DISTRIBUTED COOPERATIVE MODE IDENTIFICATION FOR COGNITIVE RADIO APPLICATIONS

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1. INTRODUCTION

In this paper, a model for defining distributed cooperative mode identification is proposed in cognitive radio applications involving multiple mobile cognitive terminals (CTs). Mode identification is a key step to allow CTs to discover transmission modes within an unknown environment. Discovery of contextual information is an essential part of *radio awareness* (RA) [1] to reach reconfigurability and adaptability but also to provide the terminal with that consciousness base of Cognitive Processes. ra can be defined as the capability to understand the external radio environment, classifying modes [2], [3], [4] and spectrum holes. A *transmission mode* (also called *air interfaces* [5]) 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]. By using mode identification (MI) a cognitive terminal should be able to recognize the spectrum holes and the available air interfaces in order to improve the efficiency of spectrum use and of radio resources in general.
Looking at the state of the art, some methods partially solve the classification of air interfaces if modes are frequency-separated; some procedures can be found in [2], [4] and [6] but they can have some problems to discriminate superimposed modes. This work proposes the use of Distributed Detection Theory [7] by using data provided by an advance Signal Processing Tool, Time Frequency Analysis [8]. A first analysis of overlapping air interface classification has been developed in [3] where time frequency analysis and neural networks have been used. In this paper the same signal processing tool is used but a more general classification framework is considered, where multiple devices, instead of a single one, cooperate to the solution of a MI problem. Devices cooperate each other to obtain a radio scene analysis more detailed and correct than in the stand alone scenario. To explain how this objective is reached, an example 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 [5]; third, the growing interest in them on the market.
The paper is organized as follows: in Section 2 the general framework and the proposed method are explained, whereas the details of each sub-module are shown in Sections 3, 4 and 5. Results and comparison can be found in Section 6.

2. GENERAL FRAMEWORK AND PROPOSED METHOD

The approach is a generalization of the one proposed in [3] to a multiple cooperative scenario. A number N of cognitive devices (CT) T_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 identified in order to increase their radio awareness. Each T_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 [9]. More precisely, each CT T_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 observations and cooperative strategies in order to identifies the available air interfaces. Let's consider that these set of CTs, $\{T\} = \{T_i : i = 1, ..., N\}$ 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 mode m in a space of possible radio modes corresponding to different air interfaces, let us say, for example M. Let us suppose that not null discrete quantized observations $O_{ik}(t)$, at each time t, for each cognitive terminal T_i, are available as effects of radio source RS_k over terminal T_i. Then the mode identification 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 of a set of Radio Sources RS which lie in the horizon of T. When $dim\{T\} = 1$ a stand alone scenario is fixed, i.e. a single cognitive terminal is considered as reported in [3]. In this paper some working hypothesis done in [3] are relaxed, by using $dim\{T\} > 1$ and, without loosing generality, $dim\{T\} = 2$,

where $\{T\} = \{T_1, T_2\}$ is composed by a set of two cognitive terminals. Let us fix $dim(RS) = 2$ where the identification of their modes remains the main objective of the study. The two terminals, T_1 and T_2, are composed by different blocks (Fig. 1) 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 (see Section 3); 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 3 and 4) and sent to the classification module (Section 5) 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 terminals we have to assess the nature of their cooperation. In particular each T_i could cooperate in different ways with the other T_j, $j = 1, 2$, to take $C_i(t)$. In this case as $M = 2$ and $dim\{RS\} = 2$ then 2^2 situations are possible. The case above described is represented in Fig. 1 where the logical architecture of sensors is shown. Each sub-modules will be analyzed in details in following Sections.

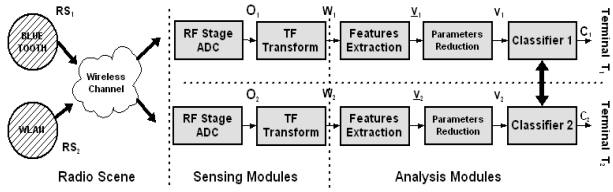

Figure 1: Logical Architecture of sensing and analysis modules of two Cooperative Terminals.

3. SENSING PROCEDURES: 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. Among TF distributions, the Wigner-Ville transform has been chosen [8]. 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 $y(t)$ 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.

4. ANALYSIS PROCEDURES: FEATURES EXTRACTION AND REDUCTION

From Wigner-Ville transform, TF features of the received signal observed on a time window T are extracted. The same two features, used in [3] with one sensor, are here considered: the standard deviation of the instantaneous frequency and the maximum time duration of signal. To obtain the first feature from a given TF distribution the first conditional moment $< \omega >_t$ is computed [8]. It is the average of frequency at a particular time t and it is considered as the instantaneous frequency ω_i [8]. Its standard deviation of ω_i is uded for the classification. 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 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, called T_M, which is the maximum time duration of the signal during the time window. At the end of the feature computation a vector $\underline{v} = \{v_1, v_2\} = \{std(\omega_i), T_M\}$ is obtained and to simplify the problem, decreasing the dimension of features space, a features reduction has been performed; the Karhunen-Loeve (K-L) method [10] has been chosen. 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 new feature is obtained from K-L, a monodimensional probability density function (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 [11]. In case of WLAN+Bluetooth signal the pdf can be modeled as a Generalized Gaussian distribution (GG) [11]. Once the pdf of features are modeled the detection process can be carried out. In following Section the steps to reach distributed classification modules are explained.

5. ANALYSIS PROCEDURES: DISTRIBUTED DETECTION

The distributed detection theory is applied to the whole system to improve the performance with respect to the stand

alone scenario. Each cognitive device shares its decision model with other terminals in an off-line phase, when no detector is immersed in the environment and no one is observing the radio scene. The exchanged information requires a very low bandwidth and no signal interferes with the present radio scene. A theoretical framework for the applied methodology can be found in the distributed bayesian detection by Varshney [7].
An M-ary classification problem can describe the considered problem of Mode Identification. To simplify the classification process, it's possible to reduce the problem to a set of binary classification tests. In fact the distribution of the probability density functions shows that only two classes are partially overlapped and they can generate ambiguities. Hence a binary tree can be built to classify the air interface by distinguishing between only four cases: presence of WLAN, presence of Bluetooth, presence of WLAN and Bluetooth together, presence of Noise.
Let's then consider a binary phenomena, i.e. two possible hypothesis are present, H_0 and H_1, with associated the own a-priori probability P_0 and P_1. The local decision $u_i, i = 0, 1$, which corresponds to the presence of one of the classes above defined, is based on the local observation y_i if no communication link is present between the two detectors. The cost assigned to each case of decision is given by C_{ijk}, $i, j, k = \{0, 1\}$ and it represents the cost of detector 1 deciding H_i, detector 2 deciding H_j when H_k is present. The target is to obtain a decision rule which minimize the average cost of the decision making [7].
It can be proved that the likelihood ratio test for detector 1 [7] is :

$$\Lambda(y_1) \underset{u_1=0}{\overset{u_1=1}{\gtrless}} \frac{P_0 \sum_j \int_{y_2} p(u_2 \,|\, y_2) p(y_2 \,|\, y_1, H_0)[C_{1j0} - C_{0j0}]}{P_1 \sum_j \int_{y_2} p(u_2 \,|\, y_2) p(y_2 \,|\, y_1, H_1)[C_{0j1} - C_{1j1}]} \tag{2}$$

where $\Lambda(y_1)$ is the bayesian likelihood function for detector 1.
The previous formula (2) shows that the right-hand side is a function not only of the observation for detector 1, i.e. y_1, but also of u_2, i.e. the decision for detector 2. This relation appears under the form of $p(u_2|y_2)$. Under the hypothesis of conditionally independence of y_1 and y_2, the right-hand side of (2) can be reduced to a threshold given by [7]:

$$t_1 = \frac{P_0 \sum_j \int_{y_2} p(u_2 \,|\, y_2) p(y_2 \,|\, H_0)(C_{1j0} - C_{0j0})}{P_1 \sum_j \int_{y_2} p(u_2 \,|\, y_2) p(y_2 \,|\, H_1)(C_{0j1} - C_{1j1})} \tag{3}$$

Noting that $p(u_2 = 1|y_2) = 1 - p(u_2 = 0|y_2)$ (3) can be expanded to show that t_1 is function of $p(u_2 = 0|y_2)$ which represent the decision rule for detector 2; it's hence possible to affirm that t_1 is a function of the decision behavior for detector 2. A similar expression for t_2 can be defined.
The proposed general definition and optimization involve the existence of two coupled thresholds even if there is no communication link between the two detectors; in the present paper an offline phase is considered for the exchange of $p(u_i = 0|H_j)$ with $i = 1, 2$ and $j = 0, 1$ to compute the thresholds.
Having computed the sufficient statistic $\ln \Lambda(y_i)$ basing on a training vector, a closed form for error probability conditioned to each class can be obtained and computed. If $t_i > m_k$:

$$P(err \,|\, H_k) = \int_{t_i}^{+\infty} \frac{c_k \gamma_k}{\Gamma(1/c_k)} e^{-|\gamma_{r,k}(x - m_k)|^{c_k}} dx \tag{4}$$

if $t_i < m_k$;

$$P(err \,|\, H_k) = \int_{-\infty}^{t_i} \frac{c_k \gamma_k}{\Gamma(1/c_k)} e^{-|\gamma_{l,k}(x - m_k)|^{c_k}} dx \tag{5}$$

6. RESULTS

The general scenario is implemented by using Matlab/Simulink. Two cognitive devices are used, moving around a room of 15×15 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 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. A path loss term has been inserted: it follows the model proposed in [12]. The received signals, corrupted by AWGN and multipath and attenuated are sampled and the TF transform is applied on it. The feature extraction and reduction methods 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. Error probabilities and error rate for the previously described scenario are shown in the following figures. In Figure 2.(a) the error probabilities are compared for the couple WLAN+Bluetooth and Noise, computed in the case of one detector fixed 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. 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

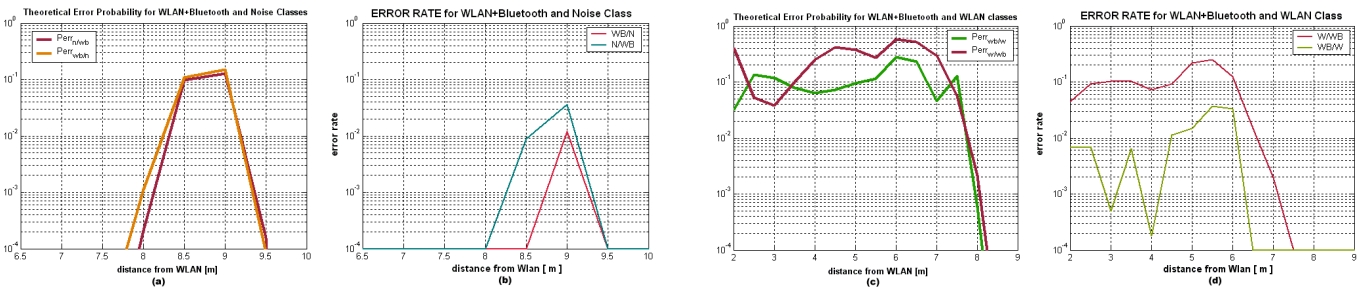

Figure 2: Error probability of WLAN+Bluetooth and Noise classes (a) and corresponding error rate (b) for the moving detector; error probability of WLAN+Bluetooth and WLAN classes (c) and corresponding error rate (d).

the other one represents the probability of deciding the presence of only Noise while WLAN+Bluetooth 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. Figure 2(b) shows the corresponding error rate obtained in the online phase. The behavior is similar to the error probability computed in closed form. The system provides good both theoretical and experimental results, except between 8 and 9.5 meters from the WLAN sources, where the pdf are strongly overlapped. In Figure 2(c) the error probability for WLAN+Bluetooth and WLAN classes is shown with the corresponding error rate 2(d). Even in this case the behavior of the experimental error rate is similar to the theoretical error probability.

7. CONCLUSION

The paper deals with a distributed decision approach to solve the problem of Mode Identification in the context of 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; moreover error rate is obtained and compared with theoretic formulas showing the same behavior and good results. 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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