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Sudharman Jayaweera

Christos Christodoulou

DEPARTMENT OF ELECTRICAL AND COMPUTER ENGINEERING

SCHOOL OF ENGINEERING
UNIVERSITY OF NEW MEXICO

Radiobots: Architecture, Algorithms and Realtime Reconfigurable Antenna Designs for Autonomous, Self-learning Future Cognitive Radios

Sudharman K. Jayaweera and Christos Christodoulou
Department of Electrical and Computer Engineering
The University of New Mexico
Albuquerque, NM 87131
e-mail: {jayaweera, christos}@ece.unm.edu

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Abstract

In current literature, the definition of a cognitive radio (CR) seems to be different from one research community to another: For communication theorists it is about dynamic spectrum sharing (DSS), for hardware/RF engineers it is an upgrade of Software-defined Radio (SDR), for networking/IT researchers CR is a device capable of cross-layer optimizations and for computer scientists it is a device capable of machine learning. We put-forth a new unified vision for a future CR by defining it to be a radio 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 avoid confusion, we call our futuristic radios as Radiobots: They are the radio devices equivalence of robots in mechanical engineering or Autobots in sci-fi movies. While every Radiobot will necessarily be a CR, none of the CRs found in current literature can be considered as a Radiobot. We emphasize that our proposed Radiobots are not aimed just at achieving DSS. Indeed, they are expected to have all of the following capabilities: (1.) autonomous operation (2.) spectrum coexistence/efficiency including DSS, (3.) inter-operability in heterogeneous RF network environments (4.) multi-mode operability (i.e. simultaneous operation over multiple modes/networks), and (5.) power efficient green communications. The Radiobots are supposed to autonomously find and join/avoid any radio networks in their vicinity to achieve their performance objectives. In this technical report we present a system level architecture of a future Radiobot device, cognitive algorithms critical for its operation and the need for real-time reconfigurable hardware and antennas.

Keywords

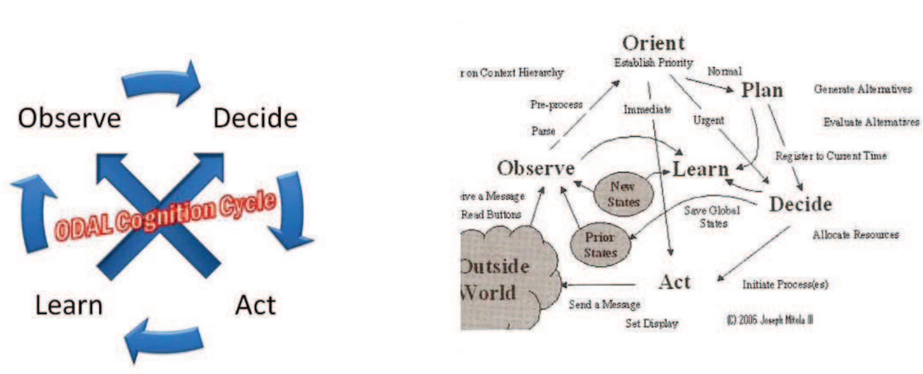
Cognitive radio, software-defined radio, dynamic spectrum sensing, radiobot, green communications, FPGA, reconfigurable antennas

1 Introduction

A closer look at the research currently being conducted under the heading of cognitive radios (CR's) reveals an interesting fact: different research communities have different definitions on what is a CR. The difference stems from what each community views as the defining feature of CR: For communication theorists it is primarily about dynamic spectrum sharing (DSS) [6]. This is not surprising since the original term cognitive radio was basically introduced in this context [9]. On the other hand, for hardware/RF antennas/circuits community CR is an upgrade from software-defined radios (SDR's). This, again, is mainly because the inventor of the term CR was also the inventor of the term SDR, and 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, all these views of CR miss the mark when it comes to the true potential of a CR device. Indeed, in many current works on DSS, CR's can simply be viewed as nothing more than adaptive radios. Our view, as developed in this technical report, is that the defining features of cognition, arguably, is (a) the ability for autonomous decision-making/reasoning and learning, and (b) the ability to modify radio's behavior based on such self-learning. In this paper, we put-forth a new vision for a future CR device. To avoid confusion with currently ambiguous terminology, we call our proposed autonomous (cognitive) radios as **Radiobots**. We propose a system architecture for a Radiobot, from RF front-end to PHY/MAC layers, which highlights the defining capabilities of a Radiobot: **self-management, self-learning and self-reconfigurability**. A Radiobot is expected to be a truly autonomous future 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 (including multi-mode) to achieve power and spectral efficiency. We specifically identify following capabilities as objectives of a Radiobot device: (1.) autonomous operation (2.) spectrum coexistence/efficiency including DSS, (3.) inter-operability in heterogeneous RF network environments (4.) multi-mode operability (i.e. simultaneous operation over multiple modes/networks), and (5.) power efficient green communications. Note that, inter-operability means the ability to communicate over many different networks/modes, whereas we define multi-operability as the ability to simultaneously communicate over a set of different communication modes/networks.

At the most basic level, a Radiobot is expected to have the ability to make both operating and performance decisions based on sensed observations of its RF environment aided by internal memory/knowledge, to physically implement these decisions in real-time on a reconfigurable radio platform, and finally to learn from the witnessed impact of these actions on achieving its performance objectives and the RF environment, forming a closed-loop as shown in Fig. 1(a).



(a) Our ODAL cognitive cycle

(b) Mitola's cognitive cycle as shown in [2]

Figure 1: Our proposed ODAL cognitive cycle and Mitola's cognitive cycle as shown in [2] ???

The simple observe-decide-act-learn (ODAL) cognitive cycle in Fig. 1(a) highlights at a very basic level how our view of a cognitive wireless device is different from other existing notions. For example, the most commonly referred cognitive cycle from [9], as shown in Fig. 1(b), has a key difference compared to ours: it contains no outgoing arrows from learning. i.e., learning is not intended to modify future behavior/actions of the device. In our view, autonomous modification of behavior/actions based on self-learnt knowledge is fundamental to a real cognitive identity. With these in mind, we define a future Radiobot device as follows:

Definition: (Radiobots) A Radiobot is an intelligent wireless communications 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.

The choice of optimality in the definition has been left open deliberately. Indeed, we envision a future Radiobot to be able to evaluate and choose among many optimality criteria: i.e. a Radiobot may develop its own optimality criteria by trading off pros and cons of conflicting requirements, similar to what a rational human being would do when faced with the dilemma of having to make a decision yet having no obvious option.

According to our proposed vision, one of the most important skills, if not the most important, a Radiobot must have is the ability to characterize the best possible communications mode when new RF conditions 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-mode operability. Specifically, we propose that the Radiobot has the capability to mix-n-match available radio networks in its RF environment (shown later in Fig. 4): i.e. a Radiobot might simultaneously use more than one radio network either in frequency, time, space, or a combination therein. As an example, a Radiobot may be operating in an environment in which it has the option to join either of two available radio networks in its vicinity. As assumed by our definition, and justified in the next section with a proposal for real-time reconfigurable hardware platform to support it, the Radiobot can communicate under either of the physical radio interfaces required for these two networks. The objective of this Radiobot may not be spectral coexistence but minimum delay. Under that optimality criterion our Radiobot might determine that it will simultaneously transmit over both radio networks. The Radiobot will divide its payload optimally between the two networks, adapt necessary transmit waveform characteristics as required by each of the network protocols so that the overall end-to-end delay is minimized, and transmit the superposition of the two modulated signals. Of course, this assumes that the intended destination has the ability to simultaneously demodulate both types of signals. Note that, we can achieve such multi-mode operation by designing proper filtering techniques to precede the reconfigurable antenna with a wide frequency response.

Another important capability of a Radiobot is its ability for spectrum coexistence: However, we do not only imply 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 DSA device for identifying and accessing spectrum holes, a Radiobot can detect, identify and characterize harmful RF interferers/jammers in its vicinity. It can then take suitable countermeasures to either avoid it, or counteract with it, as deemed necessary according to its own performance objectives. Once it has determined the best mode to operate, the Radiobot will implement it by reconfiguring itself, including its RF hardware. It will then observe the resulting outcomes of its chosen actions and learn from them to make better operating decisions in future.

2 An Operational Architecture of a Radiobot

To support the capabilities that we expect it to achieve, a Radiobot system should necessarily have the following architectural components:

1. A cognitive engine (CE);
2. A software-controllable reconfigurable hardware (including RF) platform;
3. A software-controlled interface between the CE and the reconfigurable hardware.

Fig. 2 shows a simplified view of our proposed operational CR architecture.

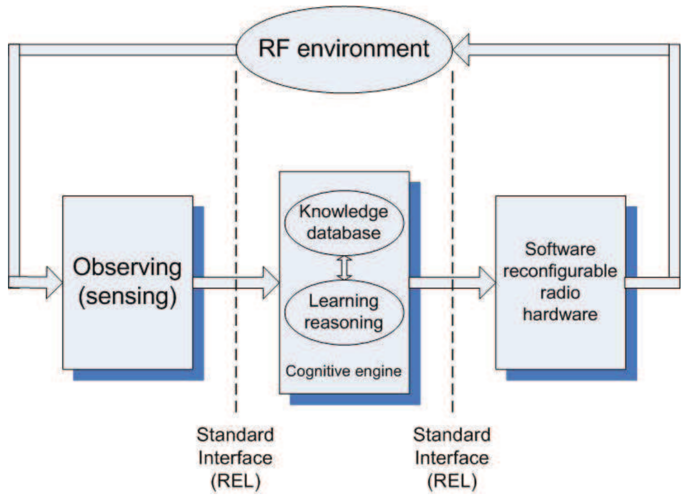


Figure 2: Basic architectural components of a Radiobot system

The cognitive Radiobot architecture is to be implemented on an SDR platform. Currently available SDR platforms, however, are grossly inadequate for the task. The software-definable parts of these SDR's are in the digital baseband, and not in the pre-digital front-end, as shown in Fig. 3. For example, by changing the code of an FPGA, current SDR architectures cannot alter the characteristics of the components in the RF and IF stages. Clearly, such a platform is inadequate for achieving our stated objectives. Based on such SDR platforms, for example, we cannot realize a Radiobot that can perform communications in one particular frequency band at a moment, and switch to a radio interface on a completely different frequency band at the next time instant. Of course, the ability to perform simultaneous communication on both bands, via different radio interfaces, is out of the question.

Our solution is to develop realtime reconfigurable RF antennas/front-ends that can be controlled by FPGAs themselves to achieve different antenna properties as we propose in Section 2.2. *At an architectural level, the algorithms making up the cognitive engine is embedded on an FPGA. Then, we envision an RF front-end that has the capability to operate in a set of different modes over a wide range of frequency bands. We think of a grid of switch connections that is implemented on an FPGA that allows activating any combination of these RF front-end modes (as specified by the cognitive algorithms) by simply choosing different switch patterns (see Fig. 4(a)).*

An argument that can be raised against our vision of a cognitive Radiobot that is capable of, for example, communicating over two broad frequency bands is that designing an antenna with enough gain over a wide band is impossible. However, this really is not a fundamental limit but an engineering limitation. For example, suppose our Radiobot is to be able to operate in both 2.4 GHZ ISM and as well as in 5.47-5.725 GHz U-NII band. For inter-operability to be achievable the Radiobot needs to be able to switch between these two frequency bands. However, the Radiobot may only switch from one band to the other when it (self) decides the current band is not the optimal band to communicate over. Thus reconfigurability of the RF antennas in our Radiobot designs can work at a much slower rate than the actual data rate. Once the RF band is chosen, the channel switching within that particular band can be carried out in baseband reconfigurability as is done currently in almost all wireless networks.

Through the standard interfaces and switching circuitry, it is the **cognitive engine of the Radiobot** that will specify how to reconfigure the software-controllable RF antennas/hardware to achieve the desired communication mode as shown in Fig. 4(b). The details of the components in Fig. 4(b) will be discussed in the following sections. For now, it suffices to note that to achieve fully flexible functioning of a Radiobot we have included two separate antennas for sensing and communications, as will be justified later in Section 2.2.

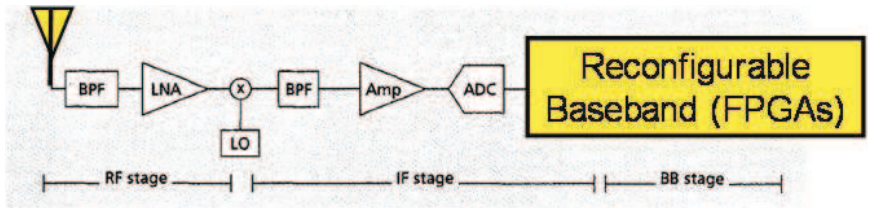


Figure 3: Basic architecture of a current SDR.

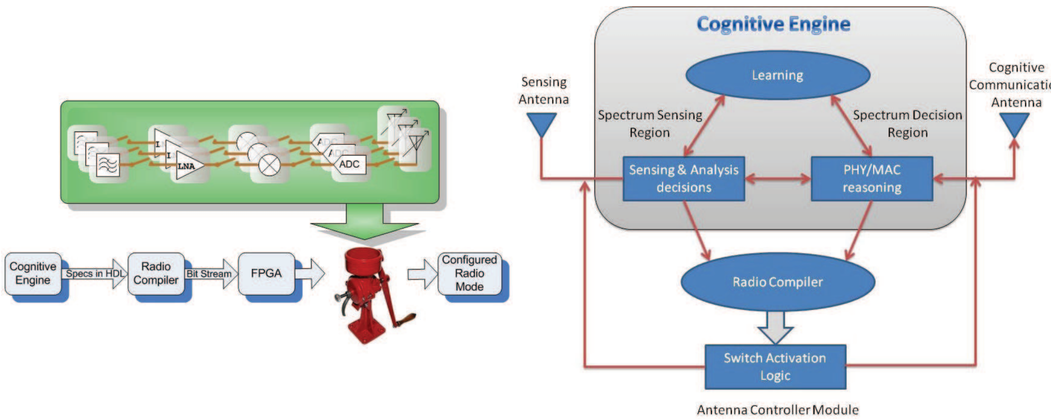


Figure 4: (a) Mix-n-match radio mode selections in a Radiobot system; (b) How Radiobot's CE controls its reconfigurable hardware through software-controlled switching circuits.

But, how exactly do we achieve antenna reconfigurability driven by the cognitive engine output? What we propose is the following: The cognitive engine is implemented on an FPGA by embedding the cognitive decision-making and learning algorithms on to the FPGA. Then the output from the FPGA-embedded cognitive engine is a set of hardware specifications detailing the characteristics of the communications mode that the Radiobot should operate in. These output specifications are expressed as a bitstream that controls the RF antenna reconfigurability via the switching circuitry, as explained in Section 2.2. Testing and validation of cognitive algorithms and antennas can be expedited by using the set-up shown in Fig. 5, in which the Matlab/Simulink code (representing cognitive engine output) is directly converted into a bitstream that can be fed to an FPGA that controls the reconfigurable antenna switching.

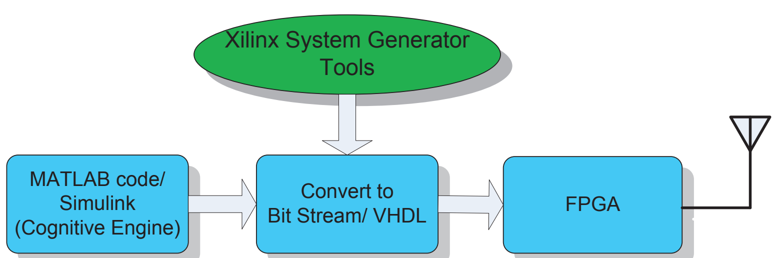


Figure 5: Radiobot Development Model.

2.1 The Cognitive Engine as the Brain of a Radiobot

We emphasize that the cognitive engine is the key to go from an SDR to a truly cognitive Radiobot. The cognitive engine acts as the brain of a Radiobot. What we envision is a cognitive engine implemented in software, partly similar to an operating system on a computer. We call this the Radio Operating System (ROS). The cognitive engine 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 device's 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 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;
3. Unsupervised/semi-supervised distributed self-learning.

The above required functionalities lead to an identification of essential architectural components of the CE, as shown in Fig. 6. Fig. 6 also shows the detailed inter-connections among these basic components of the CE. The techniques noted on the figure are there only to provide illustrative examples.

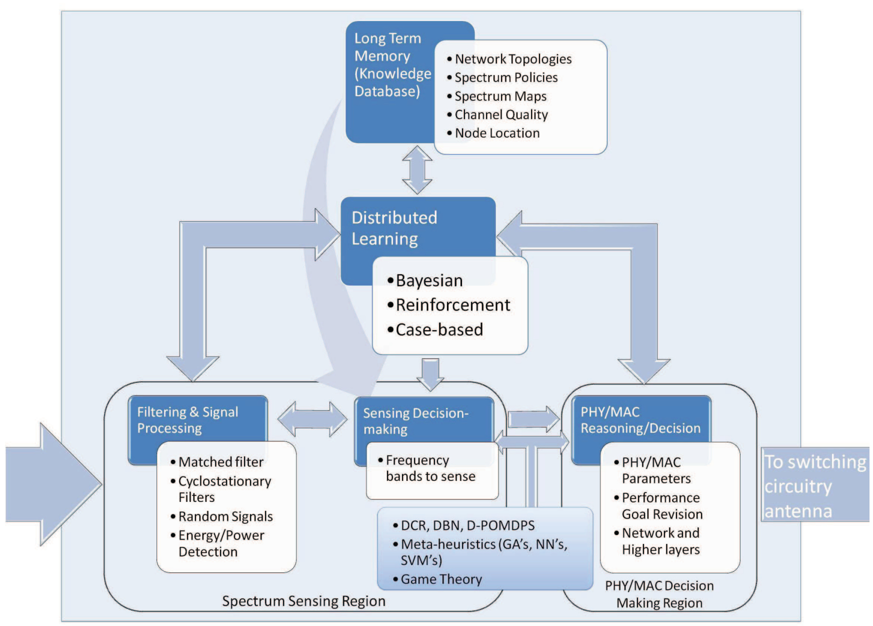


Figure 6: Proposed cognitive engine for a typical Radiobot.

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 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 are discussed separately below.

Spectrum Sensing Region of the Cognitive Engine

The ability to sense surrounding RF spectrum is crucial to everything a Radiobot can perform and achieve. Spectrum sensing measurements are to be used in (a) detecting, classifying and identifying the signals present in the Radiobot's RF environment, and (b) making decisions on its operating mode and subsequent sensing.

The sensing region of the CE manages the spectrum sensing and supports analysis of sensed data. The RF spectrum sensing module and the associated cognitive processing algorithms act together as a powerful spectrum analyzer. It allows the Radiobot to detect and identify various RF activities in its environment. The results of this analysis will be used to make decisions on spectrum coexistence, inter-operability and multi-operability, etc.

We propose a sequential architecture that processes sensing measurements through a sequence of operations depending on the application context. As shown in Fig. 7: The Radiobot first looks for possible signals in any of the frequency bands being sensed. We propose to achieve this via a sliding-window energy/power detection technique. Once a possible signal in a particular frequency band with high probability is detected, the Radiobot then applies a set of increasingly sophisticated signal detection mechanisms to identify/classify the signal.

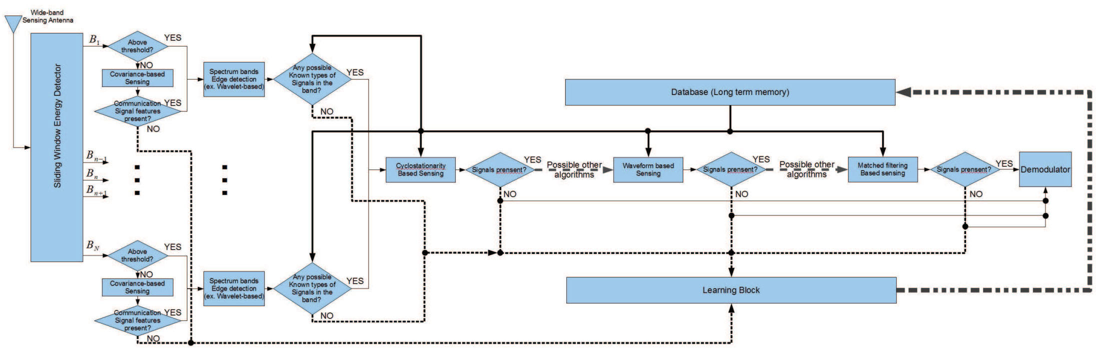


Figure 7: Sequential reasoning implementation of the proposed sensing-region of the Radiobot's CE.

For this to be achieved, as seen in Fig. 7, the sensing region of the CE consists of a chain of dedicated sensing analysis and decision-making algorithms, from simple energy/power detection to matched-filtering, that relies on increasing amounts of prior signal knowledge. Unlike in existing CE proposals for DSA, the proposed sensing region of the CE necessarily supports a set of spectrum sensing algorithms that address all contingency plans. These basic processing techniques to be applied will include energy/power detection, eigenvalue methods, cyclo-stationarity detectors, template matching, and finally matched filtering. The order they will be applied are governed by the ROS algorithm that combines the Radiobot's current observation with its long-term memory. These include the prior knowledge about certain types of signals/systems that the Radiobot anticipate to be in the part of the spectrum, as well as their characteristics and any topological information about RF networks in that region.

For example, the matched filtering stage will only be reached if all other preceding processing tests were passed by the sensed signal in question. At that stage there may be only a finitely many candidate radio networks known to the Radiobot that could have the observed spectral characteristics, and if so the Radiobot attempts to perform matched-filtering to identify the detected signal. On the other hand, if there are no known candidates, the Radiobot will launch its unsupervised/semi-supervised, distributed learning algorithms to build a possible model of the detected signal that, given sufficient learning, will lead to a new class of known signals, as shown in Fig. 8 (see Section 2.1 for details of learning process).

The processing algorithm proceeds in a hierarchical structure by eliminating possible choices. A suite of classification algorithms that can operate under different levels of such prior knowledge, including neural networks, support-vector machines, Bayesian decision trees as well as various nearest neighbor algorithms are possibly needed. To be robust, the output is to be a probabilistic soft-decision that provides information regarding how certain the Radiobot is about its decisions. These probabilistic soft-decisions are to be useful in autonomous learning processes, to be followed, that self-evaluates accuracy and effect of its decisions on the RF environment.

Merely detecting and classifying signals are not the only decisions a Radiobot will need to make. They will also include determining if multiple signals are present, if so how many, types, and their characteristics (time-frequency classification). In order to support these, the spectrum sensing region of the CE will also include source separation algorithms (not shown in Fig. 7) that will work in conjunction with the detection/classification/identification algorithms allowing the Radiobot to revise its decisions based on consistency requirements between the two aspects.

PHY/MAC Decision-making Region of the Cognitive Engine

The primary objective of a Radiobot is to achieve successful communications. All spectrum sensing and analysis are aimed at facilitating this objective. Thus, the output of the spectrum sensing algorithms is used by the Radiobot to reason and generate specifications to optimally configure its operating characteristics at any given time. The set of cognitive reasoning algorithms that makes decisions on suitable PHY/MAC modes and characteristics to be adapted is collectively referred to as the PHY/MAC decision-making region of the CE.

The PHY/MAC decision-making region of the CE should be responsible for (a) identifying PHY/MAC decisions a Radiobot needs to make in order to characterize its operating mode, and (b) developing a set of autonomous/semi-autonomous reasoning algorithms that can indeed generate these decisions/actions. An integrated set of algorithms that can handle a broad range of expected situations is needed. These algorithms possibly can be based on game-theory/mechanism design, graph theory, decentralized POMDP's, neural networks and support-vector machines, among others. Training the Radiobot with a wide-range of examples before-hand is required to make the Radiobot select reasoning algorithms accurately and effectively in real applications.

In order to generate a set of specifications that can lead to a set of specific PHY/MAC decisions, we need firstly to identify actions such an autonomous Radiobot may need to make. The specific actions may include transmitting on specific frequency channels, radio/air interface mode or the network to be used to optimize the current performance objectives, symmetric/asymmetric cooperative communications to achieve power efficient green communications, power adaptation (power control), rate control as well as signal processing for interference mitigation/avoidance. Optimizing over combinations of these requirements will be complicated.

When there is no network controller to guide it, the Radiobot needs to be able to make its own decisions. Thus, a key requirement of the PHY/MAC decision-making algorithms is that they must facilitate autonomous and distributed operation. There are many algorithms that naturally lead to distributed and autonomous implementations. Prominent among them, one technique is the game-theoretic algorithms. Especially, in crowded RF interference environments, game theory based best-response PHY/MAC actions can lead to very effective decision-making. Graph-theoretic methods are a viable technique to determine the suitable channel assignments within a given radio network that a Radiobot might decide to join in. These will also be applicable when a Radiobot decides to either cooperate with other Radiobots, or act as non-Radiobot traditional wireless devices. Such problems can be transformed into bipartite graph matching problems as we have shown in our recent work [3].

Another powerful framework for distributed and autonomous decision making in a temporally evolving dynamic RF environment is the Markov decision processes (MDP). For a Radiobot with limited sensing capabilities, an MDP-based reasoning/decision making algorithms can be implemented via the partially-observed MDP's (POMDP's). At the network-level, the theory can be used to derive optimal actions. When distributed and autonomous decisions are needed to be made by individual Radiobots, the POMDP based models can lead to effective greedy decision policies that can be simple and robust against dynamic RF channel conditions. In our current research we have developed several decision-making algorithms for spectrum sensing and access, based on the decentralized POMDP models, which have shown promising performance with reasonable computational complexities. A further advantage of POMDP-based decision-making algorithms is that they are natural candidates for learning based on the broad paradigm of reinforcement learning that is an excellent match for distributed

Radiobots, as described in the next section.

Unsupervised/semi-supervised self-learning

Arguably, the defining feature of high-level cognition is the ability to learn, especially, the self-learning or unsupervised-learning ability. Learning algorithms are indeed what distinguish Radiobots from simple SDR's. 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 machine learning algorithms to self-learn new operating modes and new signal classes from its actions and their observed impact on the RF environments as shown in Fig. 8.

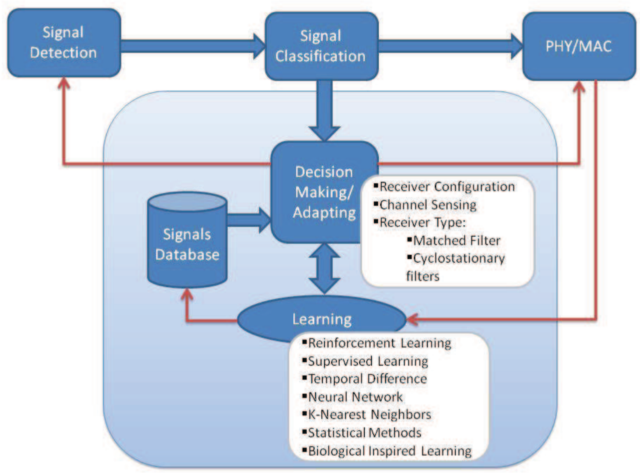


Figure 8: Inter-dependence of decision-making and learning inside the Radiobot's CE.

The learning algorithms help with extracting knowledge regarding current and long-term characteristics of its RF environment. They also help with updating current belief of state of the environment and the best strategies for given situations, among others. Their inputs consist of sensing measurements and the sensing decisions, current and past PHY/MAC decisions made by the Radiobot, and their observed impact on the RF environment. The knowledge learnt is used to be fed back into the decision-making parts of the CE as well as knowledge database (Radiobot's long-term memory).

While there is a considerable literature on machine learning that provides various learning algorithms that are possible candidates for Radiobots, these generic algorithms need to be adapted in a suitable way that will lead to efficient learning. This includes identifying quantities to be learnt in different contexts/applications, formulating various learning problems in the most suitable formulation for a specific type of learning, and computationally feasible and robust implementations.

In our proposed CE architecture, associated with each reasoning algorithm there is a learning algorithm. In most cases the pairing can be obvious: For example, MDP/POMDP based reasoning algorithms can be best learnt via reinforcement learning, whereas Bayesian learning is best suited for Bayesian reasoning/decision-making. Thus the CE will consist of a collection of learning algorithms that are paired with a collection of reasoning algorithms.

We believe reinforcement learning techniques as one of the most flexible and natural candidates for the type of autonomous Radiobots. In fact, in our current work, we have been exploring reinforcement learning, and specifically Q-learning, to autonomously learn spectrum sensing policies in a DSS environment. From our preliminary results we believe that reinforcement learning can be developed into a level that could play a major role in many spectrum access and operational decision learning processes [7, 5, 8, 4]. A drawback in many reinforcement learning based approaches, however, is the underlying assumption of Markovian state dynamics. Justifying this can be difficult in some contexts. For those situations, perhaps a more suitable learning paradigm could be either statistical or Bayesian learning.

2.2 Software-controlled Real-time Reconfigurable RF Antenna/Front-End Designs for Radiobots

Reconfigurable antennas and reconfigurable systems have the ability to modify their geometry and behavior to adapt to changes in RF environmental conditions or system requirements (such as enhanced bandwidth, change in operating frequency, polarization, radiation pattern etc.). However, as of yet, there are no guidelines on how to design the best reconfigurable antenna for any cognitive radio, let alone for the proposed Radiobots. To meet the real-time self-reconfigurability requirements of a Radiobot, antennas need to be able to change the direction of the main lobe on a real-time basis and at different frequencies. To motivate our ideas based on a concrete example, consider the spectrum occupied in the 2.4 GHz ISM Band by a single Wi-Fi transmitter (22 MHz bandwidth) and a Bluetooth Piconet (eight 1 MHz wide transmitters). Each Bluetooth transmitter can appear anywhere in space and anywhere in the 79 MHz wide ISM band. Suppose that a Radiobot is placed randomly in this environment, and that the Radiobot needs to maximize its antenna gain in the direction of the Bluetooth transmitters while directing a null towards the Wi-Fi signal to prevent saturation of its input amplifier chains. To further complicate the problem, this adjustment must be achieved on the order of no more than several microseconds (the Bluetooth transmitters hop once every 625 microseconds), quickly enough to allow the Radiobot to determine available spectrum for transmission and then actually transmit.

A fixed-delay antenna array will not be able to achieve this. Moreover, we need the capability to sense the spectrum, to communicate, and to subsequently re-sense the spectrum. Our belief is that to achieve the realtime capabilities of the proposed Radiobot, it will most likely need at least two sets of antennas, one dedicated to sensing the spectrum and the other dedicated for communication, as was shown in Fig. 4(b). 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. These designs do not make use of reconfigurable antennas. However, this approach also requires the use of amplifiers since the the UWB antenna cannot provide sufficient gain within the entire band. Our approach is to make use of high gain reconfigurable antennas that avoid the use of any additional amplification.

In our assumed architecture in Fig. Fig. 4(b)., a *wideband, omni-directional* sensing antenna is used to scan the Radiobot's RF environment. We call this the **sensing antenna**. The proposed sensing antenna is not limited to simply searching for spectrum holes as in existing CR proposals. It is looking to identify/classify all available known radio networks, learn about previously unknown radio networks and detect the existence of deliberate and harmful RF interferers/jammers. The second antenna, which is both frequency-reconfigurable and more directional (which can either be a single element or an array), is used to tune to the band(s) chosen for communication by the cognitive engine of the Radiobot. We call this the *cognitive communications antenna* or simply, the **cognitive antenna**. In order to meet the performance objectives of Radiobots, the *cognitive communications antenna* must be a realtime reconfigurable multi-band antenna that can dynamically alter its transmit and/or receive characteristics to serve multiple frequency bands (multi-mode and inter-operability). The challenge lies in how to connect the radiating elements together, such that the resulting structure will yield the desired RF response over the frequency bands of interest.

We propose a novel technique to achieve realtime reconfigurability required by the proposed Radiobots, using low-loss photoconductive Silicon (Si) pieces as the switching elements. Laser diodes are integrated within the antenna structure in order to deliver light to these photoconductive switches. This technique has certain key advantages over those found in previous proposals based on MEMs, PIN diodes or lumped elements. For example, photoconductive approach does not require the use of bias lines, which typically lie in the plane of the antenna and can interfere with the electromagnetic performance of the antenna. Also, photoconductive switches allow easier integration and faster switching than that with MEMS.

Making Antennas Cognitive

The **cognition** in the cognitive antennas **comes from the sophisticated learning and decision-making algorithms of the cognitive engine that drives them**. In our design, the specifications on required reconfigurability of the cognitive antenna is issued by the decision-making regions of the cognitive engine of the Radiobot: the spectrum-sensing region for the sensing antenna while the PHY/MAC decision-making region for the reconfigurable communications antenna. As described in Section 2, these cognitive algorithms are embedded on to an FPGA, so that the output specifications can be generated as a bitstream. **This output bitstream indicating the specifications from the cognitive engine then controls the Si switches of the reconfigurable antennas** (see below).

The optically reconfigurable cognitive antenna system is to be integrated with the cognitive engine to ensure that the cognitive capabilities are reflected in the reconfiguration process. This is a new concept in designing reconfigurable systems that will enable future radio devices/systems to change their functionality, in real time, as the conditions of RF environment or the user expectations change. In each component, a number of digitally-definable features are present, each of which is part of a configuration bit-stream that, as in the case of the FPGA, is of a format particular to the component. The bit-streams are managed through individual TAP controllers using JTAG to manage the configurations of the components individually and of the system as a whole. As explained in our architecture, these bit streams will indicate the output of the cognitive engine.

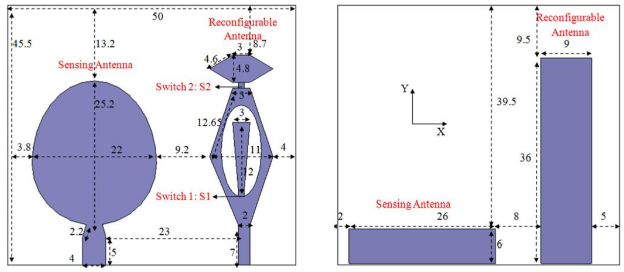
Radiobot Cognitive Antenna System based on Optically Reconfigurable Antenna Design

In a particular design method, an *n*-type Silicon (Si) piece with an initial carrier concentration of $10^{15}\ cm^{-3}$ is used as the switching element. When the Si switches are illuminated with light from the laser diode, the mobility of charges in the Si decreases but their density increases. This increase in the charge carrier density results in a general increase in the conductivity of the Si switch. A voltage of 1.9V and a current of 87 mA are needed to drive the laser diode to output an optical power of 50mW. This power level is enough to make the Si switch go from OFF state to ON state [2, 10, 11, 13].

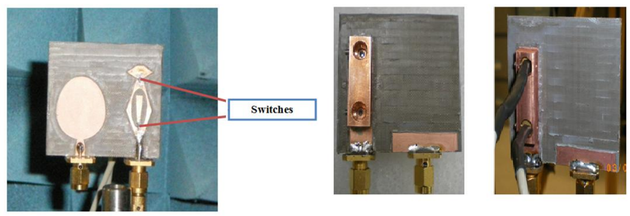
The prototype antenna structure developed as a proof-of-concept preliminary work [14, 12], consists of a *UWB sensing antenna* and a *reconfigurable cognitive narrow-band communication antenna* placed next to each other, and printed on the same Taconic TLY substrate with a dielectric constant of 2.2 and a height of 1.6 mm. The antenna top and bottom layers with the actual fabricated structure are shown in Fig. 9. The *cognitive communication antenna* is a modified printed monopole. Both structures are connected together via a Silicon switch (S1). At the end of the modified monopole, a hexagonal patch is attached via another Silicon switch (S2). Two laser diodes are needed in order to couple light to the two photoconductive switches. When the two Si switches (S1 and S2) are not illuminated by a laser light (OFF state), only the modified monopole is fed. This results in an antenna resonance between 4.15 GHz and 5.1 GHz. Upon activation of the first switch (S1) by driving the laser diode via a current of 87 mA and a voltage of 1.9 V (this correspond to 50 mW output optical power), the antenna shifts its resonance to the 4.8-5.7 GHz band. By illuminating the second switch (S2) by the same amount of pumped power, the band 3.2-4.3 GHz is covered. The case when both switches are ON produces a resonance outside the band of the sensing antenna, and is not considered in this application.

The measured antenna return losses for the different positions of the optical switches are summarized in Fig. 10(a). As is seen frequency tuning is achieved from 3 till 6 GHz. The computed radiation patterns at $f = 3.6$ GHz (thick line, S1: OFF-S2: ON), $f = 4.6$ GHz (dotted line, S1: OFF-S2: Off) and at $f = 5.2$ GHz (thin line, S1: ON - S2: OFF) are shown in Fig. 10(b). One can notice that a satisfactory omni-directional radiation pattern is obtained.

The sensing antenna is a modified elliptical shaped monopole, that covers from 3GHz up till 11 GHz. A small tapered microstrip section matches the input impedance of the antenna to the input impedance of the patch. The patch, the partial ground plane, and the feed matching section is designed to guarantee an UWB response. In order to couple the light from the laser diodes efficiently, two holes of diameter 1mm are drilled through the substrate.

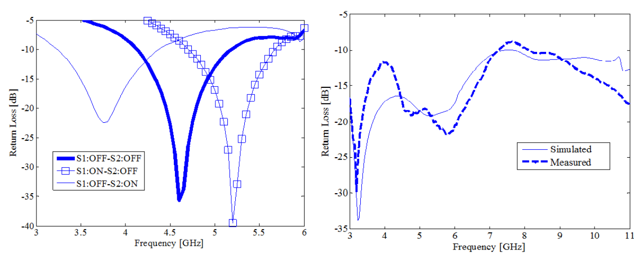


(a) Simulated Antenna Structure

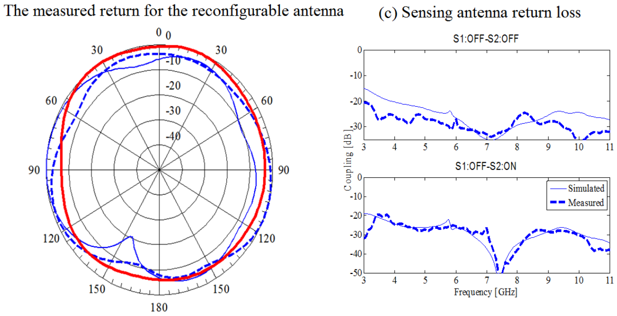


(b) Fabricated Antenna Prototype

Figure 9: Fabricated proof-of-concept cognitive reconfigurable antenna system.



(a) The measured return for the reconfigurable antenna (c) Sensing antenna return loss



(b)The normalized computed radiation pattern(XZ plane) (d) The antenna coupling

Figure 10: Performance of the combined sensing and cognitive communications reconfigurable antenna system.

The copper piece used to integrate the laser diodes with the antenna is attached to the ground of the reconfigurable antenna as shown in Fig. 9(b). This copper piece acts as the ground of the reconfigurable antenna where inside each drill a laser diode is fixed. The comparison between the measured and simulated return loss for the sensing antenna is shown in Fig. 10(c). The antenna is able to cover the spectrum from 3 GHz up to 11 GHz. Since both structures are incorporated into the same antenna substrate, it is essential to look at the **coupling between the sensing and the reconfigurable antennas**. The comparison between the simulated and the measured coupling for the case when both switches are OFF and when S2 is ON are shown in Fig. 10(d). The measured data shows that a coupling of less than -20 dB is achieved over the entire operating band of the sensing antenna.

Maintaining a constant gain at different resonant modes, however, is a major challenge in real applications. One possible solution to this problem is to integrate a reconfigurable filter with the antenna structure. This technique will not alter the antenna surface current distribution and hence the radiation pattern will be less affected by the frequency tuning of the filter than the antennas that have switches embedded in them. The aim is to end-up with a high gain reconfigurable antenna that does not change its radiation pattern, filter out any switch non-linearities and even add notches to block any interfering signals [1].

3 Conclusion

In this technical report we have proposed a futuristic vision of an autonomous cognitive radio device that we call the Radiobot. The defining features of a radiobot are the self-management, self-learning and self-reconfigurability. Our vision of an autonomous radio device goes beyond the widely used definition of a cognitive radio in several important aspects: First radiobots are not just aimed at dynamic spectrum sharing. They are targeted for achieving all of the capabilities of (1.) autonomous operation (2.) spectrum coexistence/efficiency including DSS, (3.) inter-operability in heterogeneous RF network environments (4.) multi-mode operability (i.e. simultaneous operation over multiple modes/networks), and (5.) power efficient green communications. Second, we emphasize autonomous learning as the key to real cognition. Development of a suit of powerful autonomous machine learning algorithms to learn from sensing and past actions is critical to the development of a Radiobot. Third, self reconfigurability, especially for the inter-operability and multi-mode operability, emphasizes the need for real-time reconfigurable RF hardware and antennas. Simple baseband reconfigurability is not sufficient for achieving the objectives of our Radiobots and indeed we have shown that such wideband RF switching is indeed possible with, for example, optically reconfigurable antennas. We believe that the future of truly cognitive radios will likely be along the line of autonomous radios similar to the Radiobots that we have proposed.

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