A Spectrum Sensing Algorithm based on distributed cognitive models

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ABSTRACT

In the last years, an increasing attention of the communications researchers has been focused on the Cognitive Radio (CR) concept and on its possible supporting technologies and applications.
The proposed approach deals the problem of information acquisition and handling for cooperative Cognitive Radio Terminals, in order to perform Spectrum Sensing tasks in a distributed way. The proposed solution is based on Distributed Detection theory supported by a Cognitive Modeling of Terminals.

1. INTRODUCTION

In the last years, an increasing attention of the communications researchers has been focused on the Cognitive Radio (CR) concept and on its possible supporting technologies and applications.
CR is considered as a new goal for wireless communications in the next future. This kind of technology will allow a more efficient and flexible usage not only of the electro-magnetic spectrum, but also of all the resources of the Cognitive device, like, for example, batteries and computational capacity. The capability of observing the surrounding environment, by understanding the characteristics of the operative context and by adapting their operations to it in a completely autonomous and intelligent way, will be the peculiarities of the Cognitive Terminals (CTs).
CRs can be considered as the natural evolution of Software Radios (SRs): starting from the flexible and completely digital physical architecture of SRs, the goal is to design intelligent terminals with the previously described characteristics. Different disciplines are involved in the design and development processes of CTs, from electronics to bio-information sciences, from signal processing to telecommunication engineering: all of them are required for the realization of all the required components of CTs, both on algorithmic and hardware platforms sides.
In this paper, a brief definition of CRs will be first provided, together with a proposed model for the description of the operating strategy a CT should follow. Then, the concept of Cognitive Maps (CMs) is discussed and their role in the behavioral model of a single CT will be defined. In the last paragraph, the usefulness of CMs is proposed as a basis to obtain more complex cooperation strategies among multiple CTs operating in the same environment; a simulative framework will be introduced to present results showing the validity of the proposed approach.

2. COGNITIVE RADIO TECHNOLOGY

The idea of Cognitive Radio, as a new approach for wireless communication was first presented by Joseph Mitola III [1]. It was thought as the final point of evolution for a software-defined radio platform, considered now as a black-box that changes its communication functions depending on network and/or user's requirements. After Mitola, other Researchers gave their definitions, as Bruce Fette [2] or Simon Haykin [3]. Also governmental agencies have tried to provide a standard definition for CRs, clarifying how this technology can be used too. One of the first document which deals these problems is the Notice of Proposed Rule Making and Order (NPRM), compiled by the U.S. Federal Communication Commission (FCC) [4]. In this document, the agency confirm that CR technologies can allow a more efficient and dynamic spectrum usage, self-localization of terminals, frequency, modulation and transmitted power allocation.
Summing up, it's possible to affirm that the CRs are adaptive radio terminals, aware of their potentialities, of the environment and of their target, and they are able to learn, for example, through the experience new waveforms, new environmental models and new operative frameworks.
In this paper, attention is focused in the issue of representing information acquired from radio channels into appropriate environmental models that are shared by multiple CTs in order to accomplish radio context discovery tasks. Even though represented environmental Cognitive Maps are in this paper considered as a-priori available from CTs, the capability of incrementally learning such maps can be an extension of this work. The presented approach shows how each CT can take advantage of simple existence of other CTs in the same environmental area covered by the shared CM to improve its efficiency and robustness in making simple decisions. The problem of identifying transmission modes of heterogeneous

wireless sources of known position is considered here as a case study. It is also shown that distributed decision theory [5] can be used as a way to exploit shared CMs knowledge within a well-assessed probabilistic distributed decision problem.

3. COGNITIVE MODELING

3.1. The Cognitive Cycle

The Cognitive Cycle is a model which describe the behavior of any living being. In fact, it interacts with the external world through four main steps: Sensing, Analysis, Decision and Action. In Figure 1 a representation of a Cognitive Cycle is presented. The four main steps are here clearly evidenced.

The first stage of the cycle (Sensing or Observation) represents a passive interaction of the terminal with the environment: the CT gather information about both its internal state and the surrounding environment in a continuous way. In the second step (Analysis) the acquired data are processed and analyzed in order to provide to the system an higher level synthetic representation of the context. In the Decision stage the Cognitive system has to decide which is the most proper action to the received external stimulus; the choice is based on the embedded internal knowledge, the past experience and the current context. The action represents an active interaction with the external environment because the CT tries to influence the other interacting entities in order to maximize its internal functional.

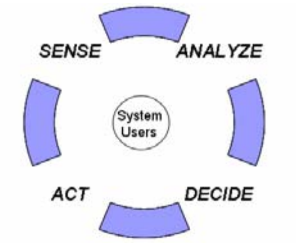

Figure 1 Simplified Cognitive Cycle

The Cognitive Cycle occurs in a continuous way and during the entire process the CT uses the observations and its decisions in order to improve dynamically its behavior: it can be considered as a continuous learning phase.

3.2. Map Concept

Any Cognitive entity which is immersed in a physical environment needs, to be able to interact with it, an internal representation of the physical world. The knowledge, acquired with the experiences, influences the behaviour of the terminal through variations of this internal representation. Hence spring out the need of maps which allow the terminal to orientate itself within the context, by creating a direct relationship between the physical world an the inner representation.

The knowledge about the physical world can be organized, within the Cognitive Cycle, into four maps, one for each stage of the cycle. The first map, the Sensing Map provides information on how to observe the environment in each point of the space. The Analysis Map allows the Cognitive Entity to reach a semantic and contextual representation of the external environment. The Decision Map contains information about which is the decisional process which has to be performed for a proper reaction, while the Action Map describe how to carry it out; this final map is the interactional interface between the terminal and the physical world.

Organizing the internal knowledge into maps has manifold advantages: first of all it allows to describe the current context in a way understandable by the system, but with an explicit relationship with the phisicity of the problem. Besides, it’s possible to improve the adaptivity to the external conditions. It’s also easier to exchange knowledge between multiple terminals, which can cooperate in order to obtain better performances.

4. DISTRIBUTED MODE IDENTIFICATION

The *Spectrum Sensing and Mode Identification (MISM)* process plays a key role in the Cognitive Radios because it provides an observation of the physical world: this is the knowledge about the channel conditions which allows to take a proper decision for the current context.

In the state of the art, different implementations for spectrum sensing are already present. The oldest and simplest one is the *Radiometer* [6]: it extracts the energy in each sub-band, identifying if the bandwidth is already occupied by a transmitted signal. This approach is characterized by a very low computational load, but it isn’t able to provide which standard is occupying the examined bandwidth. This feature grew in importance in the last years, in order to perform a fast and optimal re-configuration of the intelligent device. In fact different methods [7][8], which face also the problem of identification of modes superimposed on the same bandwidth [9][10], have been proposed. These methods, in framework of Cognitive Radios, involve also the Analysis stage, because they are able to extract proper features and to perform a suitable classification of the modes.

Cognitive Systems are thought to be used not only in stand alone mode, as all the previous algorithms work, but to create a network of cooperative terminals. A first step into this direction, even if these works are not explicitly focused on Cognitive Systems, can be found in [13][14]; these works face also the problem of distributed detection under communication [13] or energy constrains [14].

The basis for the proposed approach can be found in [15]: the same operative framework is considered consisting in an indoor environment with two sources transmitting WLAN or Bluetooth. Two *Cooperative Cognitive Radios (CCRs)* explore the environment trying do decide the current radio context in a distributed way. The peculiarity of the problem consists in the bandwidth overlapping (both are in the ISM band) of the two standards.

4.1. Proposed Framework

The proposed framework is an similar to the one proposed in [15]. A 12x12 meters room, containing a Bluetooth radio and a WLAN radio source have been considered. The room is explored by two cooperative CTs, able to move inside the room, in a 2D space. Four possible transmission situations can be present:

- Only WLAN source is transmitting;
- Only Bluetooth source is transmitting;
- Both WLAN and Bluetooth sources are transmitting;
- Both sources are switched off.

The Cognitive Maps extraction process can be considered an acquisition and formalization of a-priori knowledge about the environment and it is performed in an off-line phase. This information is used in the on-line phase to allow the two CCRs to decide the current transmission situation in a distributed way.

5. PROPOSED APPROACH

The proposed approach deals the problem of information acquisition and handling for cooperative CTs, and it can be divided into three sub-problems:

- Information acquisition
- Information representation and storing
- Information usage

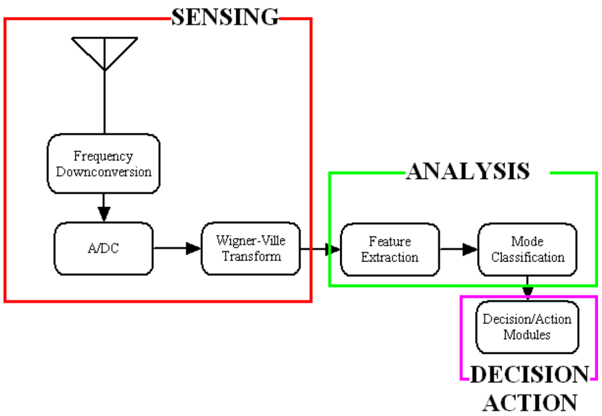

Figure 2 Proposed System Architecture

The first one strictly related to the Sensing Map, in fact the problem can be interpreted as "how to observe the world".

The second one is more complex, because its solution should respect some constrains: the representation should be synthetic, for minimizing memory occupancy and exchange easiness, but, at the same time, completely understandable by the CTs.

Once the information has been expressed in a synthetic form, the problem is how to use it, and how this usage can improve the performances of the set of CTs.

In Figure 2 the proposed system architecture is shown: after a first analog frequency down-conversion to intermediate frequency stage, an analog-to-digital converter is inserted; together with the time-frequency transform, they represent the Sensing module of the CCR device. Feature extraction and Mode Classification modules represent instead the Analysis module; finally Decision and Action modules, that are not considered yet in the paper, come.

5.1. Information acquisition: Sensing Map and procedures

In the present paper, a sensing approach based on Wigner-Ville (WV) time-frequency analysis [16], similar to the one presented in [15] is presented:

$$W(t,\omega) = \frac{1}{2\pi}\int S^{*}(\omega + \tfrac{1}{2}\theta) S(\omega - \tfrac{1}{2}\theta) e^{-jt\theta} d\theta$$

Goal of the CTs in the considered framework, is to observe the radio channel and to decide the current transmission mode. By considering similar the *"point of view"* of the two terminals, respect to the radio environment, in every point of the room, it's possible to define a uniform *Sensing Map*: in fact over all the room information about the radio channel will be acquired through WV time frequency transform and its processing.

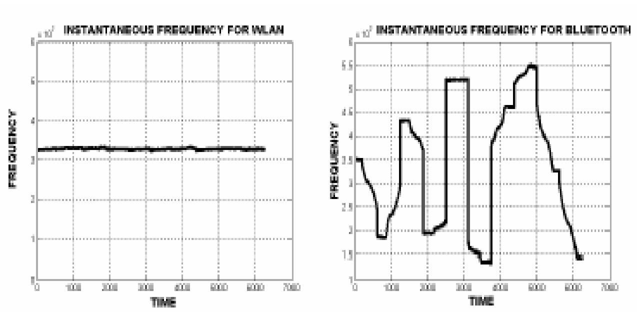

Figure 3 Instantaneous Frequency for WLAN and Bluetooth

WV transform has been used in order to exploit the signal characteristics intrinsic in the two transmission modes: in Figure 3 the different time-frequency behaviors for the two signals are shown.

It's hence possible to jump to the second stage of the Cognitive Cycle, the *Analysis* stage, where, by exploiting these differences, from the WV transform, two features are extracted:

- the standard deviation of the instantaneous frequency;
- the maximum time duration, inside a time window, of the signal components [15].

5.2. Information representation and storing: off-line data acquisition and Analysis Map creation

In an off-line phase, features have been extracted from different realizations of the radio signal, in every transmission situation, in different points of the room. Thanks to the acquired features, it's possible to model the probability density function (pdf) of each class, in each point, as a 2D Gaussian in the features space. This simplification, a 2D extension of [15], decreases the analytic complexity of the problem and it allows the usage of an inter-class distance measure, the Bhattacharyya distance [17]. It's hence possible to obtain an upper bound for the error probability for each considered class, thanks to the relationship between the distance and the Chernoff bound [18]: being *i*, *k* two classes, the upper bound for the probability of confusing *k* with another class can be written as:

$$P_{ek} \leq \frac{1}{3} \sum_{i=1, i \neq k}^{4} \sqrt{P_i P_k} \exp(-B_{ik})$$

where P_i and P_k are the prior probabilities and B_{ik} is the Bhattacharyya distance between *i* and *k*.

The upper bound of the error probability for each class in each sample point of the room is used to obtain the *Analysis Map* of the environment: in order to provide a continuous map over all the room, the obtained values are interpolated to obtain a surface which represent the goodness of the classification process in each point of the room. The interpolation has been performed through a simple cubic 2D polynomial. A "One shot" parameter estimation has been used in order to estimate the polynomial coefficients.

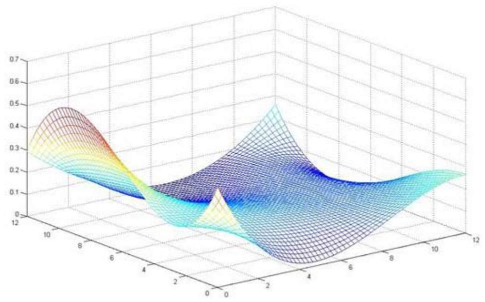

Figure 4 Analysis Map for WLAN Class obtained in a simulated environment

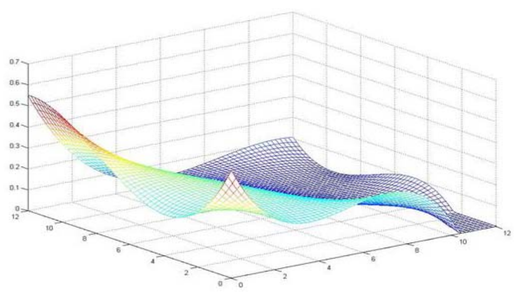

Figure 5 Analysis Map for Bluetooth Class obtained in a simulated environment

This representation of the information acquired in the off-line phase has two main advantages: the first one is that it's a complete representation of the classification behavior of a stand-alone CT immersed in the environment. The second one is that, by knowing the position of the sensor, it's possible to store only the interpolation coefficients which generate the surface.

5.3. Information usage: Distributed Classification and Maps modification

Once acquired the information, how to use it in the best way has to be decided. In the present paper, a variation of the distributed detection proposed by Varshney [5] has been considered.

Starting from the detection of a binary phenomenon, it's possible to proof that the only presence of another detector inside the environment influence the decision processes. The decision framework is the so-called Distributed Bayesian Detection without Fusion. It is substantially based on a Bayesian likelihood function compared with a threshold that depends on the position of the other CCR and which is its point-of-view about the radio world in the considered point fo the environment:

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

The right-hand side of the equation is the classical Bayesian likelihood function, while the left-hand side is the distributed threshold which can be re-written as:

$$t_1 = \frac{P_0[C_{100} - C_{000}]p(C_2 = 0 | H_0, x_2) + P_0[C_{110} - C_{010}]p(C_2 = 1 | H_0, x_2)}{P_1[C_{001} - C_{101}]p(C_2 = 0 | H_1, x_2) + P_1[C_{011} - C_{111}]p(C_2 = 1 | H_1, x_2)}$$

The threshold, such as the Bayesian test, is related to the terminal labeled as "1": it's possible to define similar test and threshold for terminal "2".

Give the presence of multiple classes in the considered framework, an architecture which allows to extend the Varshney's theory to a multi-class problem has been designed:

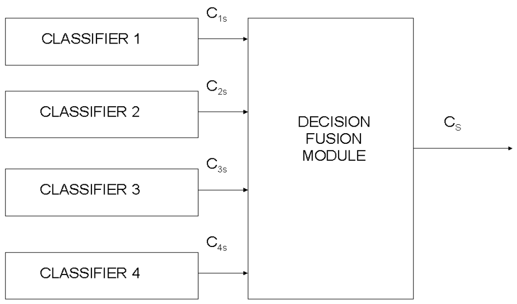

Figure 6 Multi-Class distributed architecture

Four classifiers have been considered, one for each class present in the problem. In fact each classifier tests, in a distributed way, one class against the others, i.e. in a binary way, as described by Varshney's theory. The terminal is also aware of its position and of the position of the companion terminal; it's hence possible to derive a distributed threshold for each classifier, i.e. for each class under test:

$$t_{1m} = \frac{P_0 p(C_{2m}=0 \mid H_0, \underline{x_2}) + P_0 (K-1) p(C_{2m}=1 \mid H_0, \underline{x_2})}{P_1 (K-1) p(C_{2m}=0 \mid H_1, \underline{x_2}) + P_1 p(C_{2m}=1 \mid H_1, \underline{x_2})}$$

Being the classification probability distribution for terminal "2" considered unknown, it's possible, thanks to the previously obtained Analysis Maps, to approximate the distributed threshold: in fact it is considered as a function of the error probability for the class under test:

$$t_{1m} = \frac{P_0 + (K-2)Pe_m(\underline{x_2}) - \frac{1}{8}(K-2)P_1 Pe_m(\underline{x_2})}{\frac{1}{8}(K-2)P_1 Pe_m(\underline{x_2}) + 1 - P_0}$$

where m represents the tested class, K is a decisional weight, P_0 and P_1 are the prior of the two possibilities (presence or absence of the class), while $\underline{x_2}$ represents here the position of the companion terminal.

Being the decision thresholds function of the error probability of the class, and being the error probability function of the position of the terminal, it's possible to derive new *Analysis Maps* which represent the variations of the threshold over all the room. Different surfaces for different values of K can hence be obtained:

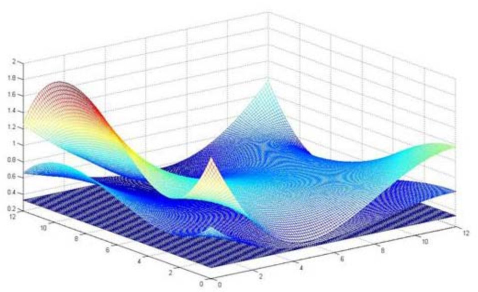

Figure 7 Modified Analysis Map for WLAN Class obtained in a simulated environment

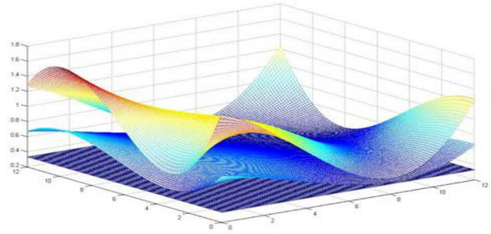

Figure 8 Modified Analysis Map for Bluetooth Class obtained in a simulated environment

In Figure 7 and Figure 8 three different surfaces for each class are shown: for K = 2 a flat surface is obtained. It represents the stand-alone classification for the considered class. For K = 3 and 5 more complex surfaces are obtained. Increasing K means to give more importance to the considered class in the comparison with the likelihood function.

For a given couple of positions of the two terminals, the following classification results have been obtained:

$K = 2$	$\underline{x_1}$ = (11,11)	$\underline{x_2}$ = (3.5, 5.3)
Real Class	Error Frequency	Error Frequency
Wlan	40%	20%
Bluetooth	100%	100%
Wlan + Bluetooth	0%	100%
Noise	0%	0%
Mean Error Frequency	35%	55%

Table 1 Error Frequency in the stand-alone mode (K = 2)

In the considered points of the environment some classes are correctly identified (Wlan+Bluetooth and Noise), one has a remarkable error frequency (Wlan, 40%) while Bluetooth is never identified in a correct way.

$K = 5$	$\underline{x_1}$ = (11,11)	$\underline{x_2}$ = (3.5, 5.3)
Real Class	Error Frequency	Error Frequency
Wlan	40%	40%
Bluetooth	0%	70%
Wlan + Bluetooth	0%	90%
Noise	0%	0%
Mean Error Frequency	10%	50%

Table 2 Error Freqeuncy in distributed classification mode (K = 5)

In the same positions it's possible to see how distributed detection mode is more efficent than the stand alone mode. But it's also possible to see that this advantage is clear for one terminal only, that has a substantial reduction of the classification error, while the other CCR has a very few improvement in classification.

These results require a specific point of view in order to completely understand the real significance of distributed detection: in fact, by considering all the CCRs in the environment a team of classifier, it's sufficent that at least one of them is able to perform a good classification. This information will be transmitted to the other terminal in an explicit (peer-to-peer or broadcast radio communication) or implicit (special motions of the CCR in the environment; these motions can be interpreted by the other terminals exploting the characteristics of the cognitive modeling) way.

In the present paper the design of only *Sensing* and *Analysis* stages has been considered. In order to complete the cycle, the development of also *Decision* and *Action* stages is subject of on-going researches.

6. CONCLUSIONS

This paper try to face the problem of information representation and usage in Cognitive Radios. After a brief overview on how their concept has been defined by international researchers, a behavioral model for CTs, together with the importance that the so-called *Cognitive Maps* have in the considered model, is provided.

For a specific problem, i.e. the Distributed Mode Identification problem, a possible extraction process is pointed out and some *Cognitive Maps*, obtained in a completely simulated framework, are shown.

Results proof that it's possible to obtain a synthetic representation of the physical world, which is completely understandable by CTs and it's useful for their target reaching. The representation respects also the requirement to be extremely compact (only interpolation coefficients are stored).

Finally classification results obtained in a completly simulated framework are presented: they proof that distributed detection theory, extended to a multi-class decision problem, is useful to improve the classification performances of a set of CCRs composed by two terminals.

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