A DISTRIBUTED APPROACH TO MODE IDENTIFICATION AND SPECTRUM MONITORING FOR COGNITIVE RADIOS

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ABSTRACT

In this paper a distributed approach to mode identification and spectrum monitoring is studied. A Wireless Network composed by Cognitive Terminals is used to classify air interfaces present in the radio scene. The use of cooperative strategies and an advanced signal processing tool, Time Frequency analysis, allows to improve the radio awareness of device. Results in the terms of error probability, modeling the probability density function of considered features as Asymmetric Generalized and Generalized Gaussian functions, are compared to error rate showing good performance and coherence of theoretical model with experimental results.

1. INTRODUCTION

1.1 Why mode identification and spectrum monitoring is important

The growing numbers of wireless standards are reducing the amount of unlicensed frequencies, making more and more difficult the use of spectrum for incoming and new wireless communication modes. However large part of licensed bands are unused both for large part of time and space: this means that, even if a particular range of frequencies is reserved for a standard, at a particular time and at a particular location it could be free and available. The Federal Communication Commission (FCC) estimates [1] that the variation of use of licensed spectrum ranges form 15% to 85% whereas Defence Advance Research Projects Agency (DARPA) claims that only the 2% of the spectrum is in use in US at any given moment, even if all bands are allocated. 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], foresees devices able to adapt themselves to spectrum environment and, in general, to external environment and to learn, as a biological cognitive process, from experience how to carry out this adaptation. CR brings to the definition of a completely adaptable physical layer where communication features, by sensing the spectrum, can change 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 *mode identification and spectrum monitoring* (MISM). By using MISM the terminal collect fundamental data from external environment, in particular from radio channel, and can carry out the adaptation typical of CR.

1.2 What MISM is

MISM is the join of a qualitative and quantitative analysis of reference band through the collection of information in terms of, respectively:

- frequencies usage;
- air interfaces classification.

To evaluate the use of frequencies in a particular band some parameters have been studied, and energy level and interference temperature [3] are the most used; both qualitatively describe with good performance the occupation of a given frequencies band. Whereas to provide a quantitatively description of spectrum, air interfaces classification (also called mode identification) is performed: 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. [4]; thus mode identification process says which standard is present providing data about its nature.

1.3 How MISM can be implemented

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 [5]: the idea is to extract energy in each sub-band identifying the presence of signals. The advantage is the computational load which is very low, but the drawback is that when signals temporally overlap on the same band, energy detection can be insufficient to discriminate the mode. Another work [6] 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 [7] a further integrated solution is proposed by means of two-stepped 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 are taken into account. The first procedure for sensing and identifying overlapping modes is presented in [8] 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 proposed also in [5] with a complete and exhaustive analysis of cognitive radios. That paper proposes a procedure composed by interference temperature estimation and spectrum holes detection. One of the biggest effort in the field of spectrum sensing is given by DARPA's neXt Generation program (XG Program) whose goals are the improvement in assured military communications through the dynamic assignment of allocated spectrum. In the Request for Comments (RFC) [9] 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, which the characteristics of the signal are (*air interfaces classification*).

2. AIM AND STRUCTURE OF THE PAPER

The aim of this paper is to present mode identification and spectrum monitoring procedure based on distributed network of cognitive terminals. Cognitive terminals can act as wireless sensors to create a wireless network (Figure 1): each radio gathers data about spectrum and by means of distributed detection theory [10] estimates which type of air interfaces are present. The same signal processing tool (Time Frequency Analysis) used in [8] is employed as part of a more general classification framework where multiple devices, instead of a single one, cooperate to the solution of a MISM problem. Each device carries out the steps of cognitive cycle working together other cognitive terminals to obtain a radio scene analysis more detailed and correct than in the stand alone scenario. To explain how this objective is reached, two air interfaces, Direct Sequence Code Division Multiple Access (DS-CDMA) and Frequency Hopping Code Division Multiple Access (FH-CDMA) are classified. 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 [4]; third, the growing interest in them on the market for their wireless connectivity, especially for communications in coexistent environment.

The paper is organized as follows: in the next Section an introduction about distributed perspective for cognitive radio is presented; then, in Section 4 the general and proposed framework are shown. Details of each part of the system are analyzed in Sections 5 and 6, with more attention to Distributed Classification (Subsection 6.1). Results and conclusion are then explained in Sections 7 and 0.

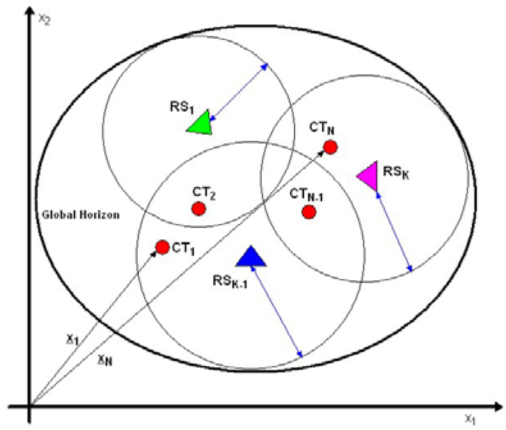

Figure 1. General Scenario.

3. DISTRIBUTED COGNITIVE PERSPECTIVE

Many cognitive radio researchers have adopted the Oxford English Dictionary definition of "cognitive" as *pertaining to cognition, or to the action or process of knowing* and "cognition" as *the action or faculty of knowing taken in its widest sense, including sensation, perception, conception, etc., as distinguished from feeling and volition*. From this definition it is possible to define a cognitive radio 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 states. These tasks can be summarized in what Mitola calls radio cognitive cycle [12]: during which *[...]cognitive radio continually observes the environment, orients itself, creates plans, decides, and then acts[...]*.

To figure out how these functionalities can be used together in the same terminal can be difficult and a real application is nowadays impossible: the solution proposed in this paper is a network of cooperative cognitive terminals sharing information and procedures in order to augment the awareness of the network itself. Due to different location of terminals and different nature of implemented functionalities, the gathered information are different and, if used in a cooperative framework, can improve the consciousness; in this paper the attention is focused on spectrum sensing and how distributed approach can solve the problem of radio awareness, getting better the probability of detect air interfaces and also the estimation of frequency usage.

4. GENERAL AND PROPOSED DISTRIBUTED COGNITIVE FRAMEWORK

The approach is a generalization of the one proposed in [8] : cognitive terminals (CT) CT_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 CT_i is able to extract information from the external world, to analyze it, to decide and act in relation to a pre-defined cognitive cycle [2]. More precisely, each CT_i 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 features 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 CT 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 air interface classification problem combined with the location estimation of sources.

The air interface classification and location problem is defined as follows :let's consider (Figure 1) 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 the areas of coverage of RSs. Let's associate with each RS_k a position $\underline{x}_{RSk}$ 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 not null discrete quantized observations $O_{ik}(t)$, at each time t, for each CT_i, are available as effects of radio source RS_k over terminal CT_i, i.e. the sensibility of each terminal CT_i is such that 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 terminal in CT. Then the mode identification, spectrum monitoring and location problem is defined as the capability of the set T of cognitive terminals 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 CT.

When $dim\{CT\}=1$ a stand alone scenario is fixed, i.e. a single cognitive terminal is considered. If $dim(\underline{X})=1$ and the position of the stand alone CT_1, are fixed, then a mono-dimensional space and horizon are considered as the *world domain* of the problem (Figure 2). A situation with $dim\{CT\}=1$ and $dim(\underline{X})=1$ was considered in [8], where a feature vector $v_1(t, x_1)$ based on time-frequency analysis of the observed spectrum, $O_1(t, x_1)$ with CT_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 x_{RS1} and x_{RS2}, i.e. the positions of the radio sources, were fixed. However, that problem even though it 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 problem), is by many cases too simple to reflect more direct situations of interest. In particular, in this paper some working hypothesis done in [8] are relaxed, by using $dim\{CT\}>1$ and, without loosing generality, $dim\{CT\}=2$, where $CT=\{CT_1,CT_2\}$ is composed by a set of two smart sensors. Let us fix $dim(X)=1$ and again $dim(RS)=2$ where positions of the two sources RS_k are known and then the problem of localization is not present, whereas the mode identification remains the main objective of the study.

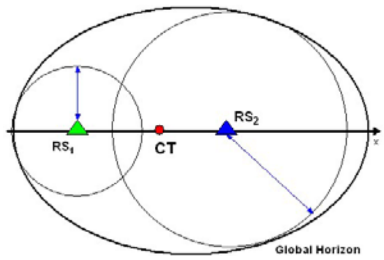

Figure 2. Stand Alone Scenario.

In the previous framework the two CTs, are composed by different blocks (Figure 3) which can be grouped in *Sensing Modules* and in *Analysis Modules*. The sensing procedures is performed by directly sampling the received signal and representing it in a bilinear space, the Time Frequency (TF) plane; once TF matrixes, W_1 and W_2, are obtained the analysis procedures begin: from W_i, $i=\{1,2\}$ the features vector $\underline{v}_i$ is computed and sent to the classification module which, by means of a cooperative strategy, extracts the classification $C_i(t)$, which in this case, as $M=2$ and d$im\{RS\}=2$, could be one of four possible choices ($RS^M=2^2=4$) and in particular:

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

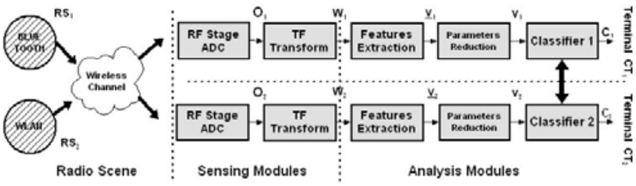

Figure 3. Proposed System.

5. SENSING PROCEDURES

Sensing modules are the same used in [8], namely Radio Frequency (RF) stage and A/D conversion and 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 [10]. For more details see [8].

6. ANALYSIS PROCEDURES

The first part of this modules, (Feature Extraction) is the same used in [8], then features are two, namely standard deviation of the instantaneous frequency and maximum time duration of signal. Once these two values are computed the new part of system is used: Parameters Reduction and Classification blocks which are completely re-studied and designed .

To simplify the problem, decreasing the dimension of features space, the Karhunen-Loeve (K-L) method [13] has been performed. Once new feature, linear combination of previous ones, 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) pdf [14].In case of WLAN+Bluetooth signal the pdf can be modeled as a Generalized Gaussian distribution (GG) [14].

Once pdfs of feature are modeled the detection process can be carried out. In following Section steps to reach distributed classification modules are explained.

6.1 Distributed Classification

As already stated in Sections 2 and 3, to improve the performances of a MISM module, in addition to an advanced signal processing technique, i.e. Time-Frequency analysis, a distributed classification algorithm is inserted in the system.

Different strategies can be thought to implement a cooperative detection, each one characterized by advantages and disadvantages, mostly based on information exchange on a wireless radio channel. In the present paper a strategy which minimize the on-line exchanged information, in order to prevent possible interferences with the radio scene has been chosen: the information is exchanged in an a priori stage, when no device is immersed in the environment and no one is sensing the radio scene. The information is exchanged under the form of probabilistic maps of features, which link the radio scene information with the position of the terminal.

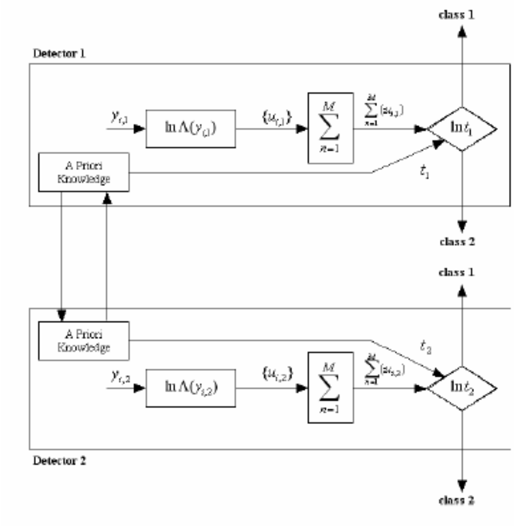

Figure 4. : Distributed Classification System

The chosen strategy finds a theoretical framework in the distributed Bayesian detection by Varshney [10]. This study foresees the application of this approach with some changes to the considered scenario.

Among the four situations to be classified (explained in Section 4), each Cognitive Terminal CT_i, 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 only the environmental noise is present. To simplify the classification process, it's possible to reduce the problem to

a binary classification test. In fact, a binary tree can be built taking into account the position of the *CT*.
Let's then consider a binary phenomena, i.e. two possible hypothesis are present, H_0 and H_1, which represent a possible couple of the previously described classes, with associated the own a-priori probability P_0 and P_1,. Being y_1 and y_2 the observed features relative to the two cognitive terminals (*CT*), taken at the correspondent distance x_1 and x_2, the local classification C_i, with $i = \{1;\ 2\}$ (where i denotes which device makes the classification), are given by:

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

the local classification C_i is based on the local observation y_i, at a given position x_i, if no communication link is present between the two terminals. The cost assigned to each case of classification is given by C_{ijk}, $i, j, k = \{0;\ 1\}$ and it represents the cost of CT_1 classifying H_i, CT_2 classifying H_j when H_k is present. The target is to obtain a classification rule which minimize the average cost of the classification making [10] for the considered positions of the two detectors, i.e. x_1 and x_2. The following bayesian risk function is used for this purpose:

$$\Re = \sum_{i,j,k} \int_{y_1,y_2} P_k C_{ijk} p\left(C_1, C_2 \middle| y_1, y_2, H_k, X\right) \cdot p\left(y_1, y_2 \middle| H_k, X\right) \tag{2}$$

where the dependence from the distance $X = \{\underline{x}_i,\ \ i = 1, 2\}$ is added to [10].
It's hence possible to derive a classification rule for device 1 which can be expressed as a likelihood ratio test [10]:

$$\Lambda(y_1) = \frac{P_0 \sum_j \int_{y_2} p(C_2 \mid y_2, x_2) p(y_2 \mid y_1, H_0, X)[C_{1j0} - C_{0j0}]}{P_0 \sum_j \int_{y_2} p(C_2 \mid y_2, x_2) p(y_2 \mid y_1, H_1, X)[C_{0j1} - C_{1j1}]} \underset{C_1=0}{\overset{C_1=1}{\gtrless}} \tag{3}$$

where $\Lambda(y_1)$ is the bayesian likelihood function for detector 1 and it's possible to note that it is also a function of C_2, i.e. the classification rule for terminal 2.
The right-hand side of the prvious formula can be reduced to a threshold:

$$t_1 = \frac{P_0 \sum_j \int_{y_2} p(C_2 \mid y_2, x_2) p(y_2 \mid y_1, H_0, X)[C_{1j0} - C_{0j0}]}{P_0 \sum_j \int_{y_2} p(C_2 \mid y_2, x_2) p(y_2 \mid y_1, H_1, X)[C_{0j1} - C_{1j1}]} \tag{4}$$

it's also possible to show explicitly that t_1 is a function of $p(C_2 = 0 \mid y_2,\ x_2)$ which represent the classification rule for CT_2. A similar conclusion can be obtained for the threshold of CT_2.

The proposed general definition and optimization of the system involve 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 probabilistic map of features is performed (See Fig. 4).
Having computed $ln(\Lambda(y_i))$ a closed form for Error Probability conditioned to each class can be defined and computed:

$$P(err \mid H_k) = \int_{t_i}^{+\infty} \frac{c_k \gamma_k}{\Gamma(1/c_k)} e^{-\left|\gamma_{r,k}(x-m_k)\right|^{c_k}} dx \ \ if\ \ t_i > m_k$$
$$P(err \mid H_k) = \int_{-\infty}^{t_i} \frac{c_k \gamma_k}{\Gamma(1/c_k)} e^{-\left|\gamma_{r,k}(x-m_k)\right|^{c_k}} dx \ \ if\ \ t_i < m_k \tag{5}$$

In the following paragraph the simulation environment, based on previously described assumptions, the theoretical error probability for the moving terminal CT_i and the relative error rate obtained in the on-line phase, are shown.

7. RESULTS

The general scenario is implemented by using Matlab/Simulink. In particular two cognitive devices are used, moving around a room of 15 X 15 meters. The radio scene to be detected can be composed by either one of two possible modes (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 [15],[16], except for protocols higher than the physical layer. The radio channel is modeled 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 [17]. A path loss term has been inserted: it follows the model proposed in [18]. The received signals, corrupted by AWGN and multipath and attenuated as reported above, are demodulated and sampled. The feature extraction and reduction methods explained in section are hence applied and their pdf are modeled as AGG and GG. With these data the detection can be carried out computing the Error Probability. An online phase test is performed, evaluating the error rate of the distributed classification system.
In Figure 5 the comparison, between the Error Probability, and the Error Rate obtained in the simulated system, are shown: the considered case is relative to confuse WLAN+Bluetooth class with WLAN class. In this situation due to overlapping of feature after K-L reduction both Error Probability and Error Rate present performance sufficient (between 10^{-4} and 10^{-2}) up to 7 meters from the WLAN source. After this distance optimal results are obtained;

during this test the Error Rate follows the theoretical behavior.

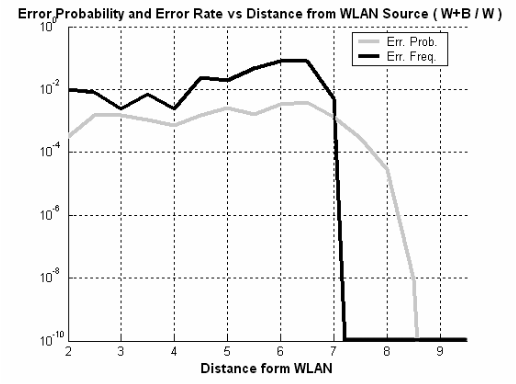

Figure 5. : Error Probability and Error Rate computed for the classes WLAN+Bluetooth adn WLAN

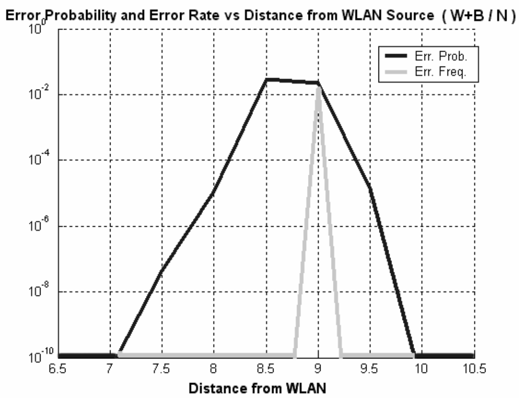

Figure 6. Error Probability and Error Rate computed for the classes WLAN+Bluetooth and Noise

The same comparison has been performed for the case of classifying WLAN+Bluetooth while only environmental Noise is present. In the Figure 6 is clear that the simulated system has optimal performances except between 8.5 and 9.5 meters but in this case too the behavior of the simulated system are similar to the theoretical model showing the coherence of assumptions.

8. CONCLUSION

The paper deals with a distributed decision approach to solve the problem of Mode Identification and Spectrum Monitoring for Cognitive Terminals. Two air interfaces are 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; it has been compared with error rate showing coherence of theoretical model and good performances. On going research are centered on the resolution of multiple hypothesis distributed decision test taken 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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