Comparative studies of artificial intelligence techniques in the context of cognitive radio

Fatima Zohra Benidris, Badr Benmammar, Fethi Tarik Bendimerad

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LTT Laboratory of Telecommunication Tlemcen, UABT, Algeria
{fatima.benidriss, badr.benmammar, ftbendimerad}@gmail.com

Abstract: Cognitive radio (CR) is considered as the key enabling technology of Next Generation Wireless Systems (NGWS). In this context, CR enables users to dynamically access and to fairly share the spectrum with other users. Our paper describes some artificial intelligence techniques like artificial neural network, metahueristic algorithms and hidden Markov model, these techniques are proposed to provide the cognition capability in a cognitive engine.
Keywords-component: cognitive radio, cognition cycle, artificial intelligence.

1 INTRODUCTION

Wireless spectrum is a costly resource which is licensed by governmental agencies to operators for long periods of use. However, a large portion of the assigned spectrum is used sporadically leading to under-utilization of valuable frequency resources. To address this critical problem, Federal Communications Commission (FCC) has recently approved the use of unlicensed devices in licensed bands. Consequently, dynamic spectrum access techniques are proposed to solve these current spectrum inefficiency problems. This new area of research foresees the development of cognitive radio (CR) networks to further improve spectrum efficiency [Wu, 2010]. The basic idea of CR networks is that the unlicensed devices (also called cognitive radio users) need to vacate the band once the licensed devices (also known as primary users) are detected. CR networks, however, impose a great challenge due to the high fluctuation in the available spectrum as well as diverse quality-of-service (QoS) requirements [Wu, 2010].
In [Haykin, 2005], CR is an intelligent wireless communication system that is aware of its environment, can also learn from experience and can make changes to certain operating parameters (e.g. transmit-power, carrier-frequency, and modulation strategy) to adapt to the incoming RF stimuli in real-time. The main objective of a CR is to have a highly reliable communications with efficient utilization radio spectrum in order to satisfy the user needs [Baldo, 2008]. From the above definition, there are six key words stand out in this definition: aware, intelligent, learn, adapt, reliable and efficient. This paper will focus only on the learning ability of a CR.
Cognitive radios will be employed according to a cognition cycle that was originally described by [Mitola, 2000] as the fundamental activities in order to interact to the environment. Figure 1 shows the activities that a CR should perform: observation, orientation to determine its importance, creates alternative plan, make decision and then implement the actions. Finally, is the learning activity that uses observation and the outcome of the decisions to improve the radio operation [Baldo, 2008]. These knowledge gathering will be exploited in the future orientation activities to produce a more effective decision.

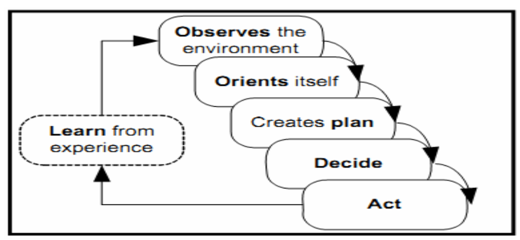

Figure 1 : Mitola's simplified cognition cycle [Ruslan, 2008].

Stated by [Rondeau, 2006a], CRs are all about optimization to suit the applications and user's needs. It is common to practice the cognition cycle in solving optimization problem. Finding effective solution for an optimization problem in implementing CR is not an easy task. Cognitive engine which is the core of a CR will performs the modeling, learning and optimization process. It will reconfigure the communication system depending on which the radio operates [Rondeau, 2006b]. The engine must be able to interpret the user needs to the radio action. This continuous activity must involve either through user intervention or assuming that the user is expected to understand its needs from the radio. The CR engine should consider all the factors that it need to learn and make the best decision. Correct learning data will produce correct decisions.
The remainder of the paper is organized as follows Section two describes the cognitive radio architecture

and discusses the reasoning and learning engines. Section three reviews AI techniques proposed for use in a CE and presents examples of their applications. Section four we take a look at the comparison of different AI techniques. Conclusions are drawn in Section 5.

2 COGNITIVE RADIO ARCHITECTURE

A software radio (SR) can be defined as a radio implemented with generic hardware that can be programmed to transmit and receive a variety of waveforms. Cognitive radio is often thought of as an extension to software radio, and here we treat it as such. A cognitive radio extends a software radio by adding an independent cognitive engine, composed of a knowledge-base, reasoning engine, and a learning engine, to drive software modifications. A well-defined API dictates communication between the cognitive engine and the SR. Figure 2 illustrates this architecture and the interaction between various components.

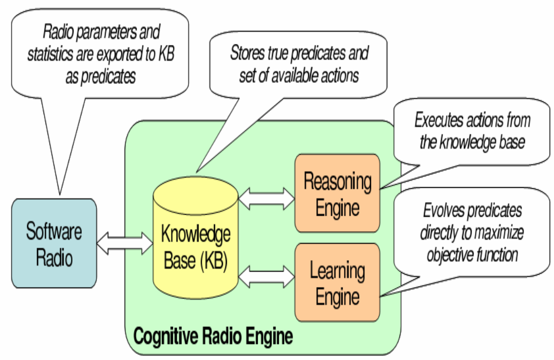

Figure 2 : The architecture of the CR and the interaction between different components [Clancy, 2007].

2.1 Types of CR

According to [Ruslan, 2008] there are three levels of CR systems which are basic CR, reasoning CR and learning CR.

A basic CR: is a radio system that senses and adapts itself to the environment but does not necessarily include any reasoning and learning techniques. It will measure all available channels and select one channel with the minimum noise and interference level. At any given time, the cognitive engine generates conclusions based on information defined in the knowledge-base, the radio's long-term memory. These conclusions are the result of extrapolations of this information based on reasoning or learning.

A reasoning CR: is an improvement of the basic CR with no interference that can automatically determines legal limits on secondary spectrum operation. The reasoning engine is often referred to in AI literature as an expert system.

The learning CR: will always updates the decision-making based on the previous action taken. The learning engine is responsible for manipulating the knowledge-base from experience. As lessons are learned, the learning engine stores them in the knowledge-base for future reference by the reasoning engine. Depending on the application, the learning engine may only be run to train a newly initialized radio, or it could be run periodically as the radio operates. Standard AI techniques may be useful to use for the learning process in CR.

3 ARTIFICIAL INTELLIGENCE TECHNIQUES FOR COGNITIVE RADIO

This section presents some AI techniques that have been proposed throughout the literature as possible candidates for CR. They are presented in the order of historical development.

3.1 ANN (Artificial neural network)

The first artificial neural was presented by the neurophysiologist W. McCulloch and the logician W. Pits in 1943 for the study of the human brain. The idea of artificial neural network (ANN) was then applied to computational models. Modeled on a nerve plexus, an ANN is nothing more than a set of non-linear functions with adjustable parameters to give a desired output [Haykin, 1999]. Different types of ANNs are separated by their network configurations and training methods, allowing for a multitude of applications. However, they are all comprised of neurons interconnected to form a network. Each artificial neuron usually produces a single output value by accumulating inputs from other neurons. While there are many types of ANNs available in the literature, only those most common and applicable to CR are presented here.

- Multi-layer linear perceptron networks: are comprised of layers of neurons, each being a linear combination of the previous layer's outputs.
- nonlinear perceptron networks although multilayer: can provide highly flexible and dynamic results, their network configuration must often reflect the data that they represent
- Radial basis function networks: have a built-in distance criterion with respect to a center (a radial nonlinear function) in its hidden layer.

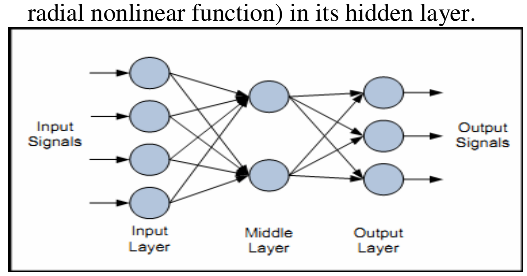

Figure 3 : Typical example of ANN [Ruslan, 2008].

Application of ANN to CRs: Because of their ability to dynamically adapt and be trained at any time, ANNs are able to "learn" patterns, features, and attributes of the system they describe. The term "learn" refers to the fact that the neurons are stored in computer memory, the outputs of which can systematically be adjusted to yield a new result for a new situation and remember the results. The attributes can be highly nonlinear, complex, and numerous, yet ANNs can be constructed by only a few examples, thus reducing the complexity of the solution.

For this reason, they have long been used to describe functions, processes, or classes that are otherwise difficult to analytically formulate. Therefore, ANNs can be used not only to classify or recognize received stimuli but to assist in the solution adaptation process as well.

The ANN has been adopted in spectrum sensing for CR [Fehske, 2005]. The ANN has also been used for radio parameter adaptation in CR [Reed, 2005]. Baldo and Zorzi propose to use the ANN to characterize the real-time achievable communication performance in CR. In [Amraoui, 2011], the authors describes a new approach using CR to improve wireless link reliability for a cognitive radio mobile terminal; it is based on supervised learning. In addition, the ANN has been used for pattern classification in a pattern-based transmission for CR [Ustundag, 2008], [Orcay, 2008].

3.2 Metaheuristic Algorithms

Explicit relations between the parameters of a CR and the desired performance metrics are usually not available. Therefore, search algorithms based on mathematical relations cannot be applied to find the optimal parameters with respect to the performance metrics. Instead, metaheuristic algorithms [Blum, 2003] can be applied to computationally hard problems to search through the solution space while learning and establishing the requisite relationships. Although the term "metaheuristic" was probably first mentioned in 1986 [Robbins, 1951], it can be traced back to earlier work on stochastic optimization methods in the 1950s [Neel, 2007].

Application of Metaheuristic Algorithms to CR: The metaheuristic techniques presented here can not only be used for reasoning or finding the optimal solution with objective/utility function but can also be used for learning with the aid of training examples when the relationship between parameters and a desired performance measure is not well understood. The objective of learning is to identify a hypothesis or a rule set from the search space that maximizes the fit of the training examples to the target concept or, in other words, to identify a hypothesis set or a set of rules that is consistent with the training examples. Although the characteristics of each search algorithm are different, as can be seen in Table I, a common challenge in the application of metaheuristic techniques is the formulation of extensive examples for target scenarios.

Among the various metaheuristic algorithms, the GA has been widely adopted to solve multi objective optimization problem and dynamically configure the CR in response to the changing wireless environment [Rondeau, 2004a].

3.3 HMM

The hidden Markov model (HMM) was first introduced in the late 1960s. It is a convenient and mathematically tractable statistical model to describe and analyze the dynamic behavior of a complex random phenomenon [Rabiner, 1989] that can be modeled as a Markov process with observable and unobservable states. The HMM generates sequences of observation symbols by making transitions from state to state, one symbol per transition. However, the states are hidden, and only the output is observable. In general, a real-world process can be expressed as a random process producing a sequence of observation symbols or patterns with hidden parameters generating the observables. The symbols or patterns may be discrete or continuous depending on the specific processes.

An HMM can be built for a specific system to explain and characterize the occurrence of the observed symbols or patterns. This model can then be used to identify the sequences of observations with the same pattern by choosing the model that would most likely produce the observed sequences. Therefore, an HMM can be used as an observation process of the CE to recognize or classify received stimuli and can achieve awareness. In addition, since it can reproduce the training sequences, it can be used for prediction. Furthermore, learning can be accomplished by creating new models. HMMs have been applied to CR research. Rondeau et al. propose to model the wireless channel online using an HMM for CR [Rondeau, 2004b]. The HMM is trained using the GA with data from a broadband channel sounder in a line-of-sight additive white Gaussian noise channel.

HMMs have also been used for spectrum sensing in CR [Kim, 2007]. In addition, HMMs have been used for spectrum occupancy prediction [Akbar, 2007].

4 COMPARISON BETWEEN THE DIFFERENT TECHNIQUES

The table below shows the AI techniques that have been described in section three while showing the strengths and limitations and options of each technique, so the choice of one or more techniques at a time (the combination) is made according to user needs and the efficient use of spectrum.

Algorithm	Strengths	Limitations	Options
Artificial neural network (ANN)	Ability to describe a multitude of functions ; Conceptually easy to scalable; Excellent for classification ; Can identify new patterns ;	Training may be slow depending on network size ; Possible over training ; No theory to link application with required network ;	Can use other learning techniques in the training phase (i.e.,GA) ; Can be combined with RBS (rule-based system);
Metaheuristic Algorithms	Excellent for parameter optimization and learning involving relationship between parameter values ; Can use other learning techniques in the training phase (GA).	Formulation of rule space is difficult when learning or optimization is not restricted to parameter values ;	Can be used in conjunction with RBS ; Learning can also be used in the search process ;
Hidden Markov model (HMM)	Can model complicated statistical processes ; Good for classification ; Easily scalable ; Can predict based on experiences ;	Requires good training sequence ; Computationally complex ;	Based on previous knowledge, RBS et CBS can help HMM determine the observation duration for a specific application and overcome issues with new situations ;

Table 1. Comparison between the different techniques

IV. CONCLUSION

AI techniques lie at the heart of CR, and understanding the tradeoffs in the selection and design of AI processes is critical to a successful CR design. This paper has reviewed some AI techniques—ANNs, metahueristic algorithms, HMMs—that have been proposed to provide the cognition capability in a CE. While we have seen that AI techniques have been applied to numerous CR applications [Baldo, 2008]–[Glover, 1986], many implementations remain rudimentary, perhaps due to the interdisciplinary nature of the field and perhaps because products are just beginning to appear.

We have seen that the appropriateness of AI techniques varied by application and implementation. The decision in choosing one or some AI techniques over other techniques in CE design needs to be made based on the application requirement, considering the tradeoffs among response time, processing complexity, training sample availability, robustness, etc. In addition, the learning capability of the AI technique needs to be considered and exploited in designing a CE as learning is critical to the performance of autonomously deployed CRs.

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