RADIO ENVIRONMENT MAP ENABLED SITUATION-AWARE COGNITIVE RADIO LEARNING ALGORITHMS

Youping Zhao, Joseph Gaeddert, Kyung K. Bae, and Jeffery H. Reed
Mobile and Portable Radio Research Group (MPRG), Wireless@Virginia Tech
Bradley Department of Electrical and Computer Engineering, Virginia Tech
432 Durham Hall, MC 0350, Blacksburg, VA 24061

ABSTRACT

This paper presents an innovative and generic approach to developing cognitive radios (CR) based on the radio environment map (REM). REM is envisioned as an integrated database consisting of multi-domain information, which supports global cross-layer optimization by enabling CR to "look" through various layers. The REM, as a vehicle of network support to CR, can be exploited by the cognitive radio engine (CE) for various cognitive functionalities such as situation awareness, reasoning, learning, planning and decision support. This paper presents the system flow and framework of REM-enabled situation-aware learning algorithms. Simulations demonstrate the effectiveness and efficiency of REM-enabled CR learning algorithms. Furthermore, by sharing information about the radio environment through REM dissemination, the hidden node problem can be mitigated and the secondary users can co-exist with primary users (PUs) with minimal harmful interference. Link level and network level simulations are conducted with MATLAB and NS-2, respectively.

1. INTRODUCTION

In recent years, cognitive radios have been introduced as a new paradigm for enabling much higher spectrum utilization, providing more reliable radio services, reducing harmful interference, and facilitating the interoperability of different wireless networks [1][2]. CRs can be autonomously aware of situations and the radio environment, learn from experience, and adapt by responding to dynamic operational conditions. However, there are many research issues yet to be addressed, such as how a CR can obtain comprehensive situational and environmental awareness. To provide CR networks with up-to-date global radio environment information, we propose the radio environment map as an abstraction from real-world radio scenarios and as a vehicle of network support [2]. Ideally, REM can offer multi-domain environmental information, such as geographical features, available services, spectral regulations, locations and activities of radios, relevant policies, and experiences. To keep REM information current, updates to the REM database should be made with observations from distributed CR nodes and then disseminated throughout the CR network [2][3]. The REM can also be viewed as an extension to the available resource map (ARM), which has been proposed as a real-time map of all radio activities in the network for cognitive radio applications in unlicensed wide area networks (UWANs) [4][5].

Several specific algorithms have been proposed for CRs in recent literature. For example, artificial neural networks and genetic algorithms have been investigated through CR test-beds under certain controlled radio environment [6][7]. In [8], Clancy *et al.* formalized the applications of machine-learning algorithms to CR and developed a framework. However, to the best of the authors' knowledge, little literature exists which addresses the efficiency of learning algorithms for CEs with appropriate performance metrics. Our recent research shows that a robust CE relies on leveraging various artificial intelligence techniques rather than a single one [9]. However, how to leverage various learning algorithms under different radio scenarios is an open research issue. This is the general motivation of this work. This paper explores the potential of REM information on cognitive radio situations and proposes a framework of REM-enabled situation-aware learning algorithms. The ultimate goal for the CE envisioned in this work is to quickly determine when to apply which specific learning algorithm with the help of REM-enabled case-based reasoning/learning, and make prompt responses to changing environment with short adaptation time.

This paper has three main contributions. First, we propose a novel and generic top-down approach for CRs to obtain situation awareness by exploiting the REM. Secondly, we propose a general framework for CR learning algorithms that incorporates both high- and low-level learning loops. Third, by conducting link level and network level simulations, we evaluate the efficiency and effectiveness of the proposed REM-enabled learning algorithms in terms of adaptation time, average received signal to interference and noise ratio (SINR), average throughput and average packet delay of incumbent primary users (PUs).

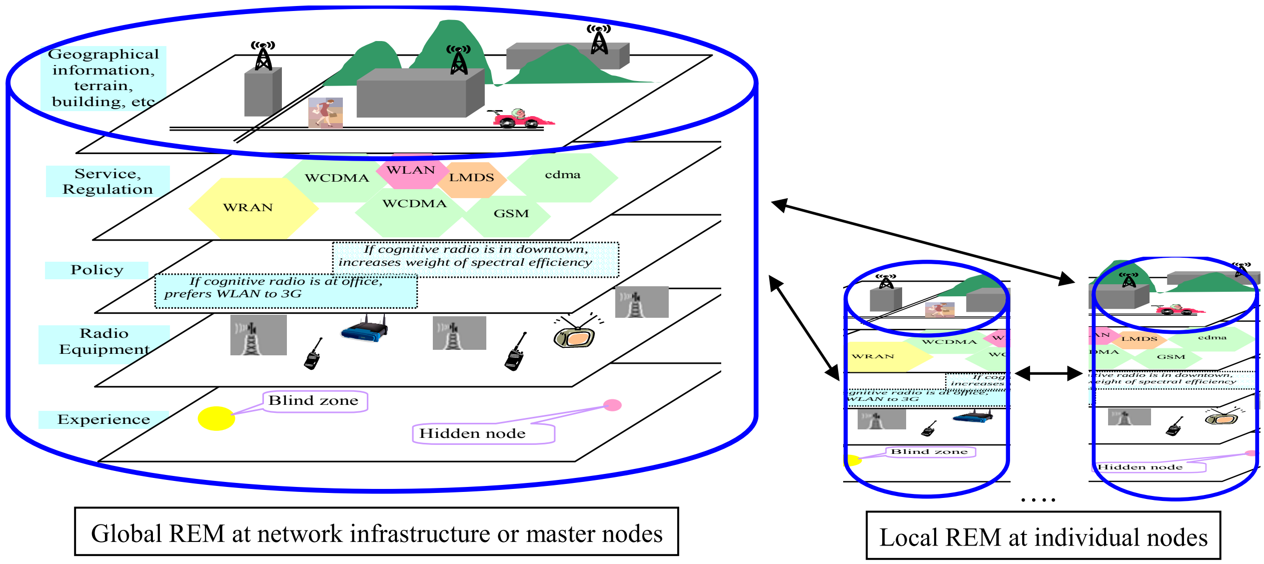

Figure 1: Global and local REMs - Integrated Databases for Cognitive Radios

The remainder of this paper is organized as follows: Section II presents more detailed explanations on REM-enabled situation awareness. Section III explains the framework and system flow of REM-enabled efficient cognitive learning algorithms and discusses how REM can help CRs make adaptations more efficiently. Section IV presents the simulation results and demonstrates the efficiency and effectiveness of REM-enabled PU protection and cooperative learning, where CR node can learn from other nodes thereby mitigating interference to PUs.

2. REM-ENABLED SITUATION AWARENESS

The most important features of CRs are the capabilities of obtaining situation awareness, learning from experience and adapting to new scenarios, which differentiate CRs from software-defined radios (SDR) and adaptive radios. This section presents more structural details about REM and explains how CRs can exploit REM for situation awareness and efficient learning from a system point of view.

Cognitive behavior, usually taking place in a rich and complex environment, is goal-oriented and a function of the dynamic environment [10]. Therefore, obtaining comprehensive radio environment information is imperative for CRs. The idea behind REM is digitizing and indexing radio environment information. The more clearly the radio environment is characterized and modeled, the better the CR can learn from experience and environment. Figure 1 shows how the REM, as an integrated database, can provide CRs with multi-domain radio environment information, such as geographical features, available services, spectral regulations, locations and activities of radios, relevant policies, and experiences. In addition, the REM can incorporate the policy layer, application layer, optimization layer, topology, and network layer information, all of which are important to CR networks. Table 1 illustrates the information domains of an example REM and the index to each REM information element. Enabled by advanced database technologies such as web-based database, REM can be accessed in a centralized or distributed way.

Rather than observing the radio environment with blind and wide spectrum sensing, REM-enabled CR may choose to have a scalable view of radio environment with an application-specific observation range. For example, for indoor wireless access, REM information pertaining to only a few rooms could suffice; whereas for outdoor wireless ad-hoc networks, a large-scale REM could be appropriate, providing more global information. To obtain situation awareness, not every CR needs to conduct sophisticated spectrum sensing so long as it maintains or has access to an up-to-date REM through the network support [2][3].

From a system standpoint, the REM enables a top-down approach for a CR to obtain situation awareness in a very efficient way. For example, the REM can inform the CR what kind of radio networks could be in service at a certain location. Based upon the radio interface specifications stored in the REM database, the CR will know the possible frequency bands and modulation types used by PUs. The CR can even obtain some prior knowledge of PUs by analyzing the historical REM data and learning from experience. Therefore, CR can conduct PU detection with focused attention instead of spending excessive processing time performing complex spectrum sensing and signal classification algorithms. This top-down approach for PU detection and/or classification is more effective and efficient. Furthermore, REM has the potential to support global cross-layer optimization by enabling CRs to "look" through various layers: from policy layer,

Table 1: Digitizing and Indexing Radio Environment Information

Domain and index range	Syntax and index
Application type => 700-799	Voice (701), packet data(702), video conference (703), etc
Optimization layer => 600-699	Minimize interference to PU (600), maximize SU throughput (601), etc
Topology and network type => 500-599	Infrastructure-based network {WCDMA(500), cdma2000 (501), WRAN (502), etc}; ad hoc network (510), mesh network (520), etc
MAC and duplex => 400-499	TDMA (400), FDMA (401), CDMA (402), OFDMA (403); FDD (410), TDD (411), etc
Geography and mobility information => 300-399	Indoor {home (300), office (301), airport (302), factory (303), etc}; outdoor {urban (310), suburban (311), open rural (312), highway (313), etc}; in-vehicle {train (320), bus (321), car (322), plane (323), etc}, etc
Modulation type => 200-299	AM (200); FM (210); M-PSK {BPSK (220), QPSK(221), etc}; M-QAM {16-QAM (230), 64 QAM (231), etc}; etc
Radio device capability => 100-199	Channel coding {Convolutional coding (100), Turbo Coding (110), etc}; maximum RF transmit power (120), sensitivity (130), operational bands (140); antenna type (150), etc
Experience => 0-99	Blind zone (10), hot spot (20), hidden node (30), etc

application layer, optimization layer, topology layer, down to the network, MAC, and PHY layers [11][12].

3. SYSTEM FLOW AND FRAMEWORK OF REM-ENABLED LEARNING ALGORITHMS

This section discusses the system flow and framework of the proposed REM-enabled situation-aware learning algorithms, as shown in Figure 2.

Triggered by certain service request from CR devices (such as a video conference call), the CR first obtains situation awareness by querying the REM and determines the optimal spectrum and network to use. For example, REM information might show that the CR is in the service area of a wireless regional area network (WRAN) and that TV channel 9 is available. The CR then senses TV channel 9 and adjacent channels to verify the information provided by the REM database. If it is confirmed that TV Channel 9 is suitable to use, the WRAN system then determines the utility functions that fit the current situation of the CR user: service type and QoS requirements, e.g., data rate, latency, bit error rate, power consumption, etc. Such a radio scenario can be defined by {703, 600, 502, 403, 411, 312, 231, etc} according to Table 1. It should be noted that different services might require disparate performance metrics and utility functions for optimization. Based on previous experiences, the WRAN CE may leverage various machine learning algorithms (such as artificial neural networks and genetic algorithms) or heuristic algorithms to fine-tune its parameter set, optimizing its performance according to link feedback information. With the help of REM, prompt adaptation and/or scheduling can be made based on spectrum usage models and predictions.

Figure 2 indicates that the proposed framework for CR learning algorithms includes both a high-level and a low-level learning loop. The high-level loop is based on case-based learning/reasoning which leverages various learning algorithms and selects the most appropriate learning method for the current radio scenario. The low-level loop optimizes the corresponding parameters used in the specific learning algorithm. Under a given radio scenario, a CR first chooses the most effective high-level learning method to use (e.g., cooperative learning or heuristic learning) with case-based reasoning, then it starts the low-level learning. For each new case, e.g., a new radio scenario that has not been previously experienced, the CR may take a “trial and error” approach and memorize its experience into case memory and REM (if the experience is associated with certain location) for future reference. In this way, the CR will be able to learn from both its own and global network experience.

With case-based learning, a CR can accumulate its learning experience continuously to increase its knowledge. The adaptation time shortens as the CR gains experiences through various radio scenarios. Furthermore, the CR will adopt a better starting point and further reduce the solution space over which it must search. Case-based learning performs very well in dynamically changing environments and is well suited for implementation with the REM [9]. By indexing REM information, radio scenarios can be characterized clearly and retrieved efficiently for case-based learning, not unlike indexing a dictionary. Further details regarding REM-enabled case-based learning will be explained in another paper [13].

Similar to the proverb, “history is the world’s finest teacher,” historical system-level REM information is valuable to CRs. For example, prior knowledge about the radio environment, such as spatiotemporal statistics of the PUs, can help a CR to improve the PU detection rate by adjusting the detection threshold [14]. Furthermore, a CR can derive the periodicity or model of PUs traffic based on REM information and specifications of wireless network standards, and then opportunistically access the spectrum with fewer collisions by exploiting the inherent periodicity of widely employed TDMA or CSMA systems [15]. Some “slow” learning algorithms (such as data mining) can be employed offline as long-term learning.