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Radiobots: The Autonomous, Self-learning Future Cognitive Radios

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***Abstract*—A futuristic autonomous self-learning cognitive radio (CR), also called as a Radiobot, is proposed. The Radiobot is defined to be a radio device that is capable of self-managing and self-reconfiguring in real-time to match its RF environment while continuously self-learning from its past experience to achieve: 1) autonomous communication and awareness of experienced RF environment, 2) spectrum coexistence/efficiency including dynamic spectrum sharing (DSS), 3) inter-operability in heterogeneous RF network environments, 4) multi-mode operability (simultaneous operation over multiple modes/networks), and 5) power efficient green communications. In this paper, we present a system level architecture of the Radiobot and our current work on self-learning guided wide-band spectrum-sensing. We also discuss future research directions in order to make the concept a reality, including necessary cognitive algorithms critical for its operation and the need for real-time reconfigurable hardware and RF antennas.**

I. Introduction

A close look in the literature of cognitive radios (CR's) reveals an interesting fact: different research communities have different definitions for CR. The difference stems from the defining feature of CR to different research communities: for communication theorists the defining feature of a CR is primarily dynamic spectrum sharing (DSS) [1], since the original term CR was introduced in [2]. However, in most of the current work on DSS, CRs can simply be viewed as nothing more than adaptive radios. For hardware/RF antennas/circuits communities CR is an upgrade from software-defined radios (SDRs). This is mainly because the original proposal for CR was implied as an evolution of SDR. In contrast, the networking/IT researchers interpret CR as a device capable of cross-layer optimization, information theorists call CR channels as channels with side information, and computer scientists view it as a device capable of machine learning.

In our view, however, these definitions miss the mark when it comes to the true potential of a CR device. Our view, as discussed in this paper, is that the defining features of cognition is, a) the ability of autonomous decision-making/reasoning and learning, and b) the ability to modify radios behavior based on such self-learning. As a result, we put-forth a new vision for a future CR device. To avoid confusion with current terminology, we call our proposed autonomous CR's as Radiobots [3]. We also propose a system level architecture for the Radiobot, from RF front-end to PHY/MAC layers. A Radiobot is expected to be a truly autonomous CR that can learn from past and optimally self-reconfigure to adapt to the observed RF environment in real-time, in order to operate in the most suitable mode to achieve these fundamental objectives: 1) autonomous communication and awareness of its RF environment, 2) spectrum coexistence/efficiency including DSS, 3) inter-operability in heterogeneous RF network environments, 4) multi-operability (simultaneous operation over multiple modes/networks), and 5) power efficient green communications.

An observe-decide-act-learn (ODAL) cognitive cycle for the proposed Radiobot is shown in Fig. 1, which highlights, at a very basic level, how our view of a cognitive wireless device is different from others: For example, the most commonly referred cognitive cycle from [2] has a key difference compared to ours: it contains no outgoing arrows from learning, i.e. actions are not assumed to be modified according to the results from learning. In our view, however, autonomous modification of actions based on self-learnt knowledge is fundamental to real cognition. With these in mind, we define a Radiobot device as follows: *A Radiobot is an intelligent wireless communication device that has the ability to autonomously reason and learn from the observed RF environment to self-decide optimal communications mode for existing conditions and to achieve current performance objectives, and can optimally self-reconfigure its hardware to physically realize the selected mode of communication* [3]. We envision a future Radiobot to be able to evaluate and choose among many optimality criteria, such as communication delay constraints, power consumption constraints, sensing accuracy requirements, and security requirements, etc. Also, we do not rule out the possibility that a Radiobot may develop its own optimality criteria by trading off pros and cons of conflicting multiple requirements such as aforementioned.

According to our proposed vision, one of the most important skills, if not the most, a Radiobot must have is the capability to characterize the best possible communications mode when new RF conditions and/or conflicting user requirements are encountered, i.e., the ability to simultaneously optimize to achieve both power and spectrum efficiency via inter-operability and/or multi-operability: A Radiobot may even simultaneously use more than one radio network either in frequency, time, space, or a combination therein.

Another important capability of a Radiobot is its ability

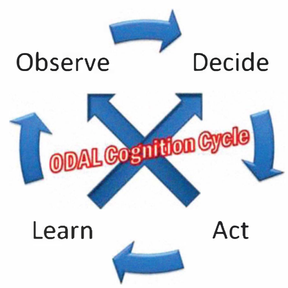

Fig. 1. Our proposed ODAL cognitive cycle of the Radiobot

for spectrum coexistence. However, we imply not only the usual DSS considered in current literature, but also the ability to coexist in the presence of adverse RF interferers/jammers. Using techniques similar to those used by a DSS device for identifying and accessing spectrum holes, a Radiobot is also supposed to detect, identify and characterize RF interferers/jammers in its vicinity, to maintained reliable and efficient communication. This can only be done through self-reconfiguration of a Radiobot, including its RF hardware and antennas. Outcomes of chosen actions are then assumed to be learned to benefit its own following behaviors.

We also point out that there are many open research problems raised from a network of collaborative Radiobots. These problems include collaborative sensing and interference management, the establishment of data links among Radiobots (since assuming fixed data links is not realistic), whether it is beneficial to split different roles among the Radiobots in the network, and dynamic hotspot/multi-hotspot selection, etc. Note that, we define a *hotspot* similarly to the one defined in cellular and LAN networks, with the only difference that the hotspot we defined is not limited to just internet access), i.e., a Radiobot that is responsible for gathering information within the network and communicating with radios outside the Radiobot network.

II. An Operational Architecture of a Radiobot

To support the capabilities of a Radiobot, we propose the following fundamental architectural components of a Radiobot: 1) a cognitive engine (CE), 2) a software-controllable reconfigurable hardware (including RF) platform, and 3) a software-controlled interface between the CE and the reconfigurable hardware. A simplified view of the proposed architecture is shown in Fig. 2.

The Radiobot architecture is assumed to be implemented on an SDR platform. However, currently available SDR platforms are inadequate for the task, due to the fact that software-definable parts of current SDRs are only in the digital baseband, not in the pre-digital front-end. As a result, by changing the code of an FPGA, for instance, current SDR architectures cannot alter the characteristics of the components in the RF and IF stages. Based on such SDR platforms, a Radiobot cannot realize the ability of performing communications back and forth in different frequency bands. To solve this problem,

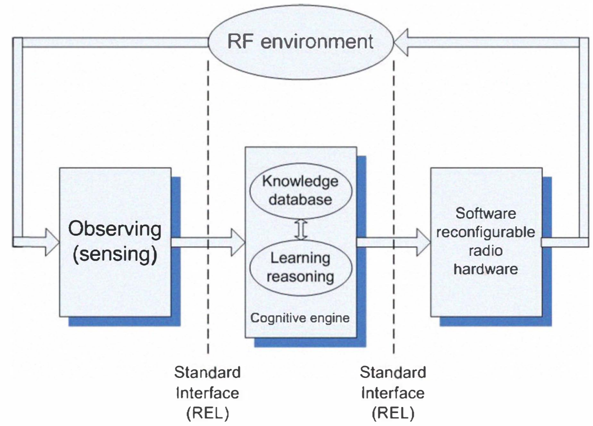

Fig. 2. Basic architectural components of a Radiobot system

a research agenda is needed to develop realtime reconfigurable RF antennas/front-ends that can be controlled by FPGAs, to achieve different antenna properties as we discuss in Section II.B. We may think of a grid of switch connections that is implemented on an FPGA that allows activating any combination of these RF front-end modes by simply choosing different switch patterns. Note that, to achieve fully flexible functioning of a Radiobot, two separate antennas for sensing and communications might be needed, as is justified later in Section II.B.

A. The cognitive engine as the Brain of a Radiobot

We emphasize that the (cognitive engine) CE is the key to go from an SDR to a truly cognitive Radiobot. The CE acts as the brain of a Radiobot. The CE that we envision for a Radiobot will have the notable abilities: a) to interpret RF environment, b) to dynamically learn from successes and failures as it operates, c) to characterize the most suitable communications mode within the devices hardware constraints under given conditions, and d) to self-reconfigure the software-controllable RF antennas/hardware to achieve this desired communication mode through the standard interfaces and a switching circuitry.

The primary functionalities that must be supported by the CE are summarized as: 1) spectrum sensing analysis and decision-making, 2) autonomous PHY/MAC reasoning (decision-making), and 3) unsupervised/semi-supervised distributed self-learning. These required functionalities lead to an identification of essential architectural components of the CE, as shown in Fig. 3, which also shows the inter-connections among these basic components of the CE. The techniques noted on the figure are there only to provide illustrative examples, and indeed we expect them to be extended/modified or refined as the concept evolves.

Architecturally, the CE may be implemented either as a central unit (similar to human brain) or as distributed across the device. For example, the cognitive algorithms that controls the RF antenna for sensing may reside in the FPGA associated with the RF antenna modules, whereas the learning algorithms that might depend on the data obtained by such sensing may

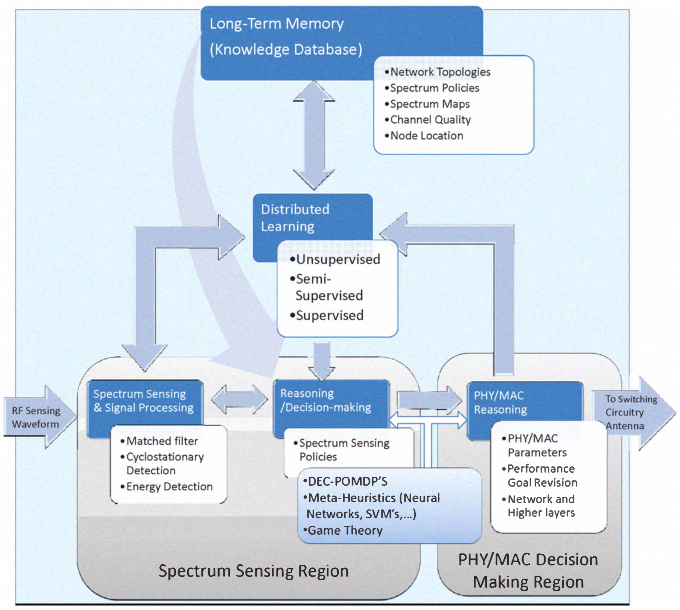

Fig. 3. CE for a typical Radiobot.

reside at an entirely different place inside the Radiobot device. We assume that such a distributed implementation of the CE might provide more flexibility in terms of the overall architecture design. The three primary functionalities/regions of the CE are discussed below.

1) Spectrum Sensing Region of the CE: The spectrum sensing is crucial for detecting, classifying and identifying the signals present in the Radiobot's RF environment. Based on the sensing outcomes, the Radiobot makes its decisions on its operating mode and subsequent sensing operations.

Well developed sensing techniques in current literature, such as the energy detection, the eigenvalue methods, cyclostationarity-based detections, template matching and matched filter-based detections can all be expected to be used in a Radiobot as candidate tools, with each having its own advantages and disadvantages to be weighed by a Radiobot according to different scenarios. The real-time selection (including the choice of a combination of multiple techniques at the same time) of sensing techniques of a Radiobot still needs to be studied as a future research direction. Taking the cyclostationarity-based detection, for example, a feature extraction algorithm may be designed and used to capture the cyclic properties of various signals in the RF environment. With the help of learnt knowledge, the Radiobot can recognize many candidate radio networks based on the extracted features. When a new feature class is encountered, the Radiobot launches unsupervised/semi-supervised learning algorithms to build a possible model of the detected signal. Several classification methods can be applied to identify unknown signals. However, for the Radiobot to be autonomous, we are interested in unsupervised classifiers which are able to identify the different classes of signals (or feature points) based on the observed data.

Possible unsupervised classifiers may rely on non-parametric learning approaches, such as the Dirichlet process which classifies the detected feature points based on the Chinese Restaurant Process (CRP), as proposed in [4]. We show in Fig. 4 the simulation results of the CRP-based clustering technique that was proposed in [4]. In this example, no prior knowledge of signals were assumed, such as the carrier frequencies, the baud rates etc. The sensing and analysis unit of the Radiobot, however, correctly picks up the carrier frequencies of the signals present and group them together according to their underlying signal properties such as baud rates and coding rates. The three clusters represented with bold circles include more than 90% of the obtained feature points, which correspond to three different systems, respectively. The feature points are obtained by using a cyclostationarity-based feature extraction algorithm. The elements of each feature point may consist of, for example, the carrier frequency (f_c), the baud rate (α_1) and the coding rates (α_2, not shown in this figure).

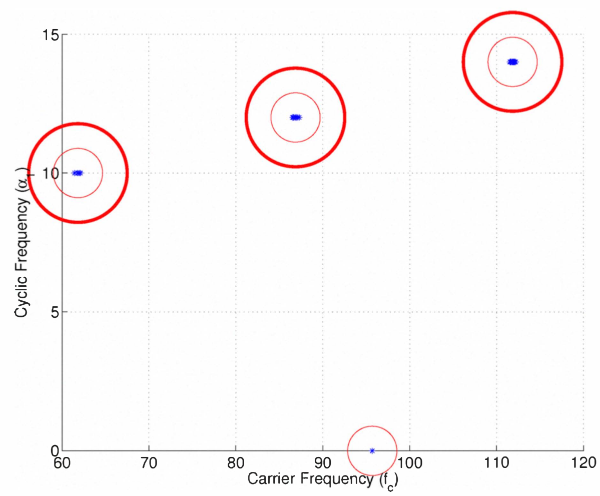

Fig. 4. CRP-based data clustering with active carrier frequencies $f_c = 62, 87, 112$ MHz, symbol rates 10, 12 and 14 Mbaud, respectively.

2) PHY/MAC Decision-making Region of the CE: The outcomes of the spectrum sensing algorithms are used by the Radiobot for reasoning and reconfiguring the operating parameters. The set of cognitive reasoning algorithms that makes decisions on suitable PHY/MAC modes and characteristics to be adapted is collectively referred to as PHY/MAC decision-making region of the CE. This module is responsible for a) identifying PHY/MAC decisions a Radiobot needs to make in order to characterize its operating mode, and b) generating the optimal parameter values (action selection) for a given RF environment. The decisions might be based on algorithms from Bayesian inference, game theory, graph theory, decentralized partially observable Markov decision processes (POMDP's), to neural networks and support vector machines, among others.

In order to generate a decision-making policy that leads to a set of PHY/MAC decisions, one needs firstly to identify possible actions that a Radiobot can make. These actions may include transmitting on specific frequency channels, radio/air interface mode or the network to be used to optimize the current performance objectives, cooperative communications, power control, rate control, and signal processing for interference mitigation/avoidance, and jamming/anti-jammng. When there is no central network controller to guide the decision-making process, the Radiobot must be able to act autonomously and derive its optimal policy. This is to be aided by unsupervised learning techniques, such as the reinforcement learning (RL) [5]. Cooperative actions among the Radiobots can help, whenever possible, to improve the overall performance of the Radiobot network.

3) Unsupervised/semi-supervised self-learning: The Radiobot is different from simple software-defined radios (SDR's) mainly because of its ability of learning, and more precisely self-learning. In our view, an SDR is a radio that can adapt its operating characteristics only within a pre-defined set of possibilities. However, a Radiobot is expected to employ sophisticated learning techniques to self-learn new operating modes and new signal classes, which can be achieved through interaction with the RF environment and by observing the impact of its past actions on the overall system performance, as shown in Fig. 5.

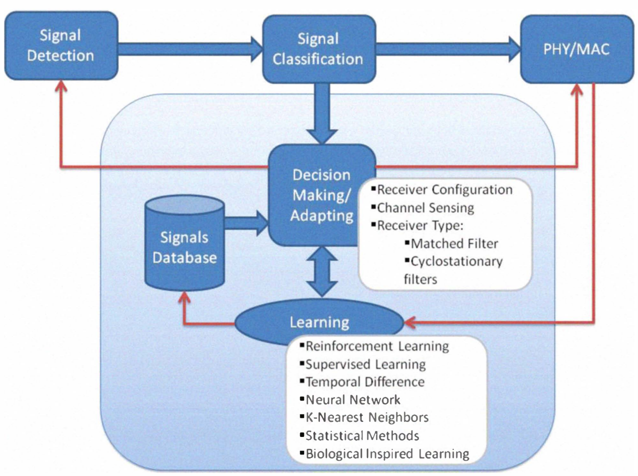

Fig. 5. Inter-dependence of decision-making and learning inside the Radiobot's CE.

The learning helps to extract knowledge on the current and long-term characteristics of the RF environment and permits updating the beliefs on the state of the environment. The main inputs of the learning module consist of the sensing measurements, and sensing decisions, and PHY/MAC decisions. By storing the sensing information in a long-term memory and observing the impact of each action, given a particular state information, the Radiobot is expected to learn and improve its policies over time. In order to learn efficiently, different decision-making algorithms might better be paired with specific learning algorithms. The fact that different learning/reasoning algorithms may have different pros and cons under different scenarios, leads to an open research area, including the problem of how to prepare a collection of candidate learning/reasoning algorithms, the problem of which algorithm or combination of algorithms works best for each possible scenario, etc.

In current CR literature, reinforcement learning has gained significant interest as a learning mechanism that can provide a promising solution to the self-learning problem. An RL algorithm was developed in [6] for self-learning by a Radiobot. It allows finding the optimal set of actions/configuration of the Radiobot in order to maximize a certain objective function. The main advantage of the RL is the ability for independent learning without complete knowledge of the RF environment, which makes it suitable for achieving autonomous Radiobot behavior. Fig. 6 shows a learning curve of a threshold parameter which is used to detect the cyclic components present in a signal from its *cyclic sub-profile* [6]. By applying the Q-learning, the Radiobot adapts this threshold parameter in order to maximize the probability of correct feature extraction [6].

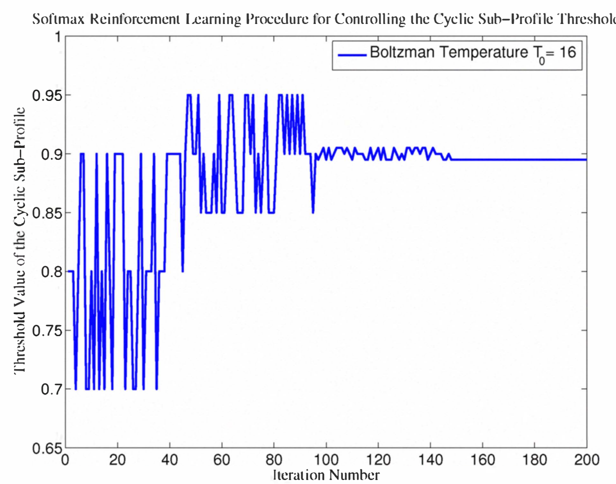

Fig. 6. Learning curve for a certain design parameter (i.e. the cyclic sub-profile threshold).

B. Software-controlled Real-time Reconfigurable RF Antenna /Front-End Design for Radiobots

Reconfigurable systems have the ability of modifying their geometry and behavior to adapt to their environment. In particular, reconfigurable antennas are supposed to be able to change their operating frequency, polarization, radiation pattern, etc. However, as yet, there is no clear guidelines on how to design the best reconfigurable antenna for any CR. This is a challenging problem since the reconfigurable antenna must be able to react in real-time and at different frequencies.

We believe that achieving real-time capabilities of the proposed Radiobot would need two sets of antennas, one dedicated to spectrum sensing and the other one to actual communications. There are several RF front end designs that make use of a single ultra-wide band (UWB) antenna attached to a bank of narrow-band filters. However, this requires the use of amplifiers since UWB antennas have small gain within the wide spectrum band. An alternative is to use high gain reconfigurable antennas and avoid the use of any additional amplification.

Since it is desirable to have a single antenna, either for spectrum sensing or actual communication, that can dynamically alter its transmit/receive characteristics to serve multiple frequency bands, in [7], [8], reconfigurable wide multiband antennas are designed. The designed antenna architecture in [7], [8] is shown in Fig. 7 and analyzed in Fig. 8: The first antenna is a wideband omni-directional *sensing antenna* that is used to scan the Radiobot's RF environment. The role of this antenna is not only limited to searching for spectrum holes in the sensed band, as is the case in current CR's for DSS. Instead, it is looking to identify/classify all available known radio networks, learn about previously unknown radio networks and detect the existence of RF interferers/jammers. The second antenna, which is both real-time frequency-reconfigurable and directional, is used to tune to the band(s) chosen for communication by the cognitive engine. This antenna is called the *cognitive communications antenna* or simply the *cognitive antenna*.

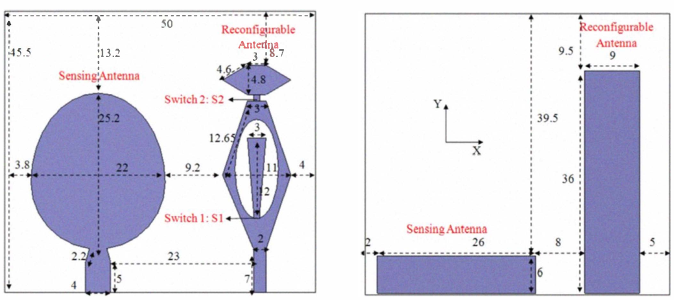

Fig. 7. Simulated Antenna Structure of the proof-of-concept cognitive reconfigurable antenna system.

In order to achieve real-time reconfiguration of the *cognitive antenna*, we may use a novel antenna design that employs low-loss photoconductive Silicon (Si) pieces as switching elements. Laser diodes are integrated within the antenna structure in order to deliver light to the conductive switches [7]. These photoconductive switches allow easier integration and faster switching, compared to MEMS.

III. Conclusion

In this paper we proposed a futuristic vision of an autonomous CR device that we call the Radiobot. The defining features of a Radiobot are the self-management, self-learning and self-reconfigurability. We emphasized autonomous learning as the key to real cognition. We pointed out that development of a suit of powerful autonomous decision-making and machine learning algorithms to learn from sensing and past actions is critical to the development of a Radiobot. The need for real-time reconfigurable RF hardware and antennas is also pointed out and discussed. We believe that the future of the

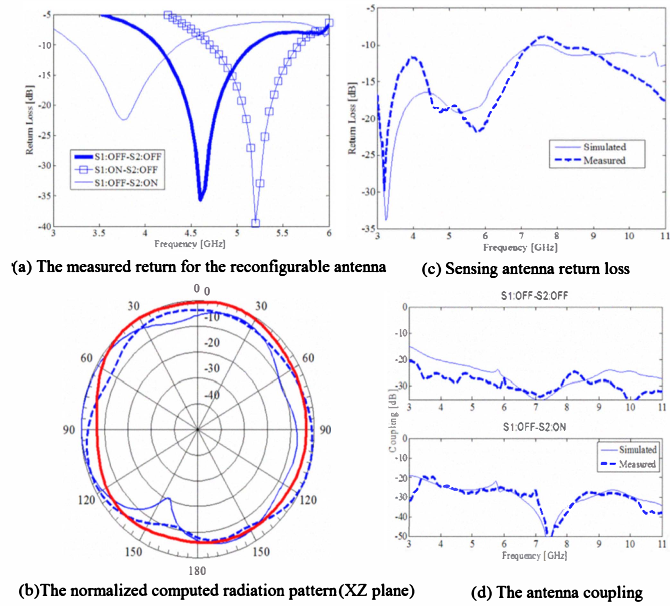

Fig. 8. Performance of the combined sensing and cognitive communications reconfigurable antenna system.

CR's will likely be along the line of autonomous radios similar to the Radiobots that we have proposed.

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