DISTRIBUTED MODE CLASSIFICATION IN EMBODIED COGNITIVE RADIO TERMINALS

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ABSTRACT

In the last decade optimal radio resources allocation has become a problem requiring more complex solutions, including the possibility of re-configurable, adaptive use of spectrum. A cognitive approach to radio spectrum management has been proposed as a suitable and potentially efficient solution. In this paper, a Distributed Mode Classification problem is here considered as a reference approach to proposing new results and a framework of development of future research. Such approach strictly relies on the definition of a Cognitive (Radio - CR) system as capable of environmental interactions. The Embodied Cognition approach, for the design of new CR terminals, here followed is based on inspiration from works in Artificial Intelligence looking at intelligence as to an emergent behavior of a set of (computational) entities provided of the possibility of active interaction with the surrounding environment. In this domain, distributed spectrum sensing is seen as a perception capability of a CR terminal strictly related to the motion action to optimize its capability to optimally perform mode classification.

Index Terms— Cognitive Radios, Embodied Cognition, Spectrum Sensing, Mode Classification, Distributed Detection.

1. INTRODUCTION

In the last years, due to the increasing of wireless standards and communication services, it has grown up the necessity of a flexible approach to bandwidth allocation. Dynamic observation of the spectrum and adaptive reactions to wireless channel conditions are important problems in improving the spectrum efficiency. It is nowadays clear that a cognitive approach to the Spectrum Monitoring and Allocation can lead to suitable solutions more efficient than existing ones.

A fundamental concept in Cognitive Radio [1] (CR) approach is *Environmental Awareness*, or more precisely in this case, *Radio Awareness*, i.e. the understanding of what is happening in the electro-magnetic (e.m.) spectrum. This concept is translated, at the process level, into the *Mode Identification and Spectrum Monitoring* (*MISM*) process (or equivalently *Spectrum Sensing*) that plays a key role in Cognitive Radios, because it provides an observation of the physical world and the knowledge about the channel conditions, which facilitate a proper decision for the current context.

In the present paper an Embodied Cognition-based framework, for the internal knowledge organization and usage and for modeling the interactions between cognitive entity, is presented. It will be proved that the Distributed Detection Theory [2], basis of the Distributed Spectrum Sensing approach [3, 4], perfectly fits within the Embodied framework, naturally embedding the interactional embodied models.

Hence a general architecture for embodied distributed spectrum sensing will be presented and a specific MISM problem will be defined and simulated through a specific usage of the general architecture. In particular, a set of cognitive terminals (CT), moving in an environment characterized by the presence of a set of radio sources RS with the associated air interfaces, will be considered. The MISM problem relies on classifying the active radio sources starting from the observations about the e.m. spectrum performed by the pool of cooperative terminals.

2. EMBODIED COGNITIVE VISION

MISM process is only a part of the whole cognitive radio system. In fact, at a more general level a cognitive system needs to be defined through the usage of behavioral models. Let us now introduce one of this models and the proposed Embodied Cognition-based Framework which will be the base of the proposed MISM distributed solution.

The Cognitive Cycle is a model which can be used to describe the behavior of living beings. It allows to describe the interactions with the external world occurring through a cycle composed by four main processes: Sensing, Analysis, Decision and Action. While the Cognitive Cycle is a shared concept among almost all the Cognitive Radio community, different research lines can be seen in how the knowledge is managed and processed within each stage of the cycle. In fact, each stage of the Cognitive Cycle requires to manage information, which can be *naturally* embedded in the entity itself or acquired during its normal *life*.

Different visions are already present in the state of the art. In the current paper a physically grounded representation model has been chosen as starting point where intelligence can *naturally* rise up. This vision takes inspiration from Robotics works of Rodney Brooks [5] and it is referred in literature as *Embodied Cognition* [6]. In this paradigm, the representation of the internal knowledge and hence the description of the context, is strictly linked with the perceptive/motory possibilities of the entity itself. As a matter of fact, the *body* of the system has an important role in the evolution of the entity. Physical limitations of motion possibilities drive, by tackling back the cognitive cycle, the possibilities of the decision stage too and hence its functioning mechanism and its internal knowledge representation. The same concept can hence be extended going backward into the cycle until to the sensing stage.

A confirmation, at a biological level, of the validity of this approach to intelligence comes from recent neuro-physiological studies[7]: from an evolutionary point of view, one of the primary goal of intelligent multicellular organisms evolving toward higher level organisms is to use contextual information obtained through sensing to move in the surrounding environment to gain an advantage in life conditions, due, for example, to the reaching of a safer or a food richer point.

This definition of the knowledge representation has a direct impact on the algorithmic development for the considered MISM problem. In particular the embodied characteristics will be particularly useful in the design process of cooperation mechanisms, such as the Distributed Spectrum Sensing.

This fact is evident when the Cognitive Radio is a sub component of a more general Cognitive System, like a mini-robot which can perform independent motions in a known or unknown hostile environment. In this situation, the Decision stage can be tuned in order to move the robot (or to suggest a motion to a human) to a location which allows the best "point of view" for spectrum monitoring and analysis. If at least two cognitive cooperative entities are present in the environment, a distributed algorithm for transmission mode classification can be developed starting from the embodied formalization and management of knowledge.

3. COOPERATIVE EMBODIED COGNITIVE TERMINAL

Let us now define the cooperative cognitive terminal (CT) that embeds embodied knowledge organization and features. The attribute *embodied* related to the representation of the knowledge means that it is all referenced to the CT's body or the CT's point of view.

Since an embodied cognitive system is so strictly related to the physicality of its body, before modeling the internal knowledge such a system requires to perform its "life", it is necessary to define how the body is, and which are the characteristics of the cognitive entity.

Let us simply define the body through its environmental interactive aspects, i.e. it is equipped with an RF omni-directional antenna and a video camera. It can perform in the space an omni-directional movement, of constant length, of the body itself. In addition to the body, each cooperative cognitive terminal have to be defined also through the knowledge, embodied in itself, that allows its survival. Starting from the basic body, the required knowledge can be defined as the set $\boldsymbol{K}_n$:

$$CT_n \rightarrow \boldsymbol{K}_n = \{\boldsymbol{K}_{P_n}, \boldsymbol{K}_E, \boldsymbol{K}_{Env}\} \tag{1}$$

where $\boldsymbol{K}_{P_n}$ is the knowledge about the space surrounding the terminal itself and the temporal set of positions assumed by the terminal during its navigation/exploration; $\boldsymbol{K}_E$ is composed by all the functions that constitute the cognitive cycle and all the embedded information required for performing it, while $\boldsymbol{K}_{Env}$ is the knowledge that the CT has available about the physical/statistical interaction characteristics of the objects present in the environment.

In particular, the embodied knowledge $\boldsymbol{K}_E$ can be structured onto two levels for each component r of the cognitive cycle:

$$\begin{gathered}\boldsymbol{K}_E = \{E^r(\underline{X}_{CT_n}), F^r(.) : \\ r = \{\text{Sense, Analyze, Decide, Act}\}\}\end{gathered} \tag{2}$$

. The first level is composed by all the "instinctual" knowledge codified into maps. The second level is the procedural knowledge represented by the survival basic functions that constitute the inter-stage information transformation processes within the cognitive cycle.

In the case of basic body, we can define $E^{\text{Sense}}(\underline{X}_{CT_n})$ as the radiation pattern of the RF antenna and the field of view of the camera the terminal is equipped with. The knowledge required to analyze the environment $E^{\text{Analyze}}(\underline{X}_{CT_n})$ is composed by all the analysis methodologies the CT has available and that can be chosen depending on the current internal/external context conditions (e.g. the status of the batteries that can condition the selection of a less accurate but less power-consuming analysis process).

The Decision knowledge too can not be completely defined without considering the specific body of the CT. At a general level, $E^{\text{Decide}}(\underline{X}_{CT_n})$ will contain the policies that guide the behavior of the terminal in all the possible environmental situations. Finally the Action Knowledge $E^{\text{Act}}(\underline{X}_{CT_n})$ describes how to translate in actions the decisions taken in the previous stage of the cycle and provides physical indication on the signals that have to be applied to the motor drivers.

In order to introduce cooperation between terminals which share the same environment and observe the same phenomenon, each CT needs information both on the physical situation of the companion terminals inside the environment and on their behavioral model. Let us consider an homomorphic set of terminals where each terminal is supposed to have the same behavioral model (e.g. a set of "cloned" robots). The available knowledge is again defined by (1) but the information about the environment is now defined as:

$$\begin{aligned}\boldsymbol{K}_{Env} \;=\; &\{\boldsymbol{K}_{P_{Room}}, \boldsymbol{K}_{B_{Room}}, \boldsymbol{K}^k_{P_{RS}}, \boldsymbol{K}^k_{B_{RS}}, \boldsymbol{K}_{P_j}, \boldsymbol{K}_{B_j} : \\ &k = 1, \cdots, K,\; j = 1, \cdots, N, j \neq n\}\end{aligned} \tag{3}$$

where $\boldsymbol{K}_{P_{Room}}$ refers to the knowledge of an environmental and shared reference coordinate system (RCS) together with

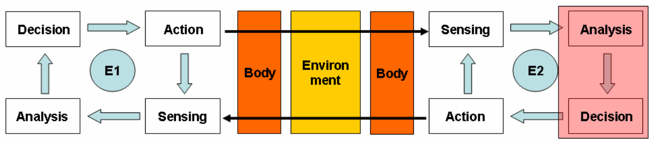

Fig. 1. Mirror representation of the interactions form E1 point of view

the transformation that links it with CT's RCS; $\boldsymbol{K}_{B_{Room}}$ contains information about which are the room physical reactions to the motion of the CT (the physical structure of the environment); $\boldsymbol{K}^k_{P_{RS}}$ gives the definition of the radio sources in terms of relative position/orientation, RCS and transformation to link to the *Room* RCS; $\boldsymbol{K}^k_{B_{RS}}$ contains a statistic description of the possible transmission situations the terminal could face for the *k*-th radio source. $\boldsymbol{K}_{P_j}$ and $\boldsymbol{K}_{B_j}$ are related to the position and to the behavior of the other cooperative terminals, being the companion CTs considering as other interactive entities. All the positions have to be considered relative to CT_n RCS.
The embodied formalization foresees an explicit representation of the interacting entities, i.e. a definition of the *self* through the environmental interactions with the *others*. Hence, at the general level, how the interactions between the CT and the other objects (cognitive or not) happen has to be defined too. Let us suppose that a CT always perceives the other interacting entities as cognitive. As stated by Marchesotti *et. al.* in [8], a cognitive entity E1 can internally represent another interactive cognitive entity E2 through a set of active *mirror* knowledge simulating a cognitive cycle through a shared medium. As depicted in Figure 1, from the cognitive entity E1 point of view, only how to influence the E2 and how E2 influences E1 (i.e. the interfaces with the physical world) are "visible". The hidden part of the cycle can be *a-priori* known (behavioral model) or it can be learned (partially or completely), in an approximated way, through interacting experiences. Interacting entities are also the room itself and the radio sources. Each one of the interacting entities is described, in this internal representation, by the sets contained in K_{Env}, while the concept of environment is here substantially translated into a virtual shared medium, used by the CT, where the internal representations of the other players perform their sensing/actions.
The above describe knowledge can be perfectly statistically known within the CT, or it has to be estimated during the normal operations. The estimation of part of this knowledge involves an introduction of uncertainty in the system. In present paper a situation where the positions of the CTs are not perfectly known (sensing-based localization) will be considered. This fact will lead to a generalization of the distributed detection theory (respect to the system proposed in [4]). The considered case has to be intended as one of the possible problematics a CT has to face in real applications.

3.1. Distributed Embodied Cognitive Core

In this Section, how to build up analysis and decision stage according to the new Embodied framework of an Embodied Cognitive Radio Terminal is presented.
Let us consider a simple framework where only two CTs and only one radio source that it can be switched on (hypothesis H_1) or switched off (hypothesis H_0) are present in the environment.
Let us now define the quantities involved in the information processing within the cognitive cycle for CT_1 (simply extensible to CT_2), starting from y_i, that are the features extracted by the i-th CT from the radio signal perceived by the RS. The probability density functions (pdfs) $p(y_i|H_j, x_i)$ statistically describe how the RS influence the perceptions of the CT_i in both the possible cases.
Generalizing the previously defined pdfs, it is possible to obtain a general behavior of the perceptual interactions between the CT and the RS in all the *Room*: $p(y|H_0, x)$ and $p(y|H_1, x)$ compose $\boldsymbol{K}^1_{B_{RS}}$. The vector of features, that each CT extracts from its observations, is hence composed by $\boldsymbol{v}(t, x_1) = \{y_i, x_1, x_2, \Delta x_2\}$.
Let $u_i = j : j = \{0, 1\}$ be the classification performed by CT_i about the presence of the hypothesis H_0 or H_1. It is hence possible to infer that the u_i represent the MISM classification. The pdfs $p(u_i = j|y_i) : j = \{0, 1\}$ describe the statistical behavior of the MISM classification algorithm in relationship with the perceived features y_i.
This knowledge is part of the behavioral model of the interacting entity $\boldsymbol{K}_{B_2}$, but, under the homomorphic assumption, it is also a part of the embodied knowledge, i.e. it is in E^{Analyze}.
Each CT estimates the behavior of the companion CT through a mirror (or inverse) decision process. Let us call this estimation $\hat{u}_i$. The context label can hence be defined as $L(t, x_1) = \{u_1, \hat{u}_2, x_1, x_2\}$.
Once defined the most important variables it is possible to analyze more in detail how the single stages of the cycle can be structured.

3.1.1. *Analysis Stage*

The analysis stage is composed by three main sub-blocks: the feature extractor, the mirror decision block and the distributed classifier
While the feature extractor derive $\boldsymbol{v}$ from the perceived observations the distributed classifier is the fundamental component of the analysis stage of the cognitive cycle for the embodied cooperative CTs. This fact will be more clear after the introduction of the generalized distributed detection theory applied to the considered MISM problem.
Let us consider the self-localization of CT_i as sensing-based. This fact introduces a certain amount of uncertainty on the considered variable of the problem. This uncertainty can be described by a proper pdf $p(x_i|\hat{x}_i)$ which is dependent by the particular combination algorithm/features used for local-

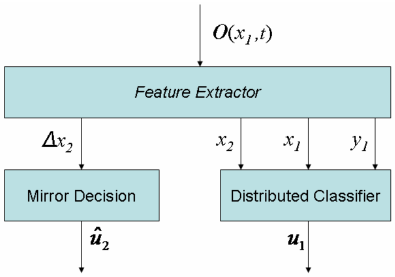

Fig. 2. Analysis Module of an Embodied CT

ize the CT. Let us also consider the relative position of the other CT respect to the 1-st one's reference system as estimated (e.g. through the usage of the video camera). Calling $\hat{d}_j$ the estimated distance vector between CT_i and CT_j, the absolute positions of the two CTs are linked through the relationship $\hat{x}_j = \hat{x}_i + \hat{d}_j$. Being $p(x_i|\hat{x}_i)$ the pdf of $\hat{x}_i$ and $p(d_j|\hat{d}_j)$ the pdf of $\hat{d}_j$, the pdf of $\hat{x}_j$, $p(x_j|\hat{x}_j)$ will be given by the convolution between $p(x_i|\hat{x}_i)$ and $p(d_j|\hat{d}_j)$.
Let us now define the generalized distributed classification function used by the classifier:

$$\Lambda(y_1, x_1) \underset{u_1=0}{\overset{u_1=1}{\gtrless}} t_1(x_2) \tag{4}$$

where $\Lambda(y_1, x_1)$ is the generalized version of classical Bayesian likelihood function and t_1 is the distributed threshold. The function Λ can hence be defined as:

$$\Lambda(y_i, \hat{x}_i) = \frac{\int_{\underline{X}} p(y_i|H_1, x_i)p(x_i|\hat{x}_i)}{\int_{\underline{X}} p(y_i|H_0, x_i)p(x_i|\hat{x}_i)} \tag{5}$$

where $\underline{X}$ is the environmental RCS. If $p(x_i|\hat{x}_i)$ is unknown an implementation approach can be its substitution with a weighting function $w'(\hat{x}_i) : \Pi' \rightarrow \mathbb{R}$ in (5), where Π' is a limited portion of $\underline{X}$.
Under the following decision costs assignment:

$$C_{000} = C_{111} = 0$$
$$C_{010} = C_{100} = C_{011} = C_{101} = 1$$
$$C_{001} = C_{110} = K_d$$

the decision threshold can be written as:

$$t_i(\hat{x}_j) = \frac{P_0}{P_1} \cdot \frac{(K_d-1)+(2-K_d)\int_{\underline{X}} p(u_j = 0|H_0, x_j)p(x_j|\hat{x}_j)}{1+(K_d-2)\int_{\underline{X}} p(u_j = 0|H_1, x_j)p(x_j|\hat{x}_j)} \tag{6}$$

if the pdf $p(x_j|\hat{x}_j)$ is unknown, in this case too it is possible a substitution with a weighting function. Let us call $w(\hat{d}_j) : \Pi \rightarrow \mathbb{R}$ the weighting function that substitutes the pdf $p(d_j|\hat{d}_j)$. Hence the weighting function to be used in the threshold is given by $w''(\hat{x}_j) = w(\hat{d}_j) * w'(\hat{x}_i)$, where * denotes a convolutional operator. It should be noticed that the Bayesian threshold computed for the distributed detection theory incorporates both the statistical behavior of the RS and the classification behavior of CT_2 computed in the point x_2. This fact corresponds to the internal simulation of the cognitive cycle of the interacting entities that each embodied CT should perform. In fact the pdfs $p(y_2|H_j, x_2)$ describe the perceptual interaction of CT_2 with the radio sources, while the pdfs $p(u_2 = j|y_2, x_2)$ represent the Analysis stage of the companion CT. This is one of the main reasons why the distributed detection theory perfectly fits within the embodied cognition framework until now described. This theory allows to simulate the behavior of the interacting entities and to compare it with the observations/classification each CT performs (represented by the likelihood function) in a one-shot computation, with a low computational load respect to other solutions (e.g. agent-based internal emulation).
Finally, the Mirror Decision stage is used in the analysis stage to estimate which class CT_2 could have classified having as input the action (motion) the CT has actuated.

3.1.2. Decision Stage

Before describing the Decision stage, it is necessary to define which is the final goal for the CT. From a physiological point of view, the final goal of a living entity is the *homeostasis* [9], i.e. the reaching of a dynamic equilibrium that allows the life of the entity itself. This concept can be extended to higher cognitive layers: it is possible to infer that *homeostasis* is the status of the CT in which it has gained the maximum advantage respect to its physical possibilities and to the environmental context. An engineering translation for this concept can be the minimization of a global cost functional:

$$x_T = \arg_{x_i} \min_{x_1,x_2} J(x_1, x_2, u_1, u_2) \tag{7}$$

where x_T is called *target point* and represents the point where the CT can reach its dynamic equilibrium. Being the u_2 unavailable to CT_1 it is possible to use a suboptimal version by substituting the u_2 with its estimated version. In the case of the MISM system here presented, the functional should evaluate how much the position of the CT provides a good point of view of the e.m. context.
The decision stage choses the motion that leads to the current dynamic target point x_T in a more direct way. This is possible through the usage of a deterministic look-up table $LT(u_i) \rightarrow \Delta x$ that associates a motion $\Delta x(x_i)$, parametrized by the position of the CT, for each classification performed by the CT.
This table should be invertible, hence it should be possible to

define $LT^{-1}(\Delta x(x_i)) \rightarrow \hat{u}_i$. This inverse function can be used in the Mirror Decision block of the analysis stage as estimator for the class decided by the companion CT.

4. SIMULATION AND RESULTS

4.1. Simulation Framework

Let us define the characteristics of the MISM problem. Two RSs are present in a *Room* of 12x12 meters. Two communication modes are possible, i.e. IEEE 802.11b WiFi and Bluetooth. The above air interfaces have the particular characteristic that they share the same bandwidth and they can be simultaneously superimposed. Furthermore Bluetooth (BT) transmits with a very low power (1mW) within a range which is much more limited than the WiFi (or WLAN) one.

Each source can be associated to only one Md and the transmitted signal is affected by the typical propagative phenomena that can be found in a common office, according to the model presented in [10]. The general framework, similar to the one presented in [3, 4], is summarized in Figure 3. The

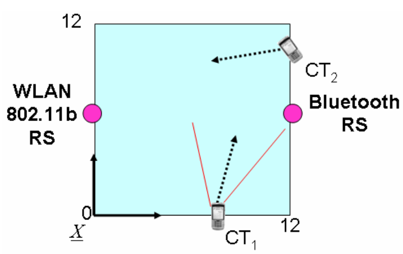

Fig. 3. Simulated MISM Problem

possible situations the CT could find in the environment are represented by four classes: WLAN, when the WLAN RS only is switched on; BLUE, when the Bluetooth RS only is switched on; WLBL, when both the RSs are switched on; NOISE, when environmental noise only is present. The two CTs involved in the MISM classification can enter the room in any of the border points and they are able to move within the room itself. Each CT is able to perform a motion of one meter in each direction from the starting point and that each action is composed by a single motion $\Delta \boldsymbol{x}$.

In order to solve the specific MISM problem two time frequency (TF) features, derived from the Wigner-Ville TF transform , have been used. In particular, the standard deviation of the instantaneous frequency (σ_ω) and maximum time duration of the signal ($T_{\max}$) have been proved [3] to be useful in the case of signals superimposed in the same bandwidth.

The vector $y_i = [\sigma_\omega \; T_{\max}]$ is used as input for the distributed classifier, together with the instantaneous positions of the two CTs. In order to face the multi-class MISM problem, the multiple classifier One-Against-All architecture [4] has been chosen. In the proposed implementation, this architecture requires the computation of the upper bound of the theoretical error probability. This information is obtained through simulated sample means and covariances of the classes. Under the assumption of Gaussian $p(y_i|H_j, x_i)$ with j corresponding to one of the possible classes, it is hence possible to compute Chernoff bound $C_{j,k}(x_i)$ for each couple of classes. The upper bound for a selected class j is hence given by:

$$P_{err}^j(x_i) = \max_{k,k\neq j} C_{j,k}(x_i) \tag{8}$$

In order to design the decision stage, the global minimum of $P_{err}^j(x)$, for each class j, has been chosen as target point where the CT can reach an homeostatic condition. It is hence easy to obtain the look-up table $LT(u_i)$, as it is easy to derive the inverse one. As weighting functions w and w' two equal 2D rectangular functions have been used. The width of the function is 1x1 square meters.

The simulation system has been developed in Matlab Simulink and it has been built up according to the organization of knowledge and the interaction models presented in Section 2. Each CT has been developed as dynamic system through a closed-loop finite state machine (FSM) whose data structures are organized in the same sets described in Section 3. Apart for the specific implementation language, the CT has been implemented in order to obtain an “emulation” of the Cognitive core of the system. In fact, with the proper language-dependent adjustments, it is possible to export the same architectural structure on an hardware platform, without any particular ad-hoc modifications. In the following, the results obtained with the simulative/emulative system for the faced problem will be presented.

4.2. Results

In order to simulate the uncertainty introduced by the sensing-based localization, a 2D Gaussian noise has been added to the absolute positions of the CTs, according to the definition of the simulated problem. Furthermore, the following simulation parameters expressed have been used:

- Maximum Number of Iterations per Simulation: 1000
- Number of Simulations per class per problem: 1000
- Standard Deviation of Positioning uncertainty: $\rho_x = \{1m, 2m\}$
- $K_d = \{2, 5\}$
- uniformly random choice of the entering position of the CTs in the room

The first presented results are related to the effectiveness of the embodied distributed classifier. The value $K_d = 2$ reduces the distributed threshold t_i to the usual Bayesian threshold commonly applied to the Bayesian stand-alone classification. Result obtained with this value are compared to the ones obtained for a choice of $K_d = 5$, already tested in [4], under the form of confusion matrices. In Table 1 and 2 the obtained confusion matrices for $\rho_x = \{1m, 2m\}$ are shown. The first column indicates the *ground truth* (GT), i.e. the real contextual situation, while the other columns represent the distribution of the classifications performed by the CT. In the following, the class labels will be further abbreviated as W (WLAN), B (BLUE), WB (WLBL), N (NOISE). As already

Table 1. Confusion Matrices for $\rho_x = 1m$

	$K_d = 2$			
GT/CLASS	W	B	WB	N
WLAN	84,9%	7,3%	7,7%	0,2%
BLUE	2,3%	87,8%	0,1%	9,9%
WLBL	72,5%	26,3%	1,1%	0,1%
NOISE	0,0%	26,7%	0,0%	73,3%
	$K_d = 5$			
WLAN	85,4%	7,8%	6,6%	0,2%
BLUE	2,5%	87,9%	0,1%	9,5%
WLBL	72,7%	26,1%	1,1%	0,1%
NOISE	0,0%	31,9%	0,0%	68,1%

Table 2. Confusion Matrices for $\rho_x = 2m$

	$K_d = 2$			
GT/CLASS	W	B	WB	N
WLAN	85,1%	11,1%	3,6%	0,2%
BLUE	0,8%	76,8%	1,1%	21,4%
WLBL	66,2%	28,4%	5,2%	0,1%
NOISE	0,0%	9,1%	0,0%	91%
	$K_d = 5$			
WLAN	85,1%	11,1%	3,6%	0,2%
BLUE	0,7%	77,0%	1,1%	21,2%
WLBL	65,7%	28,9%	5,3%	0,1%
NOISE	0,0%	10,5%	0,0%	89,5%

proved [3, 4], the distributed approach allows to reach better results than in the stand alone case. It should be noticed that the class WLBL is never well classified. This is due to the features distribution all along the room. In fact one of the two RS is always predominant in a certain area. Besides to this fact, in an office indoor environment, Bluetooth has a maximum range of less than 10m, and the combined effects of multi-path and the spurious cross-terms introduced by the Wigner distribution can create mis-classifications between the NOISE and BLUE class.

The good results obtained when the other transmitted classes show that the uncertainty is well compensated by the simple weighting functions used. A better design of w and w' could lead to a substantial reduction of these errors.

A still more important impact of the embodied framework on the MISM problem is the goodness of the mode classification in the homeostatic condition. Except the case of WLBL class, all the other classes reach a detection accuracy of at least 99,3%. It is possible to understand that, the iterative exploration of the room and the reciprocal observation of the two involved CTs lead to an almost complete reduction of the MISM mis-classification, with the only exception of the WLBL class. This exception, due to the environmental and technological problems cited above, is relatively problematic for a MISM application. In fact the CTs always decide the presence of an available communication signal and never confuses it with the NOISE class.

It should be clear that the convergence to an homeostatic condition could be very slow. In fact a not negligible number of simulations did not reach a global homeostatic condition within the fixed 1000 steps, especially in the case of WLBL class.

5. CONCLUSIONS AND FUTURE WORKS

In the present paper an embodied cognition-based approach to distributed spectrum sensing was presented. Starting from the awareness of the physical capabilities of the body, the mind of the Embodied Cognitive Radio system can be developed through an organization of the internal knowledge that directly represent the active/passive interactions of the entity with the players involved in the problem. This framework has been particularly designed addressing the MISM problem and the Distributed Detection Theory has been proved to realize Embodied capabilities in a simple and fruitful way. In fact simulated situations have proved the effectiveness of the proposed method.

Future research directions consist in a more complex definition of the CT, providing it with self-learning capabilities.

6. REFERENCES

[1] S. Haykin, "Cognitive radio: brain-empowered wireless communications," *Selected Areas in Communications, IEEE Journal on*, vol. 23, no. 2, pp. 201–220, 2005.

[2] P.K. Varshney, *Distributed Detection and Data Fusion*, chapter 3-Distributed detection without fusion, Springer-Verlag, 1st edition, 1996.

[3] M. Gandetto and C.S. Regazzoni, "Spectrum sensing: a distributed appraoch for cognitive terminals," *IEEE Journal on Selected Areas in Communications - Special Issue on Adaptive, Spectrum Agile and Cognitive Wireless Networks*, vol. 25, no. 3, April 2007.

[4] M. Gandetto R. Niu P.K. Varshney C.S. Ragazzoni A.F. Cattoni, I. Minetti, "A spectrum sensing algorithm based on distributed cognitive models," in *SDR Forum Technical Conference*, Orlando, FL, USA, November 13-17 2006.

[5] Rodney A. Brooks, *Elephants do not play chess*, chapter in "Designing Autonomous Agents", pp. 3–15, MIT press, 1991.

[6] Michael L. Anderson, "Embodied cognition: A field guide," *Artificial Intelligence*, vol. 149, no. 1, pp. 91–130, 2003.

[7] R.R. Llinas, *I of the Vortex*, Bradford Book, MIT Press, Cambridge, MA, 2001.

[8] L. Marchesotti, S. Piva, and C. S. Regazzoni, "Structured context-analysis techniques in biologically inspired ambient-intelligence systems," *IEEE Trans. on Systems, Man, and Cybernetics - Part A : Systems and Humans*, vol. 35, no. 1, January 2005.

[9] W. B. Canon, *The wisdom of the body*, W. W. Norton & Co., New York, NY, USA, 1932.

[10] A. Saleh and R. Valenzuela, "A statistical model for indoor radio propagation," *IEEE J. Select. Areas Commun.*, vol. SAC-5, pp. 128–141, february 1987.