Chapter 1

Embodied Cognition based Distributed Spectrum Sensing for Autonomic Wireless Systems

Luca Bixio, Andrea F. Cattoni, Carlo S. Regazzoni, and Pramod K. Varshney

Abstract In the last decade, the usage of portable communication devices has continued to increase. Autonomic Communications (AC) represents a new frontier for mobile communications because they will allow autonomous and self-regulated network and communication protocols procedures. Dynamic observation of the spectrum and adaptive reactions of the autonomic terminal to wireless channel conditions are hence important problems in improving the spectrum efficiency as well as in allowing a complete access to the network wherever and whenever the user needs them. Cognitive Radio probably represents the most suitable paradigm for building communication terminals/devices for AC. In this chapter, after a tutorial overview of the current State of the Art on Cognitive Radio visions and on stand-alone and cooperative/distributed approaches to spectrum sensing, the general problem of spectrum sensing will be addressed. Then a new vision, based on Embodied Cognition will be presented together with a Distributed Spectrum Sensing algorithm that is formalized within the embodied framework. Results will illustrate the effectiveness of the proposed method.

Key words: Cognitive Radio, Embodied Cognition, Distributed Spectrum Sensing, Distributed Detection Theory, Mode Identification

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1.1 Cognitive Radio for Autonomic Wireless Communications

In the last few years, the usage of portable communication devices has continued to increase at a rapid pace [3]. Together with mobile devices, new communication services have been proposed thanks also to new communications standards. On the one hand, such new standards provide flexibility in communications to end users. But on the other hand, this places a huge demand for radio spectrum that is expected to grow in the future [37]. To allow for such rapid growth, different frequency bands in the radio spectrum are selected and assigned to different standards by governmental regulatory agencies [23] in order to guarantee coexistence between different services [37].

After many years of fixed radio spectrum assignment in order to meet the increasing demands due to emerging services, the unlicensed frequencies are going to disappear [17]. In fact, a study conducted by the U.S. Federal Communication Commission (FCC) [15] has pointed out that the radio spectrum is heavily crowded with most frequency bands already assigned to licensed users for a given service [37]. Moreover, the variation in estimated use of licensed spectrum ranges from 15% to 85% [1], while the Defense Advance Research Projects Agency (DARPA) [26] estimated that only 2% of the allocated spectrum is in use in U.S. at any given moment. For these reasons, it is clear that a flexible utilization of the radio spectrum is necessary. In fact, according to Haykin [23], “in many bands, spectrum access is a more significant problem than physical scarcity of spectrum, in large part due to legacy command-and-control regulation that limits the ability of potential spectrum users to obtain such access”.

This means that radio spectrum utilization can be significantly improved if unlicensed (secondary) users are allowed to access licensed bands if and only if at a given time and in a given location licensed (primary) users are not using it. It has now become abundantly clear that a dynamic management of radio spectrum allocation is required to meet the growing demand and to have efficient utilization of the spectrum. To facilitate this, continuous and dynamic observation of the radio spectrum in order to adaptively react to wireless channel conditions are important issues in improving radio spectrum utilization [23]. In a broad sense, the Cognitive Radio provides different solutions in order to solve some of these problems [16]. A broad survey of Cognitive Radio approaches will be provided in Sect. 1.2.

Haykin [23] provides the following definition for Cognitive Radio:

> Cognitive Radio is an intelligent wireless communication system that is aware of its surrounding environment (i.e., outside world), and uses the methodology of understanding-by-building to learn from the environment and adapt its internal states to statistical variations in the incoming RF stimuli by making corresponding changes in certain operating parameters (e.g., transmit-power, carrier-frequency, and modulation strategy) in real-time, with two primary objectives in mind:

- highly reliable communications whenever and wherever needed;
- efficient utilization of the radio spectrum.

As it is clear from this definition, the common keywords for an efficient Cognitive Radio are *awareness* and *reconfigurability*. In a radio environment, awareness means the capability of the Cognitive Radio to understand, learn, and predict what is happening in the radio spectrum [16], that is Cognitive Radio is able to identify the transmitted waveform, to localize the radio sources, etc. Spectrum awareness is also known as Spectrum Sensing and it will be addressed in detail in Sect. 1.3. Reconfigurability is necessary to provide *self-configuration* of some internal parameters according to the observed radio spectrum [23]. Reconfigurability provides *self-optimization* [25] of the Cognitive Radio in order to accommodate new standards and new services as they emerge [16]. Furthermore, reconfigurability is enormously important for both civilian and military applications especially when unforeseen situations happen and some network infrastructures are not available providing *self-healing* and *self-protection* capabilities.

The capabilities listed above perfectly match with the autonomic computing vision proposed in [25]. In Table 1.1 a *self-management* capabilities comparison among classical Autonomic Computing system [25] and Cognitive Radio system is provided.

Table 1.1 Self-management capabilities comparison among Autonomic Computing system and Cognitive Radio system.

Ability	Autonomic Computing	Cognitive Radio
self-configuration	Automated configuration of components and systems follows high-level policies. Rest of system adjusts automatically and seamlessly. [25]	Automated optimal configuration of transmission parameters according to Spectrum Sensing in order to avoid harmful interference to licensed users.
self-optimization	Components and systems continually seek opportunities to improve their own performance and efficiency. [25]	Systems continuously perform Spectrum Sensing to detect opportunities to improve their own performance and spectrum utilization.
self-healing	System automatically detects, diagnoses, and repairs localized software and hardware problems. [25]	System automatically vacates the occupied band if a licensed user attempts to access it.
self-protection	System automatically defends against malicious attacks or cascading failures. It uses early warning to anticipate and prevent systemwide failures. [25]	System automatically defends against malicious attacks and avoids cascading failures while detecting opportunities.

The first example of a Cognitive Radio system equipped with the capabilities listed in Table 1.1 has been considered in the DARPA NeXt Generation (XG) radio development program [13, 26]. This Cognitive Radio senses the radio environment, identifies an opportunity in which secondary users can transmit in a given licensed frequency band, adapts the transmission parameters in order to exploit the detected opportunity, transmits and releases the occupied band if a licensed user accesses it [16]. These tasks are cyclically executed according to stored experience provided by a learning process.

1.2 Cognitive Radio approaches

1.2.1 Mitola's Definition

One of the main contributors to the definition of the Cognitive Radio paradigm was Joseph Mitola III. In [29], he defined the Cognitive Radio as a system that "can track the user's environment over time and space. Cognitive Radio, then, matches its internal models to external observations to understand what it means to commute to and from work, take a business trip to Europe, go on vacation, and so on". From this definition, the intrinsic capabilities of autonomy, transparency, and learning are evident. In his vision, such capabilities have to be implemented using a common META-Language (MTL) that he defines as Radio Knowledge Representation Language (RKRL). It is useful to describe, at a semantic level, according to classical Artificial Intelligence (AI) vision, "space-time models of the user, network, radio resources, and services" that can "personalize and enhance the consumer's experience". He models the behavior of the proposed Cognitive Radio using a state/transition representation known as a *cognitive cycle* [29]. It represents the possible time-varying states the Cognitive Radio can assume and which are the transitions that link the states with each other. In Mitola's cognitive cycle, the transitions are triggering events or situations that can happen in the surrounding environment (e.g., external world).

Mitola focused his work on the mass market civilian applications. As a matter of fact, he was interested in the impacts of a dynamic and multipurpose cognitive device on the possible service provisioning from a network provider side. Starting from this civilian and market oriented framework, this original work (and the following ones) gave a great impetus to the scientific community for facing the various open issues/challenges in order to implement a practical, cognitive radio device, with self-management capabilities.

1.2.2 Haykin's Definition

Six years after Mitola, another important researcher, Simon Haykin, provided a more precise and detailed definition of Cognitive Radio in his paper *Cognitive Ra-*

dio: Brain-Empowered Wireless Communications [23]. As stated in Sect. 1.1, in autonomic wireless communications, a Cognitive Radio can be defined as a system provided with some sort of *intelligence*. Such a system is able to sense the surrounding environment and using a "methodology of understanding-by-building to learn from the environment" adapts its internal parameters in order to achieve two global goals: 1) "highly reliable communications", and 2) "efficient utilization of the radio spectrum" [23].

While Mitola was mainly interested in the impact of the cognitive and self-management capabilities onto the communications market. Haykin addressed the problem from a more general point of view providing a more detailed and explicit definition. Both agreed on the fact that the Software Defined Radio systems [29] can be used for developing a practical and efficient Cognitive Radio. Furthermore, according to Haykin [23], "Software-Defined Radio (SDR) is a practical reality today, thanks to the convergence of two key technologies: digital radio, and computer software". It is now clear that in order to implement a Cognitive Radio, it is necessary to provide some cognition capabilities (sometimes also known as *intelligence* or *smartness*) to a flexible and highly reconfigurable system, provided by the SDR architecture [23].

The behavior of the cognitive dynamic system proposed by Haykin can be represented by a cognitive cycle [23], similar to Mitola's one [29] (as explained in Sect. 1.2.1), but much more clustered in macro-processes. This behavioral approach is based on three macro-states which establish, the cognitive foundations of the Cognitive Radio [23]:

- "Radio-scene analysis": Cognitive Radio has to detect opportunities and adapt its transmission parameters in order to avoid harmful interference to primary users.
- "Channel identification": Cognitive Radio has to estimate the Channel-State Information (CSI) in order to predict the channel capacity that it can exploit.
- "Transmit-power control and dynamic spectrum management": Cognitive radio has to perform power control and dynamic spectrum utilization in order to achieve the above listed tasks.

Such active states and their characteristics define the main characteristics of a Cognitive Radio from a signal processing/communications point of view and they are widely accepted by the Cognitive Radio scientific community.

1.2.3 Other Visions

In [22], Palicot discusses his idea for the evolution of a Cognitive Radio device from a common SDR platform. In fact, he proposes to add self-management capabilities in order to provide awareness to a reconfigurable radio and he supplies some assumptions for adding such capabilities to the considered system [22]:

Sensing means refer to all the possible methods the Cognitive Radio system has at its disposal for observing its environment, which can be categorized in four main families described below:

- *electromagnetic environment*: spectrum occupancy, Signal to Noise Ratio (SNR), multi-path propagation, etc.
- *hardware environment*: battery level, power consumption, computational resources load, etc.
- *network environment*: telecommunication standards (GSM, UMTS, WiFi, etc.), operators and services available in the vicinity, traffic load on a link, etc.
- *user-related environment*: position, speed, time of day, user preferences, user profile (access rights, contract, ...), video and audio sensor (presence detection, voice recognition), etc.

Such collected observations are stored and processed to provide self-awareness to the Cognitive Radio system. Palicot's work is focused on the design of a cognitive "engine" for implementing the reconfiguration operations on the SDR platform.

Other researchers are much more interested in the self-management and learning capabilities of the Cognitive Radio, such as Doyle and Sutton. In [31] and [39], they design the high-level cognitive capabilities of their platform through classical AI approaches and the usage of a META-Language. In their system, both the cognitive cycle and the reconfiguration manager, a type of middleware able to control hardware and software reconfiguration abilities, has been implemented by programming languages such as the eXtensible Markup Language (XML) or the Web Ontology Language (OWL).

Another semantic rule-based approach is the one proposed by Clancy *et al.* in [10]: "a cognitive radio extends a software radio by adding an independent cognitive engine, composed of a knowledge base, reasoning engine, and learning engine, to drive software modifications". All these characteristics are implemented in semantic or sub-semantic states which interact with each other through binary logic operators. Clancy's Cognitive Radio is implemented on an open source Software Communications Architecture (SCA) and it is able to learn from the acquired knowledge.

In [16], Bostian *et al.* propose a system that jointly exploit a feature based optimization algorithm and a classical case-based reasoning engine. The strength of the system relies on the Multi-Objective Decision Making (MODM) approach for optimal reconfiguration. It takes into account all the different quantitative parameters about the goodness of the wireless link, such as packet delay, data rate, Signal-to-Noise Ratio (SNR), the fading statistics, and it jointly optimizes all the parameters of the Physical (PHY) and Link (LLC) levels of the ISO-OSI stack. The optimization is performed using a genetic algorithm which allows us to find optimal solutions in multi-dimensional and heterogeneous optimization spaces.

1.3 Spectrum Sensing

As has been pointed out in the previous sections, a Cognitive Radio has to be able to sense the environment over a wide portion of the spectrum and autonomously adapt to it since the Cognitive Radio does not have rights to any frequency bands.

This task performed by Cognitive Radio is known as Spectrum Sensing [1, 16, 23] (or Spectrum Monitoring [17–19]). Generally speaking, Spectrum Sensing in wireless communications is one of the most challenging tasks that a Cognitive Radio has to perform. Depending on the required level of automation and self-management capabilities, Spectrum Sensing has to provide to the Cognitive Radio different infomation in order to predict the radio spectrum utilization. For these reasons, in some applications, providing information only about the frequency usage would not be sufficient, and other characteristics about the portion of the spectrum under investigation have to be provided in order to predict the radio spectrum utilization (e.g. number of transmitted signals, carrier frequency, power, transmission technique, modulation, etc). In fact, prior knowledge about the transmitted signal and its parameters (e.g. carrier frequency, power, modulation, etc.) is usually not available. Moreover, received signals are corrupted by channel distortions (e.g. severe multipath fading), and spread spectrum transmission techniques are often used in order to obtain a low probability of interception.

Generally, Spectrum Sensing techniques can be classified as stand alone, and cooperative and distributed, as shown in Fig. 1.1.

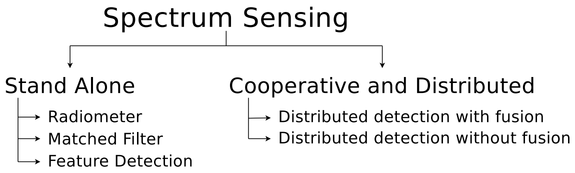

Fig. 1.1 Classification of Spectrum Sensing techniques: Stand Alone, and Cooperative and Distributed

In the following subsections a survey on these Spectrum Sensing techniques will be provided and advantages/disadvantage for the different approaches will be discussed.

1.3.1 Stand Alone Spectrum Sensing

Stand alone Spectrum Sensing techniques have been treated extensively in the literature [1, 2, 8, 14, 16, 17, 20, 21, 34, 41]. This kind of techniques have been studied for military and civilian applications for signal detection [21], automatic modulation classification [14], radio source localization [8], and communication jamming [21] purposes.

In the past, the most commonly used approach to Spectrum Sensing was based on *energy detector* [21, 41] (or *radiometer*), that is measurement of received energy in selected time and frequency intervals. Radiometer is one of the most used techniques thanks to its low computational load. However, it is well known that this strategy is highly sensitive to unknown and varying noise level [21]. In order to overcome this limitation, some modified radiometers, with adaptive thresholds and filtering, have been proposed [20]. In spite of these modified approaches, unknown and varying noise level is the most serious impediment to reliable Spectrum Sensing [21]. Moreover, in the last decade, different spread spectrum transmission techniques have been proposed in order to obtain a low probability of interception. If such techniques are used, received signal power is close to the noise threshold (or sometimes under, i.e. negative SNR) and it is undetectable by a radiometer without increasing the false alarm probability [21].

When some information about the transmitted signal is known to the Cognitive Radio, the optimal detector, under assumption of stationary Gaussian noise, is the *matched filter* since it maximizes the received SNR [34]. The matched filter requires perfect knowledge of the transmitted signal parameters, such as modulation type, order, and pulse shape in order to provide optimal detection. But if perfect knowledge of the transmitted signal is not available or it is not accurate, the performance of the matched filter degrade quickly [1]. In a Cognitive Radio environment *a priori* knowledge about the transmitted signal is usually not available. In spite of this, it is possible to use a matched filter in a Cognitive Radio that relies on SDR [23] as it is able to autonomously select the correct filter according to the radio environment under investigation. This means that a wide range of matched filters (one for each signal that is expected to be present in the considered radio environment) have to be implemented on a software platform with self-management capabilities. Thanks to self-management and reconfigurability capabilities, it is still possible to obtain optimal detection at the price of high computational load. For this reason, the matched filter approach is not suitable for practical Cognitive Radios, especially when a crowded frequency band is considered (e.g. Industrial, Scientific and Medical band).

An alternative Spectrum Sensing technique is based on *feature detection*. In this context, a feature is defined as an inherent characteristic which is unique for each class of signals. In the literature [1, 2, 14, 16, 17, 21, 32, 40], different features have been considered in order to detect and classify signals in a given radio environment. Some of the most intuitive features considered are instantaneous amplitude, phase, and frequency [2]. Such features are usually used to detect and classify linear modulation [14].

More recently, Analog-to-Digital Conversion (ADC) has made the use of transforms practical [16] in order to localize the changes in instantaneous amplitude, phase, and frequency. Typical transforms used are Discrete Fourier Transform (DFT) [16], Wavelet Transform (WT) [14], and Wigner-Ville Transform (WVT) [17]. The above mentioned feature detection approaches have advantages depending on the considered application, computational complexity, and radio environment.

One of the most used and interesting feature detection technique is based on the cyclic-feature. This technique was first introduced by Gardener in [21] for signal interception purposes but, in the last years, Jondral *et al.* [32] and Doyle *et al.* [40] have proposed the use of the cyclic-feature as a Spectrum Sensing technique for Cognitive Radio applications. Cyclic-feature detection approaches are based on the fact that modulated signal are usually coupled with sine wave carriers, hopping sequences, cyclic prefixes, spreading codes, or pulse trains, which result in a built-in periodicity [1]. These modulated signals are said to be cyclostationary since their mean and autocorrelation functions exhibit periodicity [21]. Such periodicity can be used as a feature and can be detected by analyzing a Spectral Correlation Function (SCF) [1, 21], also known as cyclic spectrum [21]. The main advantage obtained by using SCF analysis is that it is possible to distinguish between noise and signal (even at negative SNR) thanks to the fact that noise is a wide-sense stationary random process [33], with no spectral correlation, while the modulated signals are cyclostationary, with spectral correlation due to embedded periodicity. Therefore, a cyclic-feature detector can overcome the energy detector limits in detecting signals in low SNR environments [1]. In fact, signals with overlapping features in the power spectrum, can have nonoverlapping features in the cyclic spectrum [21]. Moreover, the cyclic spectrum is a much richer domain for signal detection than classical power spectrum. This property allows us to use this technique as a more complete tool [21] for Spectrum Sensing. In spite of these advantages, cyclic-feature detection is computationally complex and requires significantly long observation time [1].

1.3.2 Cooperative/Distributed Spectrum Sensing

In spite of the advances made on stand alone techniques, Spectrum Sensing can remains a complex task when “difficult” scenarios are considered [16]. In real radio environments, the received signal is corrupted by multipath fading, frequency selectivity, time varying channels, and noise [23]. In fact, it is well known that radio propagation across a wireless channel is affected by path loss (that is, received signal power decreases with the distance between transmitter and receiver) and shadowing (that is, received signal power fluctuates around the path loss) [23]. These phenomena can cause significant fluctuations of the signal level at the Cognitive Radio, which is then unable to perform reliable Spectrum Sensing [23] if a stand alone technique is used. This is of particular importance in Cognitive Radio, since a “false opportunity” could be detected due to a sudden fading of the received signal caused by multipath resulting in incorrect spectrum allocation.

In order to overcome such limits and to improve the performance of Spectrum Sensing, cooperative and distributed techniques have been proposed [12] in order to exploit spatial diversity [36] inherent in Cognitive Radios that are geographically separated in the considered environment. Such techniques may significantly improve the reliability of Spectrum Sensing at the cost of increased computational complexity and bandwidth usage for exchanging information among Cognitive Radios [12]. It is necessary to remark that additional algorithms are needed in order to combine shared information about "local" Spectrum Sensing. Moreover, a dedicated feedback channel has to be allocated in order to share collected information. When Cognitive Radio applications are considered where a dedicated channel is not available [23], other methods which require low or no overhead should be considered [23].

To this end, different methods are available in the literature [42] and they can be categorized on the basis of the exchanged information between Cognitive Radios [42] (or on the basis of the computational capabilities of the Cognitive Radio). According to Varshney's distributed detection theory book [42], it is possible to identify two classes of distributed Spectrum Sensing techniques: *distributed detection with fusion* and *distributed detection without fusion*.

In the former [12], a set of N cooperative Cognitive Radios share the same radio environment. Each Cognitive Radio performs Spectrum Sensing by one of the techniques proposed in Sect. 1.3.1 according to its computational capability. Then, it sends the output of the Spectrum Sensing task to a data fusion center, which provides a "global" Spectrum Sensing decision based on gathered data [12]. It is necessary to remark that in this context, different solutions can be proposed depending on the level of cooperation among cognitive radios [42]. An example of distributed detection with fusion is shown in Fig. 1.2. Although distributed detection with fusion Spectrum Sensing techniques achieve better performance than stand alone Spectrum Sensing, there are some open issues for implementing them in practical Cognitive Radio applications [42]:

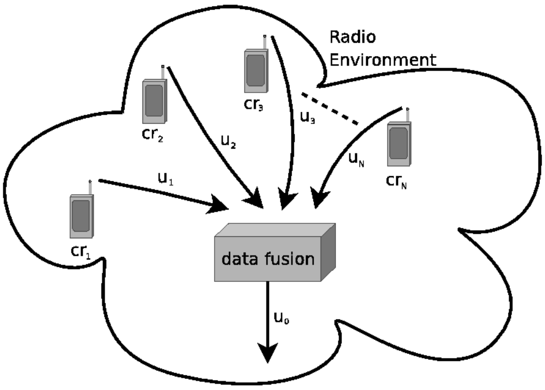

Fig. 1.2 Example of distributed detection with fusion scenario: N Cognitive Radios share the same radio environment and observe it. Each cognitive radio performs Spectrum Sensing using one of the proposed techniques in Sect. 1.3.1. It sends the output of its processing (u_i, $i = 1,\ldots,N$) to a data fusion center. This center computes a global Spectrum Sensing decision u_0 based on received messages u_i.

- a dedicated channel to share observations may not be available;
- on the one hand, a dedicated channel can improve the performance of Spectrum Sensing; but on the other hand, it can alter the observed radio environment;
- high computational capabilities at the Cognitive Radios are required;
- the shared observations/decisions are "local" and could be corrupted by shadowing as discussed in Sect. 1.3.1 and can affect the performance of distributed

Spectrum Sensing. In order to overcome such limitation, each terminal can associate a measure of accuracy (or confidence) to its shared information at the cost of an increase in dedicated channel bandwidth.

In order to overcome the above listed issues, distributed detection without fusion Spectrum Sensing techniques have been developed. In these approaches a set of N cooperative Cognitive Radios share the same radio environment. Each Cognitive Radio performs Spectrum Sensing based on its local observation. These local decisions are not fused to obtain a global decision and no sharing of information is required. Cognitive Radios operation is coupled (dashed line in Fig. 1.3) to obtain a single decision based on a global goal [42]. An example of distributed detection without fusion is shown in Fig. 1.3.

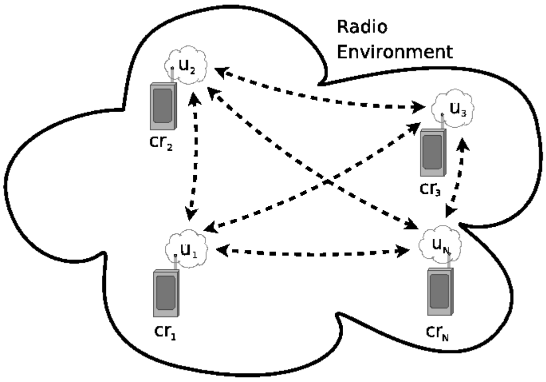

Fig. 1.3 Example of distributed detection without fusion scenario: N Cognitive Radios share the same radio environment and observe it. Each Cognitive Radio performs local decision (u_i, $i = 1, \dots, N$). The Cognitive Radio do not communicate with each other, but their operation is coupled (dashed line) to obtain a global goal.

In Sect. 1.5.3 a detailed description of a distributed detection without fusion Spectrum Sensing technique based on distributed detection theory [42] will be provided. As will be shown, such a technique is based on "implicit" cooperation among terminals and it does not require any dedicated channel.

1.4 Embodied Cognition-based Systems: their role in Cognitive Radio

The algorithmic solutions for Spectrum Sensing (or often called Mode Identification and Spectrum Monitoring – MISM) developed until now, are only a part of the whole Cognitive Radio system. As a matter of fact, there are operative methodologies which describe the entire behavioral model, the so-called Cognitive Cycle (CC). These methodologies could be adapted for the Cognitive Radio system.

In order to introduce the proposed Embodied Cognition-based framework, let us recall the basic characteristics of a CC. The first stage of the cycle (Sensing or Observation) represents a passive interaction of the terminal with the environment:

the Cognitive Terminal (CT) gathers information about both its internal state and the surrounding environment. In the second step (Analysis), the acquired data are processed and analyzed in order to provide the system with a representation of the perceived context. In the Decision stage, the Cognitive system has to decide which is the most proper (re)action to the received coupled external/internal stimuli (i.e. a contextual response). The action represents an active interaction with the external environment because the CT tries to influence the physical context through its actions, in order to gain an "advantage". In engineering terms, the CT evaluates a functional that represents a cost/merit related to a certain potential action.

While the Cognitive Cycle is a shared concept among almost the entire 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 management of information, which can be *naturally* embedded in the entity itself or acquired during its normal *life*. This knowledge can be organized according to two principal models:

- Symbolic Representation – Semantic Inference.
- Physically (body) grounded signal-based representation.

The former model tries to describe the knowledge in the classical rule-based approach for the construction of Artificial Intelligences (AIs) [30]. The latter, and perhaps more interesting, vision takes inspiration from the work on Robotics of Brooks [5] and looks at intelligence as emerging from the active (interactional) body capabilities, the basic one of which is surely the possibility of motion. It is referred in the literature as *Embodied Cognition* [38]. A confirmation, at a biological level, of the validity of this approach to intelligence comes from recent neuro-physiological studies: the neuro-scientist Llinas [27] hypothesized that, 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. Motion can provide to the living entity an advantage in life conditions, due, for example, to the ability to reach a safer or a food-rich point. In the human brain, these kinds of motion, which are genetically codified into the human being, are generated by specific groups of neurons called *Fixed Action Patterns* (FAPs), whose output is able to modulate motor muscles actions.

These preliminary assumptions can lead to the definition of cognitive models (and hence of specific CCs) characterized by specific *embodied* features that are particularly useful in the design process of cooperation mechanisms, such as distributed Spectrum Sensing.

The representation of the internal knowledge in *embodied* systems, and hence the description of context, is hence strictly linked with the perceptive/motory possibilities of the entity itself. Physical limitations of motion possibilities drive, tackling back the cognitive cycle, the possibilities at the decision stage too and its internal knowledge representation. The same concept can hence be extended going backward into the cycle until to the sensing stage.

This fact is evident when the Cognitive Radio is considered as a sub-component of a more general Cognitive System, like a mini-robot which can move independently in a known or unknown 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.

However, a coherent problem definition together with a knowledge representation is needed to allow a quantitative engineering approach. In the following, these concepts, ranging from general knowledge representation to specific analysis and decision tools needed to provide a suitable framework, are presented.

1.5 Spectrum Sensing in Embodied Cognition based system

1.5.1 Spectrum Sensing problem definition

Let us consider a set of CTs $CT = \{CT_n : n = 1, \cdots, N\}$ moving in an environment characterized by the presence of a set of radio sources $RS = \{RS_k : k = 1, \cdots, K\}$ Each source is defined by the pair $RS_k = \{x_{RS_k}, \mathrm{Md}_m\}$ where x_{RS_k} is the position of the single source in the sources' common reference system $\underline{X}_{RS}$ and $Md = \{\mathrm{Md}_m : m = 1, \cdots, M\}$ defines one of the possible air interfaces considered in the problem. The single air interface is hence defined by $\mathrm{Md}_m = \{\mathrm{Mod}^m, B^m, C^m, P_t^m\}$ where Mod^m is the transmission modality (e.g. OFDM, CCK), B^m is the occupied bandwidth, C^m is the central carrier frequency and finally P_t^m is the transmitted power level.

According to the above notation, the general problem addressed in this paper can be defined as finding the active air interfaces $\mathrm{Md}_m, m = 1, \cdots, M' \leq M$ associated with a set of active radio sources $RS_k, : k = 1, \cdots, K' \leq K$ starting from spectrum sensing performed by the pool of N cooperating CTs which embed embodied cognition capabilities.

1.5.2 Embodied Cognitive Sensor Definition

The Embodied knowledge representation is derived from the physical body capabilities. For this reason, it is necessary to define the body of the CT first. Ideally, the definition should be in terms of mass/volume/inertia, but here it will be related to the CT's interactive capabilities which influence the behavior of the CT itself.

Let us define the body through its environmental interactive aspects, i.e. it is equipped with a set of sensors $\boldsymbol{Se} = \{Se_h : h = 1, \cdots, H\}$ and it can perform a set of possible actions $A = \{A_p : p = 1, \cdots, P\}$ in the space.

As a starting point, let us define a basic cooperative body where $\boldsymbol{Se}_c = \{Se_h : h = R, V\}$ with R and V representing the radio (omni directional antenna) and video sensing modalities respectively and the index c refers to the cooperative terminal.

The possible actions, at time t, are $A = \{\Delta x = (\rho\cos(\theta), \rho\sin(\theta)) : 0 \leq \theta \leq 2\pi, \rho = constant\}$, i.e., they are limited to an omni-directional movement, of the body itself, of constant length ρ. A basic FAP (Sect. 1.4) can hence be defined as $FAP = \{\Delta x(t) : t = t_0, \cdots, t_0 + \Gamma T\}$, where Γ is the maximum number of successive actions to pursue, while T is the discrete time interval.

Besides the body, each CT can also be defined through the knowledge, embodied in itself, that allows it to function. Let us consider a homomorphic set of terminals where each terminal is supposed to have the same behavioral model (e.g. a set of "cloned" robots).

Starting from the basic body, the required knowledge can be defined as the set $K_n = \{K_{P_n}, K_E, K_{Env}\}$, where K_{P_n} is the knowledge about the space surrounding the terminal, K_E is composed of all the *embodied* functions that constitute the CC, and K_{Env} is the knowledge that the CT has available about the physical/statistical interaction characteristics of the objects present in the environment.

The space surrounding each cooperating terminal is referred to via its own reference coordinate system (RCS) and hence $K_{P_n} = \{x_{CT_n}(t) \in \underline{X}_{CT_n} : t = t_0, \cdots, t_0 + \omega T\}$, where ω is the running time index.

The embodied knowledge K_E can be structured into two levels for each component r of the CC: $K_E = \{E^r(\underline{X}_{CT_n}), F^r(.) : r = \{\text{Sense, Analyze, Decide, Act}\}\}$. The first level $E^r(\underline{X}_{CT_n})$ is composed of all the *naturally* embedded knowledge codified into embodied maps. 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. In Table 1.2 a more detailed explanation the maps for each stage of the CC is shown.

Table 1.2 Instinctual knowledge codification

$E^r(\underline{X}_{CT_n})$	Description
$E^{\text{Sense}}(\underline{X}_{CT_n})$	Antenna radiation pattern, video-camera field-of-view
$E^{\text{Analyze}}(\underline{X}_{CT_n})$	Available algorithms/methodologies (time/space/condition choice)
$E^{\text{Decide}}(\underline{X}_{CT_n})$	FAPs library–all the possible motion strategies
$E^{\text{Act}}(\underline{X}_{CT_n})$	Physical driver signals (voltage,current,time)

The second level is the procedural knowledge represented by the operational basic functions that constitute the inter-stage information transformation processes within the CC. Given a certain environmental context $E_c(t)$, how this condition of the external world is processed within the CT in Table 1.3 is shown.

Table 1.3 Procedural Embodied Knowledge

Functions	Description
$O(t,x_{CT_n}) = F^{\text{Sense}}(x_{CT_n},E_c(t),K_n)$	Extraction of the observation set $O(t,x_{CT_n}) = \{O_n^h(t,x_{CT_n}) : h = 1,\cdots,H\}$
$v(t,x_{CT_n}) = v(x_{CT_n},K_n,O(t,x_{CT_n}))$	Features extraction (encapsulated in the Analysis Stage)
$L(t,x_{CT_n}) = F^{\text{Analyze}}(x_{CT_n},O(t,x_{CT_n}),K_n)$ $= C(x_{CT_n},K_n,v(x_{CT_n},K_n,O(t,x_{CT_n})))$	Label extraction–Context Representation. Classification+Feature Extraction.
$D(t,x_{CT_n}) = F^{\text{Decide}}(x_{CT_n},L(t,x_{CT_n}),K_n)$	Taken Decision Choice of the motion direction.
$a(t,x_{CT_n}) = F^{\text{Act}}(x_{CT_n},K_n,D(t,x_{CT_n}),O(t,x_{CT_n}))$	Pilot signals generation.

Let us remark that in the present work only the design process of the Analysis and Decision functions will be considered. Furthermore, the semantic or sub-semantic label $L(t,x_{CT_n})$ is one out of all the possible C' labels considered for the Spectrum Sensing problem, i.e. detecting the active air interfaces Md_m of the active radio sources RS_k.

The environmental knowledge can be generally defined as $K_{Env} = \{K^i_{P_E},K^i_{B_E} : i = 1,\cdots,I\}$, i.e., it contains the information about the relative position ($K^i_{P_E}$), with respect to the CT, and the behavioral model ($K^i_{B_E}$) of all the I entities interacting with the CT itself. Let us suppose that the CT always perceives the other interacting entities as cognitive (see Figure 1.4). This concept will be used in the following as the basis for designing the simulation tool, since each one of the interacting entities is described through the sets contained in K_{Env} while the environment is substantially translated into a virtual shared medium, where all the players *read/write* performing their sensing/actions.

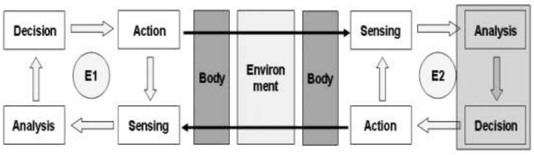

Fig. 1.4 Cognitive entity E1 can represent the cognitive entity E2 through a set of active *mirror* knowledge simulating a cognitive cycle [28].

The specific environmental knowledge can finally be represented as:

$$K_{Env} = \{K_{P_{Room}},K_{B_{Room}},K^k_{P_{RS}},K^k_{B_{RS}},K_{P_j},K_{B_j} : \\ k = 1,\cdots,K,\ j = 1,\cdots,N, j \neq n\} \tag{1.1}$$

where each component is analyzed in Table 1.4.

In the following, a specific formalization for a Spectrum Sensing embodied algorithm will be presented.

Table 1.4 Components of the Environmental Knowledge

Knowledge	Definition	Description
$K_{P_{Room}}$	$\{\underline{X}_{Room}, T^n_{Room}(\underline{X}_{CT_n}, t) : x^{Room}_{CT_n}(t) = T^n_{Room}(x_{CT_n}(t), t)\}$	Information (Reference Coordinate System – RCS, Transformation Function) required for computing the absolute position of the CT in the environment (or *Room*).
$K_{B_{Room}}$	–	Behavior of the *Room* (e.g. walls, doors)
$K^k_{P_{RS}}$	$K^k_{P_{RS}} = \{x^n_{RS_k}(t) \in \underline{X}_{CT_n}, \underline{X}_{RS_k}, T_{RS_k}(\underline{X}_{RS_k}, t)\}$	Relative position/orientation of the *j*-th radio source; transformation function for linking with *Room* RCS.
$K^k_{B_{RS}}$	–	Statistical description of the feature distributions for all the possible transmission situations allover the *Room*.
K_{P_j}	$\{x^n_{CT_j}(t) \in \underline{X}_{CT_n}, \underline{X}_{CT_j}, T_{CT_j}(\underline{X}_{CT_j}, t)\}$	Relative position/orientation of the *j*-th CT respect to the *n*-th one (whose point of view is under analysis) and transformation functions respect to *n*-th RCS.
K_{B_j}	–	Under homomorphicity assumption is a *mirroring* (as previously seen for interactions) of the Embodied knowledge of *n*.

1.5.3 Distributed Embodied Cognition Approach

In this section, a general architecture for the Analysis and Decision stages of an Embodied Cognitive Radio Terminal is presented. We leave out the interactional parts (i.e. the sensing and action stages), under the assumption of a physically ideal body.

Let us start by assuming that the *Room* and the radio sources can be managed as only one single, more complex, entity. In fact, the features the CT can observe are the results of the interaction between the e.m. field emitted by the radio sources and the physical component of the *Room* (e.g. the multi-path effect).

As a starting point, let us consider a simple framework where only two CTs and only one radio source (able to communicate with the Md_1 air interface) that can be switched on (hypothesis H_1) or switched off (hypothesis H_0) are present in the environment.

After re-writing $x^{Room}_{CT_i}(t) = x_i(t)$, 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) $p(y_i|H_0, x_i)$ and $p(y_i|H_1, x_i)$ 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*: $K^1_{B_{RS}}$ comprises $p(y|H_0, x)$ and $p(y|H_1, x)$. The vector of features, that each CT extracts from its observations, is hence composed of $v(t, x_1) = \{y_i, \hat{x}_1, \hat{x}_2, \Delta x_2\}$, where the *hat* represented an estimation of the considered variable.

Compared to the framework presented in [7, 17], in the current work the hypothesis of perfect location knowledge is relaxed. The two variables are considered as estimated by proper feature extraction functions, each one related to a pdf that describes the statistical behavior of the function itself. The random variable (rv) $\hat{x}_1$ is hence described by the pdf $p(x_{CT_1}|\hat{x}_{CT_1})$, while the rv $\hat{x}_2$ requires further analysis, $\hat{x}_2$ being a function of $\hat{x}_1$. Let us consider, as an example, a transformation function $\hat{T}_{CT_1}$ composed of the only translational component. Calling $\hat{d}_2$ the estimated distance vector between CT_1 and CT_2, the absolute positions of the two CTs are linked through the relationship $\hat{x}_2 = \hat{x}_1 + \hat{d}_2$. In this simple case, $p(x_1|\hat{x}_1)$ being the pdf of $\hat{x}_1$ and $p(d_2|\hat{d}_2)$ the pdf of $\hat{d}_2$, the pdf of $\hat{x}_2$ will be $p(x_2|\hat{x}_2) = p(x_1|\hat{x}_1) * p(d_2|\hat{d}_2)$, where * denotes the convolutional operator.

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. This classification is associated with the presence of the air interface Md_1. It is hence possible to infer that the u_i represents 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 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 estimate $\hat{u}_i$. The context label can hence be defined as $L(t,x_1) = \{u_1, \hat{u}_2, x_1, x_2\}$.

Once the most important variables are defined, it is possible to analyze in more detail how the single stages of the cycle can be structured.

1.5.3.1 Analysis Stage

The analysis stage is shown in Figure 1.5. The Feature extractor corresponds to the function $v(x_{CT_n}, K_n, O(t, x_{CT_n}))$ defined in Sect. 1.5.2 and extracts from the perceived observations the vector of features described in Sect. 1.5.3.

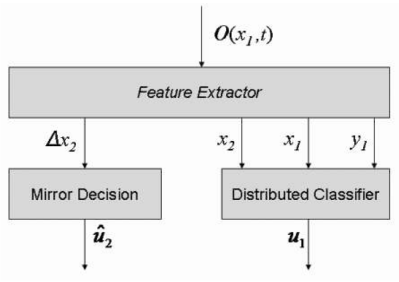

Fig. 1.5 Analysis Module of an Embodied CT. The analysis stage is composed of three main sub-blocks: the feature extractor, the mirror decision block and the distributed classifier

In particular, distributed detection 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 distributed detection theory applied to the considered MISM problem.

Starting from basic Distributed Detection Theory [42] and its application to an ideal (in terms of location knowledge) MISM problem [7, 17], it is possible to reformalize the theory, in order to keep into account the uncertainty introduced by the estimated locations.

Let us now define the distributed classification function [42]

$$\Lambda(y_1, x_1) = \overset{u_1=1}{\underset{u_1=0}{\gtrless}} t_1(x_2) \tag{1.2}$$

where Λ is the classical Bayesian likelihood function [24], u_n represents the classification performed by the n-th CT, and t_n is the distributed detection threshold [42].

The likelihood function has to be arranged in order to manage the uncertainty of $\hat{x}_1$:

$$\Lambda(y_n, \hat{x}_n) = \frac{\int_{\underline{X}_{Room}} p(y_n|H_1, x_n)p(x_n|\hat{x}_n)}{\int_{\underline{X}_{Room}} p(y_n|H_0, x_n)p(x_n|\hat{x}_n)} \tag{1.3}$$

while the distributed classification threshold is now computed as:

$$t_n(\hat{x}_j) = \frac{P_0}{P_1} \cdot \frac{(K_d - 1) + (2 - K_d)\int_{\underline{X}_{Room}} p(u_j = 0|H_0, x_j)p(x_j|\hat{x}_j)}{1 + (K_d - 2)\int_{\underline{X}_{Room}} p(u_j = 0|H_1, x_j)p(x_j|\hat{x}_j)} \tag{1.4}$$

If the pdfs $p(x_1|\hat{x}_1)$ and $p(d_2|\hat{d}_2)$ are unknown, a possible approach for practical implementation can be their substitution with weighting functions $w(\hat{d}_2) : \Psi \rightarrow \mathbb{R}$ and $w'(\hat{x}_1) : \Pi \rightarrow \mathbb{R}$ where the domains Π and Ψ are limited portions of $\underline{X}_{Room}$.

It should be noticed that the Bayesian threshold computed, based on distributed detection theory, incorporates both the statistical behavior of the RS and the classification behavior of CT_2 computed at the point $\hat{x}_2$. This fact corresponds to the internal simulation of the cognitive cycle of the interacting entities that each embodied CT should perform. In fact, the pdf $p(y_2|H_j, x_2)$ describes the perceptual interaction of CT_2 with the radio sources, while the pdf $p(u_2 = j|y_2, x_2)$ represents 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 described here. This theory paradigm allows us 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 compared to other solutions (e.g. agent-based internal emulation).

This simple binary case can be extended to multiple radio sources/air interfaces as shown in [7, 17] by using binary tree-based parameters selection for a single binary classifier or a multiple classifier approach where each classifier tests the presence or absence of a specific hypothesis. The Mirror Decision stage is used in the analysis stage to estimate which class CT_2 could have classified having the action (motion) the CT has actuated as input. This block will not be here considered, but let us postpone some general considerations about it until after the introduction of the Decision stage of the Embodied CTs.

The Distributed Classifier and the Mirror Decision, that work in parallel, comprise the classification function $C(x_{CT_n}, K_n, v(x_{CT_n}, K_n, O(t, x_{CT_n})))$, defined in Sect. 1.5.2, and together with the feature extractor above described they form the Analysis survival function F^{Sense}.

1.5.3.2 Decision Stage

Before describing the Decision stage, it is necessary to define the final goal for the CT. From a physiological point of view, the final goal of a living entity is *homeostasis* [6], i.e., 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 (as previously cited in Sect. 1.4) with respect to its physical possibilities and to the environmental context. In engineering terms, this situation corresponds to having reached a maximum/minimum of a merit/cost functional. In the case of the MISM system presented here, the functional should evaluate how much value the position of the CT provides in the e.m. context.

The decision stage is devoted to choosing the best way to reach an homeostatic situation. An engineering translation for this concept can be the minimization of a global cost functional:

$$x_T = \arg_{x_i} \min_{x_1, x_2} J(x_1, x_2, u_1, u_2) \tag{1.5}$$

where x_T is called the *target point* and represents the point where the CT can reach its dynamic equilibrium. Since u_2 is unavailable to CT_1 it is possible to use a suboptimal version

$$x_T = \arg_{x_1} \min J(x_1, x_2, u_1, \hat{u}_2) \tag{1.6}$$

by replacing the u_2 with its estimated version.

The decision stage choses the FAP that leads to the current dynamic target point x_T in a more direct (or with minimal effort) way. This is possible through the recursive 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.

In the following, how the proposed architecture can perform in a particular simulated case will be presented.

1.6 Simulation and results

1.6.1 Simulation Framework

Let us define the characteristics of the MISM problem, starting from the basic one, addressed here. The simulated framework is presented in Figure 1.6. The chosen Mds have the particular characteristic that they share the same bandwidth and they can operate simultaneously with their signals superimposed on each other. 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 with 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 [35]. The possible situations the CT could find in the environment are represented by four classes: WLAN, when only the WLAN RS is switched on; BLUE, when only the Bluetooth RS is switched on; WLBL, when both the RSs are switched on; NOISE, when only environmental noise is present. The two CTs involved in the MISM classification can enter the room at any point of the perimeter, without the consideration of the presence of fixed doors/walls, and they are able to move within the room itself. Each CT is considered provided with the basic cooperative body defined in Sect. 1.5.2 with $\rho = 1m$ and $\Gamma = 1$. Each FAP is composed of a single motion Δx.

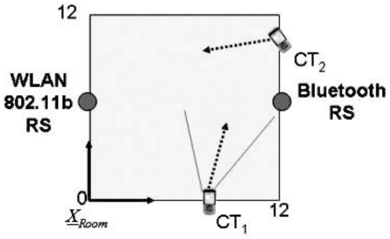

Fig. 1.6 Simulated MISM Problem. Two RSs are present in a *Room* of 12x12 meters. The absolute RCS $\underline{X}_{Room}$ has its origin in one of the corners of the room. Two communication modes are possible: $\text{Md}_1 \rightarrow$IEEE 802.11b WiFi; $\text{Md}_2 \rightarrow$Bluetooth

In order to solve the specific MISM problem, two time-frequency (TF) features, derived from the Wigner-Ville TF transform [11], 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 [17] to be useful in the case of signals superimposed in the same bandwidth.

The vector y_i is hence composed of $y_i = [\sigma_\omega \;\; T_{\max}]$ and it is used as input for the distributed classifier, together with the instantaneous positions of the two CTs. In order to address the multi-class MISM problem, the multiple classifier One-Against-All architecture [7] 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 $p(y_i|H_j,x_i) : j =$

$\{WLAN, BLUE, WLBL, NOISE\}$, it is possible to compute the Bhattacharyya distance [4] and the Chernoff bound [9] $C_{j,k}(x_i)$ for each pair of classes. The upper bound for a selected class j, $P^j_{err}(x_i)$, is hence given by $P^j_{err}(x_i) = \max\limits_{k,k\neq j} C_{j,k}(x_i)$. The values obtained at different training points of the environment have been interpolated in order to obtain a continuous surface all over the room $P^j_{err}(x)$. In order to design the decision stage, the global minimum of $P^j_{err}(x)$, for each class j, has been chosen as the target point where the CT can reach the homeostatic condition $x^j_T = \arg\min P^j_{err}(x)$. It is hence easy to obtain the look-up table $LT(u_i)$ (see Table 1.5). The chosen motion is hence parametrized by x_i before passing to the action stage that will translate it into control signals (not considered in the present paper):

Table 1.5 Look-up Table of the Decision Stage

u_i	Δx
WLAN	move to x_T^{WLAN}
BLUE	move to x_T^{BLUE}
WLBL	move to x_T^{WLBL}
NOISE	move to x_T^{NOISE}

$$\begin{aligned} &\theta = \angle(x^j_T - x_i) \\ &\Delta x(x_i) = [\cos(\theta)\ \sin(\theta)] \end{aligned} \tag{1.7}$$

The inverse decision stage is hence defined as:

$$\hat{u}_i(t^* - T) = \arg\max_j \Delta\mathbf{x_i}(t^*) \cdot \mathbf{x_T}^j(x_i, t^* - T) \tag{1.8}$$

where $\Delta\mathbf{x_i}(t^*)$ is the unit vector of the motion vector of CT_i, perceived by the other CT at the time instant t^* while $\mathbf{x_T}^j(x_i, t^* - T)$ is the unit vector of the direction that links the previous position of CT_i with the target point of the j-th class.

As weighting functions w and w', two equal 2D rectangular functions have been used. The width of each function is 1x1 square meters.
The developed simulation architecture is presented in Figure 1.7 . Each CT has been

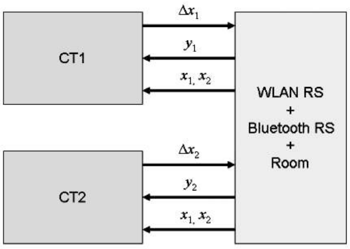

Fig. 1.7 Simulation Architecture. The simulation system has been developed in Matlab/Simulink© and it has been built up according to the organization of knowledge and the interaction models presented in Sect. 1.5.2.

developed as a dynamic system through a closed-loop finite state machine (FSM) whose data structures are organized in the same sets as described in Sect. 1.5.2. Apart from 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 a hardware platform, without any particular ad-hoc modifications. Furthermore the embodied framework is so general that it is possible to add new functionalities (or to improve/modify the existing ones) without any impact on the simulation structure itself.

In the following, the results obtained with the simulative/emulative system will be presented.

1.6.2 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 have been used:

- Maximum Number of Iterations per Simulation: 1000
- Number of Simulations per class per problem: 1000
- Standard Deviation of Positioning uncertainty: $\rho_x, \rho_d = \{0m, 1m, 2m\}$
- $K_d = \{2, 5\}$
- uniformly random choice for the entrance points of the CTs in the room

In the conditions considered, the simulator is able to perform a complete cognitive cycle in about $0.019s$ on a 1.86 GHz Intel Core $2^{©}$ equipped general purpose PC with 1GByte DDR2 RAM.

Results for $K_d = 2$, that represent substantially a stand-alone classification, will be omitted because they further confirm what was shown in [7] and [17]. As a matter of fact, results obtained prove the effectiveness of the distributed method compared with the stand-alone one.

Let us now consider the distributed algorithm with $K_d = 5$ (focus of the present chapter) and let us analyze its behavior with the generalized computation of the likelihood function and of the threshold. Results will be displayed in the form of confusion matrices, where 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, for simplicity of reading, the class labels will be further abbreviated as W (WLAN), B (BLUE), WB (WLBL), N (NOISE).

An error on the localization of the companion terminal has been introduced. As previously mentioned two cases has been evaluated: Gaussian errors with 1m or 2m of standard deviation. The introduction of this uncertainty, partially compensated by the weighting function, has little impact on the performances of the classifier as shown in Table 1.6. A better design of w could lead to a substantial reduction of these errors. The introduction of the weighting function w', in the computation of both Λ and t_i, has an unexpected results on the robustness of the system. In fact, despite the error introduced in the self localization of the terminal, the obtained results are similar to the ones obtained with perfect knowledge.

Table 1.6 Confusion Matrices for $\rho_x = 0m$

$\rho_x = 0m$	$\rho_d = 1m$				$\rho_d = 2m$			
GT/CLASS	W	B	WB	N	W	B	WB	N
WLAN	79.1%	7.4%	13.3%	0.2%	79.9%	7.6%	12.3%	0.2%
BLUE	30.5%	68.5%	0.0%	1.0%	30.6%	68.6%	0.0%	0.8%
WLBL	79.1%	20.1%	0.7%	0.1%	79.1%	20.1%	0.7%	0.1%
NOISE	0.0%	41.2%	0.0%	58.8%	0.0%	40.6%	0.0%	59.4%

Since we are interested to evaluate the system performances in the worst conditions, onl variances of 2m will be considered.

Table 1.7 Confusion Matrix for $\rho_x = 2m$

$\rho_x = 2m$	$\rho_x = 2m$			
GT/CLASS	W	B	WB	N
WLAN	85,8%	11,2%	2,8%	0,2%
BLUE	0,7%	76,7%	1,2%	21,4%
WLBL	63,2%	30,4%	6,3%	0,1%
NOISE	0,0%	10,7%	0,0%	89,3%

Probably more interesting results are provided by the simultaneous usage of the distributed classifier and of the embodied cognition framework. The previous results are referred to one-shot classifications, while the embodied cognition framework employs an iterative approach which has as its goal reaching the homeostatic condition. For this reason, let us analyze the performances of mode classification in the homeostatic condition. The confusion matrices of the final mode classification at homeostasis, for the most complex simulated problems, in Table 1.8 are shown. We observe that, even with memoryless terminals, the iterative exploration of the room and the reciprocal observation of the two involved CTs, lead to an al-

Table 1.8 Confusion Matrices in Homeostatic Situation

$\rho_x = 2m$	$\rho_d = 0, \rho_x = 2$ - Homeostasis				$\rho_d = 2, \rho_x = 2$ - Homeostasis			
GT/CLASS	W	B	WB	N	W	B	WB	N
WLAN	100,0%	0,0%	0,0%	0,0%	100,0%	0,0%	0,0%	0,0%
BLUE	0,0%	100,0%	0,0%	0,0%	0,0%	100,0%	0,0%	0,0%
WLBL	100,0%	0,0%	0,0%	0,0%	100,0%	0,0%	0,0%	0,0%
NOISE	0,0%	0,7%	0,0%	99,3%	0,0%	0,2%	0,0%	99,8%

most complete reduction of the MISM mis-classification, with the only exception of the WLBL class. As a matter of 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 misclassifications. This exception is relatively problematic for a MISM application. In fact, the CTs always decide the presence of an available communication signal and never confuse it with the NOISE class. These errors hence do not limit the *always on* communication capabilities of the CT.

1.7 Conclusions

This chapter introduced the methodology to solve the Autonomic Computing problems with CR terminals. A discussion on the state-of-the art on the different visions on how to build up a CR and how different Spectrum Sensing capabilities can be implemented, has been provided. Then an embodied cognition-based approach to distributed spectrum sensing was presented. The new framework was designed by combining knowledge coming from different fields of cognitive neuro-sciences, robotics, and AI. 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 some mathematical tools, fitting with the framework, for the implementation of such a system have been provided. In particular, Distributed Detection Theory has been shown to realize Embodied Cognition capabilities in a simple and fruitful way.

A simulation/emulation tool has been implemented in order to prove the effectiveness of the Embodied Cognition framework. The simulated problems were intended as the first steps in the direction of the applicability of Distributed Spectrum Sensing to more realistic and more complex Autonomic Computing problems compared to the ones that could be found in the state of the art.

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