sensor 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 making [24] for the considered positions of the two detectors, i.e. $\underline{x}_1$ and $\underline{x}_2$. The following bayesian risk function is used for this purpose:

$$\begin{aligned} \Re &= \sum_{i,j,k} \int_{y_1,y_2} p(C_1, C_2, y_1, y_2, H_k|X) C_{ijk} \\ &= \sum_{i,j,k} \int_{y_1,y_2} P_k C_{ijk} p(C_1, C_2, y_1, y_2|H_k, X) \\ &= \sum_{i,j,k} \int_{y_1,y_2} P_k C_{ijk} p(C_1, C_2|y_1, y_2, H_k, X) \\ &\quad \cdot p(y_1, y_1|H_k, X) \end{aligned} \tag{10}$$

where the dependance from the distance $X = \{\underline{x}_i, i = 1, 2\}$ is added to [24].

Being the local classifications C_1 and C_2 independent and based respectively on the local observation y_1 and y_2, and on the positions of the sensors $\underline{x}_1$ and $\underline{x}_2$, it's possible to express the risk function as follows:

$$\Re = \sum_{i,j,k} \int_{y_1,y_2} P_k C_{ijk} p(C_1|y_1,\underline{x}_1) p(C_2|y_2,\underline{x}_2) p(y_1,y_2|H_k,X) \tag{11}$$

Explicitly summing over C_1, considering that:

$$p(C_1 = 1|y_1,\underline{x}_1) = 1 - p(C_1 = 0|y_1,\underline{x}_1) \tag{12}$$

and ignoring the constant terms with the respect to C_1, it's possible to re-write $\Re$:

$$\Re = \int_{y_1} p(C_1 = 0|y_1,\underline{x}_1) \sum_{j,k} \int_{y_2} P_k p(C_2|y_2,\underline{x}_2) p(y_1,y_2|H_k,X)[C_{0jk} - C_{1jk}] \tag{13}$$

It's now possible to derive a classification rule for sensor 1 [24]:

$$\sum_{j,k} \int_{y_2} P_k p(C_2|y_2,\underline{x}_2) p(y_1,y_2|H_k,X)[C_{0jk} - C_{1jk}] \underset{C_1=0}{\overset{C_1=1}{\gtrless}} 0 \tag{14}$$

Expanding the sum over k, the following formula can be obtained [24]:

$$\sum_j \int_{y_2} P_0 p(C_2|y_2,\underline{x}_2) p(y_1,y_2|H_0,X)[C_{0j0} - C_{1j0}] \underset{C_1=0}{\overset{C_1=1}{\gtrless}} \sum_j \int_{y_2} P_1 p(C_2|y_2,\underline{x}_2) p(y_1,y_2|H_1,X)[C_{0j1} - C_{1j1}] \tag{15}$$

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

$$p(y_1,y_2|H_k,X) = p(y_2|y_1,H_k,X),\ k = 0,1 \tag{16}$$

the (15) can be expressed as a likelihood ratio test [24]:

$$\Lambda(y_1) \underset{C_1=0}{\overset{C_1=1}{\gtrless}} \frac{P_0 \sum_j \int_{y_2} p(C_2\,|\,y_2,\underline{x}_2) p(y_2\,|\,y_1,H_0,X)[C_{1j0} - C_{0j0}]}{P_1 \sum_j \int_{y_2} p(C_2\,|\,y_2,\underline{x}_2) p(y_2\,|\,y_1,H_1,X)[C_{0j1} - C_{1j1}]} \tag{17}$$

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

$$\Lambda(y_1) = \frac{p(y_1|H_1, \underline{x}_1)}{p(y_1|H_0, \underline{x}_1)} \tag{18}$$

The previous formula (17) shows that the right-hand side is a function not only of the observation for sensor 1, i.e. y_1, but it's possible to note that it is a function of C_2, i.e. the classification rule for sensor 2 too, and this dependance appears under the form of $p(C_2|y_2, \underline{x}_2)$.
Under the hypothesis of conditionally independence of y_1 and y_2, i.e. when

$$p(y_2 \mid y_1, H_k, \underline{x}_1, \underline{x}_2) = p(y_2 \mid H_k, \underline{x}_2) \tag{19}$$

the right-hand side of (17) can be reduced to a threshold given by [24]:

$$t_1 = \frac{P_0 \sum_j \int_{y_2} p(C_2 \,|\, y_2, \underline{x}_2) p(y_2 \,|\, H_0, \underline{x}_2)[C_{1j0} - C_{0j0}]}{P_1 \sum_j \int_{y_2} p(C_2 \,|\, y_2, \underline{x}_2) p(y_2 \,|\, H_1, \underline{x}_2)[C_{0j1} - C_{1j1}]} \tag{20}$$

Noting that

$$p(C_2 = 1|y_2, \underline{x}_2) = 1 - p(C_2 = 0|y_2, \underline{x}_2) \tag{21}$$

it's possible to expand (20) in order to show explicitly that t_1 is a function of $p(C_2 = 0|y_2, \underline{x}_2)$, which represents the classification rule for sensor 2. A similar conclusion can be obtained for the threshold of sensor 2.
The proposed general definition and optimization of the whole system involves the existence of two coupled thresholds even if there is no communication link between the two detectors; but for the setup considered in the present paper, an offline exchange of information consisting in $p(C_i = 0|H_j, \underline{x}_i)$ with $i = 1, 2$ and $j = 0, 1$ is performed (See Fig. 11).

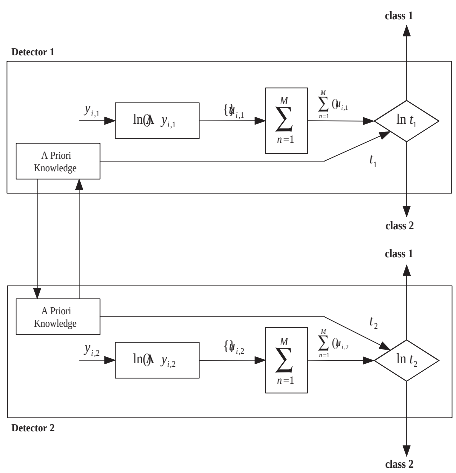


Figure 11: Structure of a distributed detection system

Let's now consider a special assignment of the costs as follows [24], where the cost value doesn't depend on which sensor makes the error:

$$\begin{aligned} C_{000} = C_{111} &= 0 \\ C_{010} = C_{100} = C_{011} = C_{101} &= 1 \\ C_{001} = C_{110} &= k \end{aligned} \tag{22}$$

The resulting threshold for sensor 1 becomes [24]:

$$t_1 = \frac{(k-1) + (2-k)p(C_2 = 0 \mid H_0, \underline{x}_2)}{1 + (k-2)p(C_2 = 0 \mid H_1 \underline{x}_2)} \tag{23}$$

A similar expression can be used to compute the threshold for sensor 2. These obtained thresholds are, in general, different from the ones computed if each sensor was considered independently.
Given the position of the sensor, it's possible to apply the binary tree shown in Figures 8 and 9, transforming the M-ary classification problem into a binary one.
For each likelihood function, it's possible to consider two different cases, i.e. both $p(y_i \mid H_j, \underline{x}_i)$ and $p(y_i \mid H_k, \underline{x}_i)$ are modelled as generalized gaussians, or, in alternative, one is a generalized gaussian, and the other one is an asymmetric generalized gaussian. In the first case, the decision rule can be written as:

$$\sum_{n=1}^{N}[-|\gamma_j(y_n - m_j)|^{c_j} + |\gamma_k(y_n - m_k)|^{c_k}] \underset{u_i=0}{\overset{u_i=1}{\gtrless}} \ln(\frac{c_k\gamma_k}{2\Gamma(1/c_k)}) - \ln(\frac{c_j\gamma_j}{2\Gamma(1/c_j)}) + \ln t_i \tag{24}$$

A similar expression can be obtained even in the second case, but the right side and the left side of the asymmetric gaussian have to be treated separately, because a different variance is involved for each side [29].
In the off-line phase, once computed the thresholds t_1 and t_2, it's possible to define an error probability conditioned to each class (denoting with $i = \{1, 2\}$ the sensor, and with $k = \{0, 1, 2, 3\}$ the class) if $t_i > m_k$:

$$P(err \mid H_k) = \int_{t_i}^{+\infty} \frac{c_k\gamma_k}{\Gamma(1/c_k)} e^{-|\gamma_{r,k}(x-m_k)|^{c_k}} dx \tag{25}$$

if $t_i < m_k$

$$P(err \mid H_k) = \int_{-\infty}^{t_i} \frac{c_k\gamma_k}{\Gamma(1/c_k)} e^{-|\gamma_{l,k}(x-m_k)|^{c_k}} dx \tag{26}$$

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

8 Results

The general scenario explained in Section 5 is implemented by using Matlab/Simulink. In particular, two cognitive sensors, CS_1 and CS_2, are used, as shown in Figure 12, moving around a room of 15 $\times$ 15 meters. The radio scene to be detected can be composed by either one of two possible modes, M_1 or M_2 (Direct Sequence Code Division Multiple Access (DS-CDMA) or Frequency Hopping Code Division Multiple Access (FH-CDMA)), or both or none of them. The two modes are implemented taking into account all parameters defined in the standards [30], [31] except for protocols higher than the physical layer. 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 [32]. A path loss term has been inserted: it follows the model proposed in [33]. This is composed by two parts: for distances lower than 8 meters, the path loss L_p has a value dependent on frequency f and on the distance d from the source; for distances larger than 8 meters, L_p is only a function of d. The attenuation is obtained by:

$$L_p = \begin{cases} 32.45 + 20\log(f \cdot d) & d \leq 8 \\ 58.3 + 33\log(d/8) & d > 8 \end{cases} \tag{27}$$

where d is expressed in meters, and f in GHz.

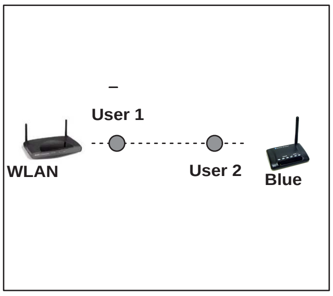
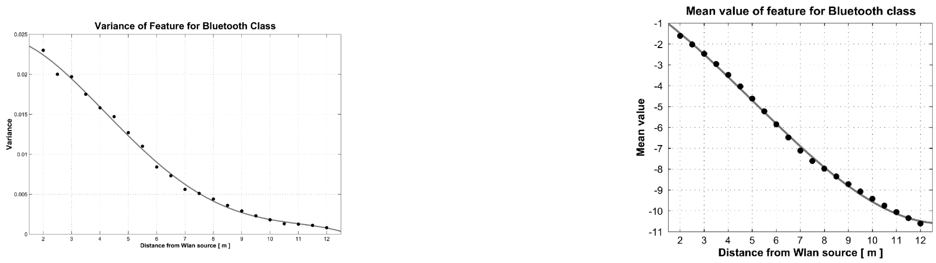


Figure 12: Considered Indoor Scenario.

The received signals, corrupted by AWGN and multipath and attenuated as reported above, 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 7.1. Then, the features are reduced with K-L method (Section 7.1), and their pdfs are modelled as AGG and GG. Due to the relation between the feature vector $\underline{v}$ and the sensor position $\underline{x}_i$, a study of statistical parameters of pdfs in different sensor positions has been carried out. For instance, the behaviour of variance and mean value of feature of Bluetooth class is shown in Fig. 13. This study has been developed for each of the four classes obtaining all parameters in function of sensor position, and inserting them in pdf general formula. At the end of this step, the distributions, i.e. Generalized or Asymmetric Generalized Gaussian, are available for all the considered scenario. With these data the



(a) (b)

Figure 13: Parameters of feature (after KL reduction) for bluetooth class in relation to user's distance from WLAN source. Variance (a), mean value (b).

detection can be carried out computing the Error Probability as explained below. This approach arises a problem: the sensor CS_i has to be aware of its position; in this work, this quantity is assumed to be known, but on-going research are dealing with a methodology to relax this constraint applying methods for hidden parameters estimation.

To have a clear idea of 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.

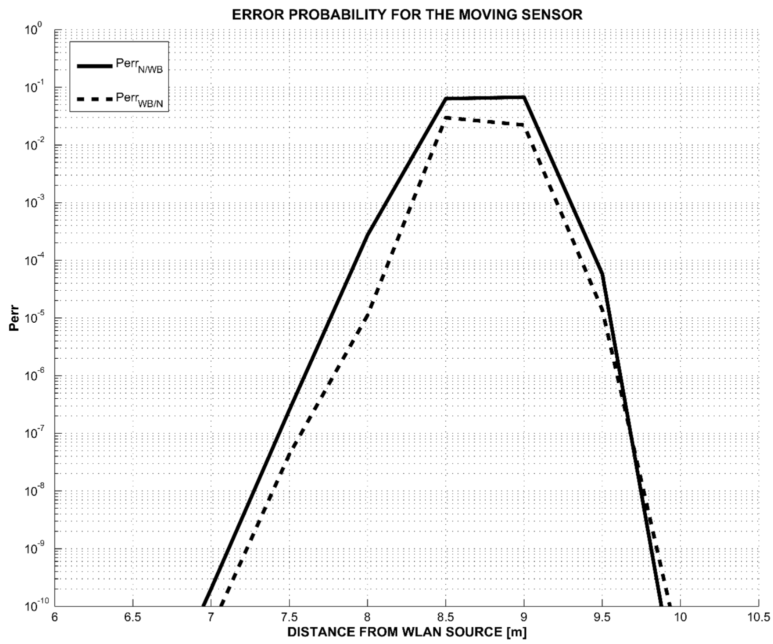


Figure 14: Error probability of WLAN+Bluetooth and Noise classes for the cooperative scenario.

In Figure 14, error probabilities are compared for the couple WLAN+Bluetooth and Noise, computed in case of one sensor 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 taken equal to 10. Two error probabilities are shown in the Figure: one represents the probability of classifying WLAN+Bluetooh instead of Noise when all sources are switched off, and the other one represents the probability of deciding the presence of only Noise while WLAN+Bluetooth is present. In

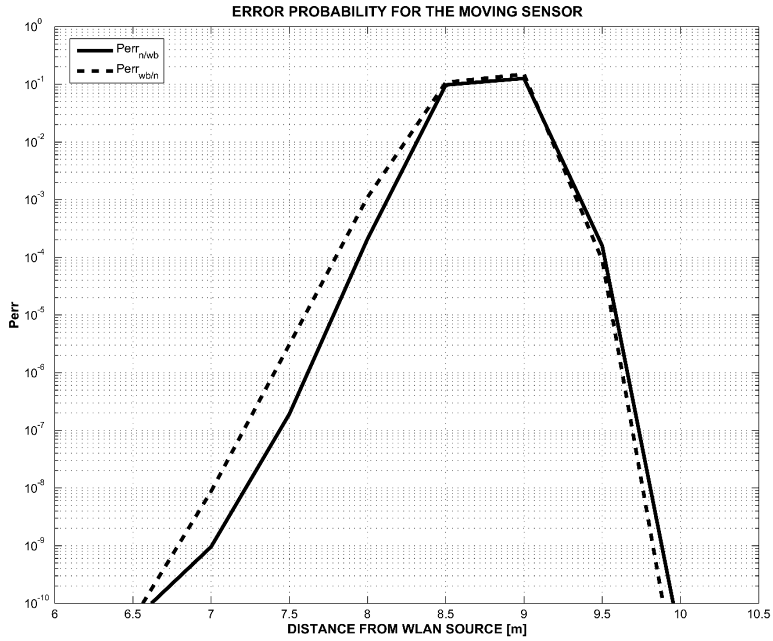


Figure 15: Error probability of WLAN+Bluetooth and Noise classes for the stand alone scenario.

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 Figure 15, it's possible to see the error probability for the classes WLAN+Bluetooth and 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 a higher Error Probability than the one obtained with distributed detectors.

In Figure 16, the error probabilities computed for the couple WLAN+Bluetooth and 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 (identifying WLAN when WLAN+Bluetooth 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 this case the system presents good performances, and the closed form of the error probability, (25) and (26), 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 as it can be noticed in the two Figures 16 and 17.

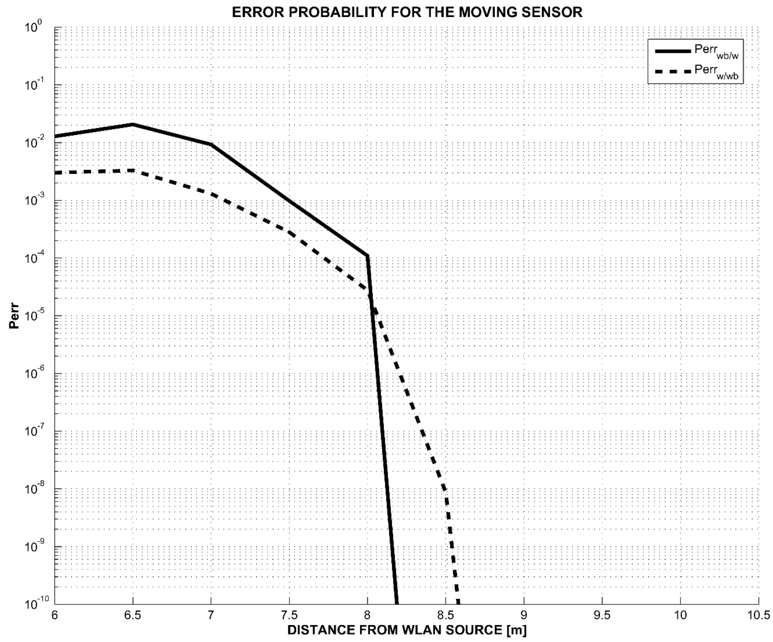


Figure 16: Error probability of WLAN and WLAN+Bluetooth classes for the cooperative scenario.

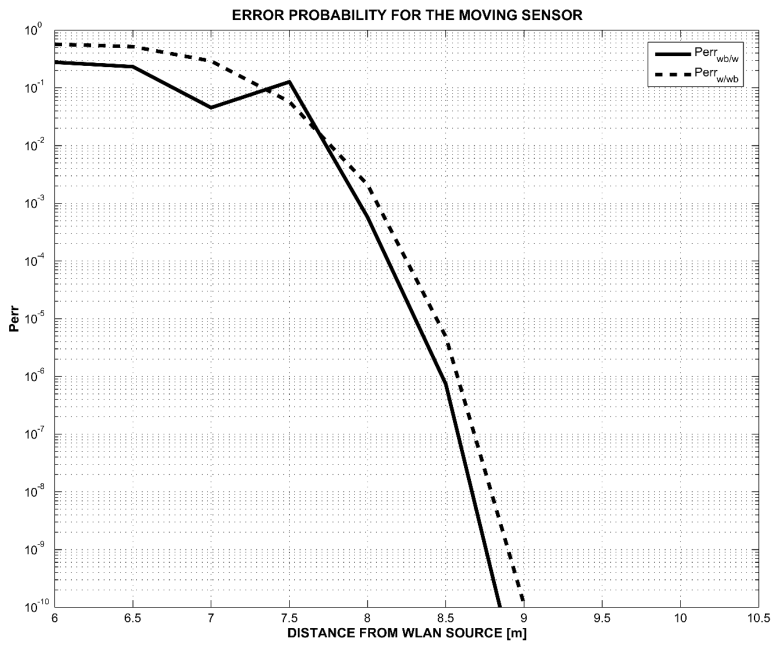


Figure 17: Error probability of WLAN and WLAN+Bluetooth classes for the stand alone scenario.

9 Conclusion

The paper deals with a distributed decision approach to solve the problem of Mode Identification in the context of Cognitive Wireless Sensor Networks. Two air interfaces have been considered to be classified, namely Frequency Hopping Code Division Multiple Access and Direct Sequence Code Division Multiple Access. A binary and distributed likelihood test has been computed obtaining a closed form for error probability in case of Generalized and Asymmetric Generalized Gaussian probability density function. 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.

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