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REVIEW ARTICLE

A Survey on Cognitive Engine

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Abstract

Today's wireless networks are characterized by fixed assignment policies. The limited available spectrum and the inefficiency in the spectrum usage necessities pose a new communication paradigm to exploit the existing wireless spectrum opportunity. Cognitive radio network is a promising technique for overcoming the apparent spectrum scarcity problem as well as improving communication efficiency. In cognitive network, most of the existing work only focused on physical layer issues like dynamic spectrum access, channel selection and identification free holes etc. Very few works are focused in higher layer cognitive network issues. In this survey, the characteristic features, advantages, implementation issues and limitation factors of various existing cognitive architectures are thoroughly investigated. First overviews of the cognitive resource management requirements are given and it clearly specifies the components of the resource management systems. Next, a detailed explanation of the various resource management systems is presented, while considering the optimization support, cross layer adaptation functionalities, machine learning procedures and policy management schemes. The main challenges and future research directions are presented, while highlighting the close coupling of the resource management design with the other cognitive functionalities.

Keywords: Wireless networks, spectrum, cognitive radio network, resource management systems.

Introduction

Cognitive radio network is a promising technique for overcoming the apparent spectrum scarcity problem as well as improving communication efficiency (Whitley, 1994; Fonseca and Fleming, 1998). An ideal cognitive node can be defined as wireless system with the capability for sensing, perceiving, orienting, planning, decision making and machine learning (Mitola, 1995). A cognitive radio needs to continuously observe and learn the environmental parameters and identify the primary requirements and objective of the user and apparently decide upon the transmission parameters in order to improve the overall efficiency of the radio communications. It adds its own challenges especially in the domains of complexity, architecture design and resource management. The objective of this survey is to investigate various cognitive resource management systems and its architecture. Cognitive Resource Manager (CRM) provides a framework where complex control, cross-layer optimization and learning mechanisms can be implemented as easy as possible in order to solve the resource management problems in a multi-objective, multi-parameter and multi-technology concept (Qi Wang and Abu, 2003). The key issue in cognitive resource manager is that it is an enabling technology that allows dynamic use of different algorithms, optimization methods and should support flexible addition of artificial intelligence and machine learning based tools.

The three core components of a cognitive resource management framework are multiple objective optimization tool, cross-layer design with vertical calibration, efficient interfaces and learning capability. The analysis in CRM in terms of optimization, cross layer adaptation and machine learning will provide new research issues in the cognitive domain.

Cross-layer Optimization

The Cross layer paradigm in cognitive radio network is interrupted in different ways by the researchers. In this section we attempt to classify the main cross layer system architecture and layer approaches that have been proposed in the architecture, according to Gavrilovska and Prasad (2006). The relevant parameter for the cross layer optimization at the different protocols layers are given in Qi Wang and Abu (2003). Cross-layer Optimization (CLO) architecture should make possible to collect and set this parameter while in traditional system architectures, they are generally confined within border of their respectable layers. A first approach shown in figure1 is taken from Petrova and Mahonen (2007) which have the focus in specific interactions among layers, and the needed signaling messages. In particular, each layer needs to exchange control interactions only within a subset of the remaining layers and the corresponding message function is also introduced. In particular, not the interaction between the application and the physical layer that can be used to adjust the user demand according to the physical performance and vice versa. A more general concept refers to the enhancement of the existing control messages among different layers. As one example, figure 2 reports the proposal in Sutton *et al.* (2006). Whereas, the classical stack is guaranteed by superimposing transversal control plans. Each control plans is in charge of a different functions and can interact with at the layer in order to achieve its optimization goal. A further general approach is presented in figure 3. In this proposal, all the layer communicates within a single control plane, which is devoted to controlling all the layers function in a confined way according to some of the optimization criteria. In this case, the control plane, which becomes the core of the network node, can actually be used to create a new abstraction of the network functionalities.

Fig. 1. Cross-layer vertical architecture.

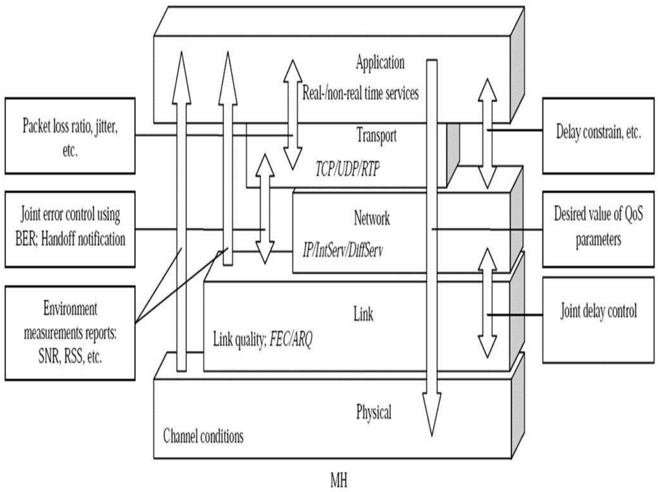
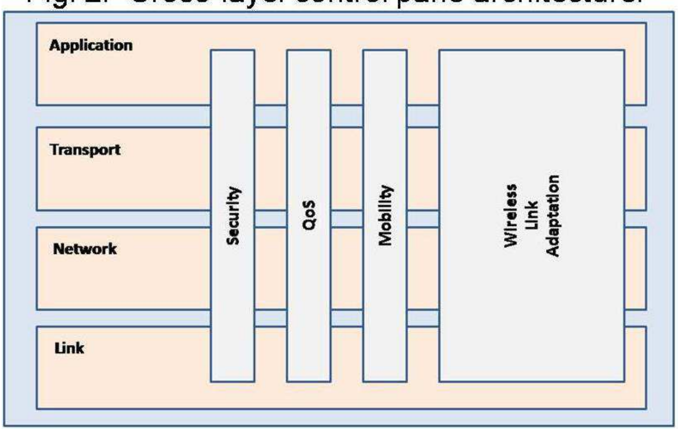
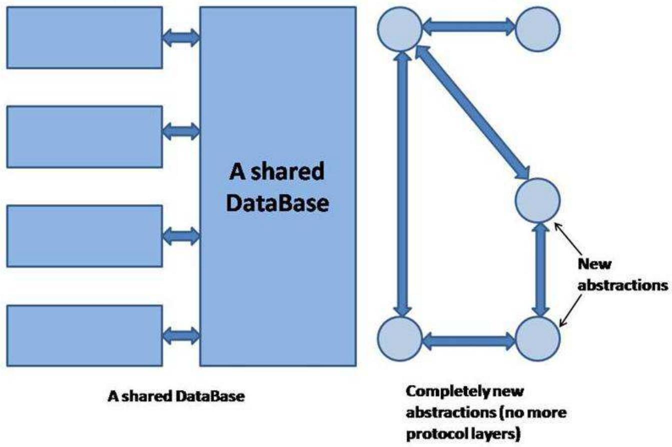


Fig. 2. Cross-layer control pane architecture.



Nadkar *et al.* (2011) formulates cross-layer optimization problems, which maximize the transmission opportunities for the SUs in the multi-hop multichannel relay network and offer a guaranteed throughput to the PU. To make the SCR scheme practically realizable, a MAC scheduling protocol was proposed within a unified framework for both the PU and SUs. Furthermore, cross-layer formulations were also proposed for multiple SUs to efficiently access the time or frequency incentive for their own communication. Simulation results are furnished for each of the proposed SCR schemes to demonstrate their effectiveness from the perspective of both the PU and SUs.

Fig. 3. Vertical parameter adaptation.



Optimization tool

In cognitive network systems, the environmental parameters are defined as input to cognitive radio whereas, the transmission parameters will be the system outputs, the relationships between the environmental and transmission parameters are formed by mathematical equation (Ossama *et al*., 2010; Yuqing *et al*., 2010). Ayman have proposed hybrid generic algorithm based optimization tool which contains genetic algorithm module and local search module. In that work, the output functions were defined into the optimization engine, minimize the BER, maximize the throughput and minimize the power consumption.

$$f_{min}\text{–BER} = 1\text{-}\log_2 (0.5)/ \log_2(p) \quad (1)$$
$$f_{min}\text{- throughput} = \log_2 (m) / \log_2(M_{max}) \quad (2)$$
$$f_{min}\text{-power}=1\text{-} p/ p_{max} \quad (3)$$

Baldo and Zorzai (2009) proposed fuzzy logic for cross layer optimization in cognitive radio network, they address optimization for cross layer architecture and implemented 802.11 Mac and TCP based cross layer architecture. Packet loss, tcp fuzzy and network congestion were considered as fuzzy input variables, CWND Increment and buffer size were considered as fuzzy output variables. They defined the following Fuzzy rule.

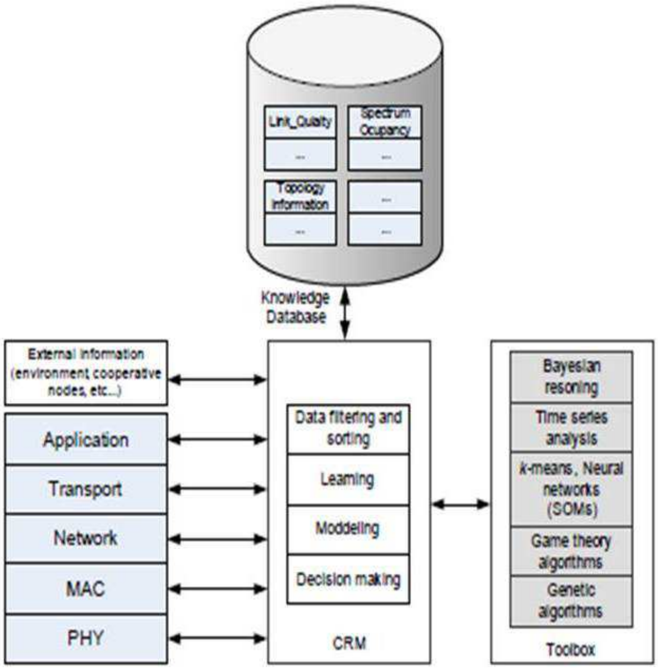
IF (link errors are high AND network congestion is low OR mid)
OR (link errors are low AND network congestion is low)
THEN cwnd reduction is small
IF (link errors are low AND network congestion is mid)
OR (link errors are high AND network congestion is high)
THEN cwnd reduction is average
IF (link errors are low AND network congestion is high)
THEN cwnd reduction is strong
IF (network congestion is high THEN cwnd increment is small

IF network congestion is mid THEN cwnd increment is average
IF network congestion is low THEN cwnd increment is strong

Cognitive engine prototype

Petrova *et al*. (Petrova and Mahonen, 2007) and sulton *et al.* (Ian *et al.,* 2006) proposed a prototype for cognitive systems which includes all the steps of cognitive cycle while considering upper layers. The cross layer optimization adopts the vertical calibration structure as proposed by Mitola (2006), the benefits of such an approach were demonstrated by means of simulated network when the optimal resource allocation is calculated with a genetic algorithm as a function of the multi layer parameter such as bit load, transmission power, contention window, transmission range, number of associated access points etc. It shows cognitive with machine learning capabilities. Carneiro *et al.* (2004) described some of the implemented architecture specific for their CRM concept. The key building blocks are the data interchanging APIs and storage area as shown in figure 4.

Fig. 4. Cognitive resource manager.



Huang and Wang proposed (Yuqing *et al.,* 2010) cognitive radio learning inference and decision-making engine based on Bayesian network (BN) and was proposed to obtain the optimum configuration rules adapt to the variation of the environment with the learning and inference algorithm of Bayesian network. Simulation results show the feasibility and validity of modeling the cognitive learning inference and decision-making engine with Bayesian network. The proposed cognitive engine utilizes learning and inference technology of Bayesian network to make decision of the optimum radio-configurations which can adapt to the variation of wireless environment and satisfy the requirement of users. Cognitive engine is composed of test database, environment, cognitive learning based on BN, cognitive inference and decision-making based on BN, knowledge base and reconfiguration (Fig. 5). Database is the historic communication events for learning from cognitive radio system. Environment parameters can reflect the variation of system. The cognitive learning based on BN learns from the test database to discover and form the knowledge, and store the rules into knowledge base. The knowledge and rules guide the cognitive inference.

Fig. 5. Model of cognitive engine based on BN.

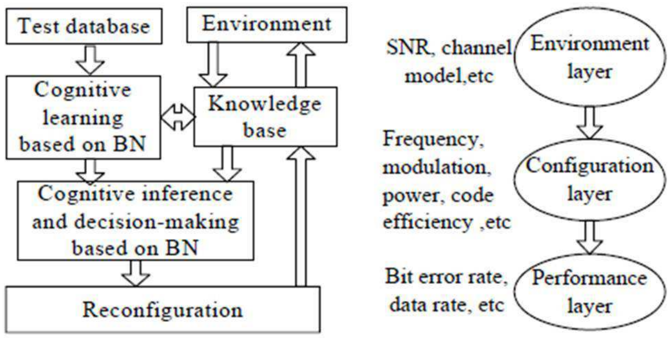


Table 1. BER analysis for 60 trials.

	Number of Trials Performed					
	50	50	50	500	500	500
	Discount Factor, γ					
Method	.5	.7	.99	.5	.7	.99
Gittins Index, NRP	.73	.73, .70[a]	.72	.93	.93, .93[a]	.94
Gittins Index, BRP	.60	.59, .65[a]	.56	.89	.89, .87[a]	.85
	Exploration Parameter, ϵ					
Method	.01	.1	.2	.01	.1	.2
ϵ-greedy strategy	.53	.65, .50[a]	.70	.74	.87, .87[a]	.87

[a]The maximum pairwise antenna correlation, ρ, equal to .5 for these scenarios. For all others $\rho = 0.1$.

Haris *et al.* proposes CE as an intelligent agent that enables the radio to have the desired learning and adaptation capabilities. The AI agent senses its environment, acts by using a communication method based on its past experience and observes its own performance to learn its capabilities. The CE is designed with respect to the packet success rate of the transmitted data packets. The PSR is easier to observe than BER that simplifies the design process. Using PSR allows design to be centered on only two numbers, success rate and failure rate at each set of channel condition and configuration pair. In the proposed CE, our knowledge is translated to {α, β} pairs from which designs are made by statistical inference. The author adopted a confidence interval method based on bays rule. This method estimates a confidence interval for the PSR of a communication method based on the prior observations of successful and failure at certain channel condition.

$P(\theta/y) = P(y/\theta)\, P(\theta)$

$P(\alpha+\theta)=\binom{n}{a}\theta^{\alpha}(1-\theta)^{n-\alpha}$ $(\alpha=0,1,2,\ldots..n)$ (4)

$P(\theta/\alpha)=1/B(\alpha+1,n-\alpha+1)\ \theta^{\alpha}(1-\theta)^{n-\alpha}$ (5)

Table 1 represent the available total return as a fraction of the optimal total return, the average total fraction for all the SNR levels tested. This applies for all methods and parameter tested. There are two set of results, the first measured after 40 trials per channel condition and second measured after 100 trails. The results for 90 trails represent the performance over a relatively short time frame while the results for 100 trails represent a significantly longer time frame (Fig. 6 and 7).

Fig.6. SNR trial result.

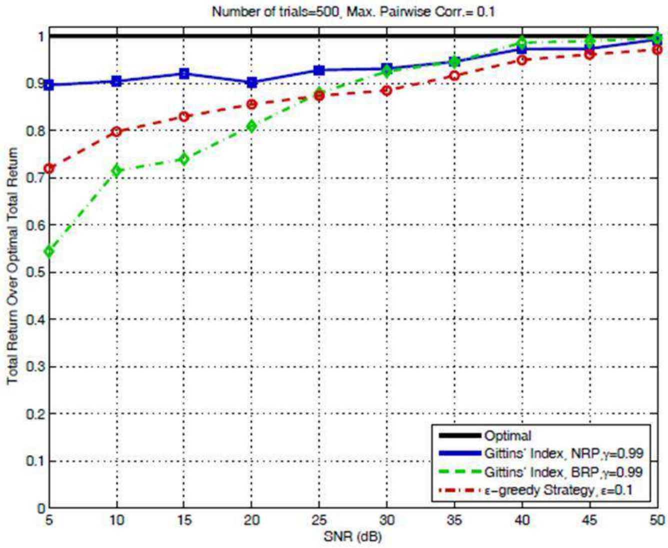
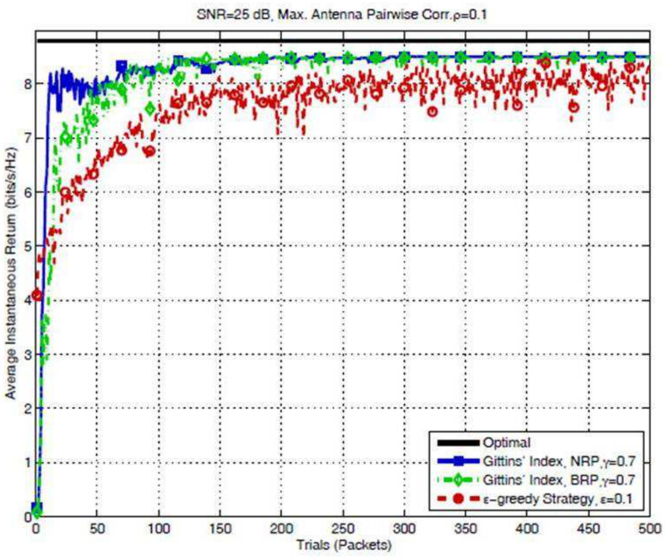


Fig.7. SNR trial (> 500) result.



Conclusion

In this paper we presented an overview of the state of the art of for cognitive entity in cognitive radio networks. The existing works in the three main modules of cognitive entities, namely multiple objective optimization and prototype implementation were discussed with respect to the multiple objective optimizations that are further needed to develop suitable application oriented optimization algorithms. Most of the existing prototype implementation designed only for physical and data link layer analysis. Thus, we believe that cognitive entity design for cognitive radio networking in an open area of research and will be of interest to both the industry and of academia as this technology mature in the next few years.

References

1. Carneiro, G., Ruela, J. and Ricardo. M. 2004. Cross-layer design in 4G wireless terminals. *IEEE Wireless Communications.* 11(2):7–13.
2. Gavrilovska, L. and Prasad, R. 2006. AdHoc networking towards seamless communications. Springer.
3. Ian F. Akyildiz, Won Yeol Lee, Mehmet C. Vuran and Shantidev Mohanty. 2006. Next generation/dynamic spectrum access/cognitive radio wireless networks: A survey. *Comp. Networks.* 50(13): 2127-2159.
4. Mitola, J. 2006. Cognitive radio architecture. J. Wiley & Sons, New York.
5. Mitola. J. 2007. The software radio architecture. *IEEE Communication magazine*. Vol. 33, pp. 26-33.
6. Nadkar, T., Thumar, V., Shenoy, G., Mehta,A., Desai, U.B. and Merchant, S.N. 2011. A Cross-layer framework for symbiotic relaying in cognitive radio networks. Int. Symp. on dynamic spectrum access networks.
7. Petrova, M. P. and Mahonen (2007). Cognitive resource manager: A cross-layer architecture for implementing cognitive radio networks. In: Fittzek & Katz (eds.), cognitive wireless.
8. Qi Wang and Abu, M.A. 2003. Cross-layer signaling for next generation wireless systems. In IEEE WCNC, Vol. 2, pp.1084–1089.
9. Sutton, P., Doyle, L. and Nolan, K. 2006. A reconfigurable platform for cognitive networks. In Proc. of IEEE CROWNCOM '06, Mykonos, Greece.
10. Whitley, D. 1994. A genetic algorithm tutorial, statistics and computing. Vol. 4, pp. 65–85.
11. Younis, O., Latha Kant, McAuley, A., Manousakis, K., Shallcross, D. and Sinkar, K. 2010. Cognitive tactical network models. *IEEE Communications Magazine*.
12. Yuqing Huang and Jiao Wang Hong Jiang. 2010. Modeling of learning inference and decision-making engine in cognitive radio. Second Int. Conf. on networks security, wireless communications and trusted computing.