Enhanced Multi-Parameter Cognitive Architecture for Future Wireless Communications

Kaiqing Zhang, Feifei Gao, and Qihui Wu

Abstract

The very original concept of cognitive radio (CR) raised by Mitola targets at all the environment parameters, including those in physical layer, MAC layer, application layer as well as those obtained from reasoning, which is also referred to as “full cognitive radio”. Due to its difficult implementation, FCC and Simon Haykin separately proposed a much more simplified definition, in which CR mainly detects the spectrum holes via various sensing technologies, also called as “spectrum sensing cognitive radio”. With the rapid development of wireless communication, say the approaching of 5G cellular networks, the infrastructure of a wireless system becomes much more complicated, and hence, the functionality at every node is desired to be as intelligent as possible. It is then essential to look back into Mitola’s CR definition and ask whether one could, besides obtaining the “on/off” status of the licensed user only, achieve more parameters in an cognitive way. In this article, we propose a new cognitive architecture targeting at multiple parameters in future cellular network. This effort is a step closer to the “full cognition” and is elaborated in three detailed stages. Three representative examples are provided on the basis of recent research progress to illustrate the feasibility as well as the validity of the proposed architecture. We hope the article could lead to some promising guidelines for future cognitive strategy in complicated communication systems.

Index Terms

Enhanced cognition, multiple parameters, detection and estimation, machine learning, cognitive network.

K. Zhang and F. Gao are with Tsinghua National Laboratory for Information Science and Technology, Beijing, 10084, China, email:(zkq11@mails.tsinghua.edu.cn, feifeigao@ieee.org)

Q. Wu is with the College of Communications Engineering, PLA University of Science and Technology, Nanjing, 211101, China, email:(wqhqhw@163.com)
I. INTRODUCTION

The rapid development of wireless communications has engendered quick proliferation of media-rich mobile devices as well as significant enhancement of communication ability. The actual mobile traffic in 2010 is five times greater than an official forecast made by the International Telecommunication Union (ITU) in 2005 and would continuously increase 1000 times till the end of 2020 [1].

To cope with the huge traffic, heterogeneity becomes a key feature of the network due to the mixed usage of cells with diverse sizes and access points with different characteristics. On the one hand, the total system capacity is enhanced by increasing the network coverage (via relays, mobile femtocell, etc.), number of subchannels (via massive MIMO, interference management, etc.), bandwidth efficiency (via cognitive radio technology, etc.), and energy efficiency (via green communications, etc.) [2]. On the other hand, complex dynamic network (via D2D, M2M, software-defined network, self-organized network, etc.) are adopted to speed up the service innovation in a more intelligent way.

In order to optimize the overall network performance, information about system parameters, e.g., spectrum occupancy, transmit power, modulation, coding scheme, etc., and the environment parameters, e.g., location, cell edge, etc., should be shared among most nodes. Unfortunately, the current information exchanging still relies on the cooperative feedback between nodes, which causes severe overhead especially when the scale of network and the amount of the data traffic is huge. Hence, an intelligent way to cognitively obtain as many parameters as possible at every node could greatly reduce these overhead and enhance the network efficiency.

In fact, the terminology “full cognitive radio” has already been proposed by Mitola [3] in which every possible parameter observable by a wireless node or network is demanded. “Full cognition” thus represents the ultimate goal of an intelligent cognitive radio (CR). However, the recent 10 years’ study on CR only targets at one single parameter, i.e., the occupancy of a particular spectrum. Although spectrum-sensing cognitive radio has provided great relief from spectrum scarcity and spectrum under-utilization, it is still not adequate to characterize the intricate wireless networks in future cellular networks with voluminous high-dimensional parameter sets. Hence, it is necessary to extend the parameter space from a single “spectrum
hole” a step further towards “full cognition” by introducing the concept of “multiple parameter” space, which involves as many parameters depicting the network status as possible, including but not limited to channel occupancy, transmit power level, signal modulation scheme, channel coding, as well as cell coverage, network topology, user preferences, communication protocol, and sensing policies, etc.

Apart from the high dimensionality and enormous volume, the multi-parameter space also share the highly structured and mutually coupled characteristics, which could be further utilized to enhance the parameter recognition. Recognition of multiple parameters is similar to the conventional estimation and detection problem if sufficient prior knowledge are available at each node but with an enlarged dimension of parameter space. Hence, the multiple hypothesis testing may be applied instead of the conventionally popular binary hypothesis testing. Nonetheless, in practical 5G network structure, the prior knowledge is normally unavailable with proliferation of traffic data, for which the conventional estimation and detection techniques can hardly be applied. A solution to achieve the parameter cognition is, then, to introduce the intelligent learning theory that is able to establish the prior knowledge base automatically based on the received signal data. The amount of signal data could be accumulated within very short time considering the signal transmission speed over Mega or Giga bits in the future cellular networks. In fact, machine learning has already emerged as one of the most booming area these years, whose core idea is to mine the regular patterns behind massive number of data samples and further identify or predict unknown patterns. Moreover, the inherent coupling and inter-relationship of network parameters can be recognized as prior knowledge for cognition through learning techniques.

Furthermore, the parameters that determine the resource allocation in practical cellular networks are quite changeable. The cognitive techniques should then be as adaptive and predictive as possible to cope with the dynamic characteristics of the coverage, topology and transmission patterns, etc. If the cognitive techniques is able to provide accurate predictions of the network status based on the patterns behind multiple-parameters space, such as the user behaviour and cell deployment, better quality of service can be achieved via resource pre-distribution.

In this article, we propose a new cognitive architecture either based on the conventional detection/estimation theory or the machine learning techniques, targeting at multiple-parameters
in future wireless communication networks. The remainder of the article is organized as follows. We first describe the core idea and framework of the proposed cognitive architecture. We then give three examples about the multi-parameter cognition scenario under different prior knowledge. Summary and some prospects are highlighted at the end of the article.

II. ARCHITECTURE OF ENHANCED MULTI-PARAMETER COGNITIVE TECHNIQUES

The architecture of enhanced multi-parameter cognitive techniques are elaborated as three main stages: parameter structuralization, multi-parameter cognition, and parameter prediction.

A. Parameter Structuralization

Quite a few efforts in literature have been made for parameter identification in wireless systems, and some fine results have been established concerning parameters like channel estimation and spectrum detection. However, these parameter identification techniques purely focus on extracting the expected parameter, ignoring the potential correlation among different parameters. As illustrated in Fig. [1] gigantic amount of parameters describing the networks are supposed to be structured for a more comprehensive cognitive strategy. Different from spectrum-sensing cognitive radio, where spectrum occupancy is the only parameter to be detected, other system parameters could also be obtained via a cognitive approach, such as transmit power, modulation scheme, channel coding, as well as network topology, user preferences, communication protocol, sensing policies, etc. Specifically as in amorphous cellular networks, except for the on-off status of neighbouring nodes, information about the instantaneous channel, frame structure, the number of active nodes, the position of the nodes as well as the distance between stations are supposed to be measured with the evolution of the network constructs. These parameters are actually structured with each other in a concentric circle way as shown in Fig. [1] and the more central the layer lies, the more abstract the categorized parameters are. Moreover, the regular patterns of inner layer parameters may be deduced from the parameter patterns of the outer layer, e.g., detected symbol constellation indicates the spectrum occupancy status of the wireless networks, which further suggests behaviour patterns of some users. A well-organized and internally-consistent cognitive parameter structure will definitely upgrade the cognitive performance in terms of quality as well as efficiency.
Fig. 1. Enormous number of parameters involved in cognitive cellular communication systems.

B. Multi-Parameter Cognition

In face of the proliferate data traffic and enormous overhead in cognitive cellular networks, the multi-parameter cognition architecture is proposed as in Fig. 2 to satisfy the parameter cognition demands.

It is not difficult to realize that the information of multiple parameters such as the transmit power level, user modulation and coding schemes, are imbedded in the received raw signal data. Actually certain parameters of them can be achieved using similar approaches. For example,
higher order statistics of the received symbols can be exploited to identify the transmit powers and modulation of transmitters simultaneously, which stays beyond the basic usage of just detecting the existence of signals. Hence, a cognitive way to achieve as many parameters as possible, i.e., self-obtaining the multiple parameters, sounds very attractive in future heterogenous network.

In general, the cognition can be categorized into two cases, i.e., prior-sufficient case and prior-deficient case, depending on how much the prior knowledge is available before the cognition. For the prior-sufficient case, where the key information, e.g., interference level, noise characteristics, channel statistics, etc., are known to users, the multiple parameter cognition problem can be converted to an detection/estimation problem. In this case, closed-form theoretical results for multiple parameter space cognition normally exist and could then serve as the upper bound for other sub-optimal algorithms.

When the prior knowledge is insufficient to apply the conventional detection/estimation algorithms, one may resort to learning techniques, e.g., machine learning and pattern recognition, to
intelligently establish the cognition knowledge base. Indeed, some machine learning algorithms have been proposed for various tasks for CR network. In [4], a spectrum sensing engine based on support vector machine (SVM) was designed, advancing the sensing performance with small samples compared to the energy detector. In cooperative spectrum sensing paradigm, [5] presents reinforce learning methods to reduce the sensing overhead by releasing network flow congestion. Most of these learning strategies, however, are still designed to achieve the single parameter of the spectrum occupancy, ignoring the possible learning of other useful parameters.

More attentions are supposed to be paid when incorporating learning algorithms for multi-parameter cognition. In particular, some learning algorithms applied in the architecture need to be custom-made to various scenarios with different transmit patterns and network constructs so that the cognition capability and adaptivity are independent of other irrelevant factors such as frequency band, RF environment and time. Moreover, incorporation of low-complexity learning algorithms, e.g., non-parametric learning, can lead to reduced system complexities and holds great advantage over the conventional detection/estimation techniques.

C. Parameter Prediction

Through the multiple parameters cognition, users are able to utilize the underlying discipline as well as the internal structure of parameters of different layers to further improve the network performance. For example, channel occupancy status can be predicted by learning the traffic characteristics of the licensed systems using the neural network model in [6]. The reliable predictions of channel status considerably reduces the energy consumed in spectrum sensing for the reason that only those channels which are predicted to be idle need to be sensed in the next time-slot. Moreover, if the unlicensed user can predict other parameters of licensed users, e.g., power level, symbol modulation, coding-scheme of the licensed user, it could then adjust its own power-level, symbol modulation, coding-scheme such that the interference caused to the licensed user could be optimally reduced. The unlicensed user may also be able to predict the communication patterns and behaviours of the licensed user from the cognized primary parameters and further identify group of users due to the coupling of multiple parameters.
III. Examples

In the following, we provide three representative examples to show how the estimation/detection algorithms and machine learning technologies could cognize the parameters other than channel occupancy. These examples are carefully chosen as they reflect the latest research progress in what we consider as the most promising applications. Possible extensions of the architecture towards further full parameter cognition are envisioned at the end of each example.

A. Example 1: Detection and Learning of Transmit Power Levels

In this example, we consider a more practice-matching CR scenario, where the licensed user could work under more than one discrete power levels, as opposed to single power level in conventional CR. The parameter that could be cognized is not only on-off status of the licensed user, but also its transmit power level. More elaborated information about transmit power level could be utilized to protect different powered PU with different interference levels [7].

If the candidate power levels and noise statistics are known in prior, the spectrum occupancy as well as the current transmit power levels can be obtained via multiple hypothesis detection [7] that is mainly based on the maximum a posterior (MAP) detection rule. Besides the false alarm probability and detection probability that are used to evaluate the conventional spectrum sensing, one may further define a new performance metric called discrimination probability, which describes the capability of correctly recognizing each power pattern. An example of numerical simulations is provided in Fig. [3] and these theoretical results can serve as an upper bound of performance for any sub-optimal detectors.

However, the assumption that the an unlicensed user fully knows all prior information cannot be true in realistic setup. In this case, the machine learning based cognitive techniques, such as clustering analysis and classifier construction, shall be integrated to replace the multiple hypothesis testing approach. The unlicensed user may collect the energy statistic and formulates the energy feature vector through multi-slot sensing scheme [8], and licensed transmission patterns can be discovered by clustering analysis from a sufficient number of energy feature vectors collected, which are noted as training data. Feature vectors that share the same transmit power of PU can be grouped together so that the number of power states and corresponding
vector clusters are determined by clustering analysis and unsupervised K-means algorithm. Thus, the transmit power levels can be evaluated by the averages of the vectors in each cluster, from which the knowledge about transmit patterns and preferences, e.g., the power states a licensed user usually takes on, the average power level of each power states, etc., are learned. Moreover, each energy feature vector would be labeled by the cluster number it is partitioned into, based on which classifiers can be constructed through supervised learning to determine the decision boundaries between different power states. We provide an example here where the SVM for multiple classes is used to train the classifiers and perform sensing task. The corresponding clustering result and decision boundary are shown in Fig. 4.

Once the power level is detected, the unlicensed user could adjust its own power value such that the interference temperature for that particular power level is fulfilled, by which means the unlicensed user could fully squeeze the tolerance of the licensed user. In fact, FCC has already regulated different protection for different powered services in their recent reports [9].
Fig. 4. Clustering results and SVM trained decision boundary on normalized energy feature vectors when average signal noise ratio (SNR) is -12 dB.

B. Example 2: Discovery and Learning of Modulation Pattern

In this example, we address the problem of automatic modulation recognition (AMR) in CR scenario, a technique to identify underlying modulation format of an unknown signal from noisy measurements in order to identify the existence of the licensed user and to decode the transmitted message. In fact, quite a few researches have been conducted in conventional modulation recognition systems, where two main methods were proposed: the theoretical maximum likelihood based method and the statistical pattern recognition methods [10].

However, these modulation recognition differs from the proposed cognition approach. First, the existing modulation recognition methods assume a prior knowledge of the candidate signal constellations, which can be denoted as the modulation dictionary. It is obligatory for the dictionary to contain as many potential modulation types as possible while a redundant dictionary would definitely degrade the recognition performance, especially in low signal-to-noise ratio region [11]. Hence the modulation dictionary should be pruned tactfully before recognition.
Secondly, the existing methods do not cope with CR scenario such that the transmitter is always assumed to be “on”, whereas in the proposed cognitive architecture, the channel occupancy status is also unknown and is always coupled with modulation recognition since an identification of an licensed constellation would indicate the existence of the licensed user; Thirdly, the existing methods do not consider different transmit power levels, which can, in fact, be coupled with modulation recognition to characterize the transmit behaviors of the licensed user.

We provide this example to shed light on how to make up for the above defects. In our example, higher order statistics (HOS) is used as the feature because they characterize the distribution shape of the noisy baseband samples with low complexity \[10\]. We apply the concept “Modulation Pattern” to denote the combination of the modulation type and the transmit power level. We then organize the estimations of different order cumulant and lags as a multiple cumulant vector, serving as the input feature of the machine learning algorithms. It can be proved that the feature vector is an multivariate asymptotic Gaussian approximation \[12\]. Specially, the first cumulant in the vector should be the second-order cumulant in order to indicate the energy information. In order to construct the modulation dictionary and identify different modulations as illustrated in Fig. 5 we exploit Dirichlet Process Gaussian Mixture Model (DPGMM), a type of unsupervised clustering analysis approach, to construct dynamic and flexible statistical representations for the training data. With DPGMM, we formulate a mixture model in which the number of mixture components is infinite and is not required at the beginning of clustering. After the convergence of Gibbs Sampling of DPGMM \[13\], the cluster of vectors that assembles around the origin of the coordinate system represents the “noise constellation”, from which the second-order cumulant, i.e., the variance of noise, can be evaluated. Similar to example 1, the first dimension of the projection of each cluster presents the transmit power patterns. The mean of energy-normalized vector of any other cluster is evaluated so that the alive modulation types are identified to establish the minimal dictionary, including the “pure noise constellation”. Consequently, the “modulation pattern” can be efficiently recognized using Maximum a Posterior rule based on the estimated mixture model distributions.

Our simulation results in Fig. 5 shows the efficacy of the modulation type recognition and indicates superior discrimination capability if compared with the pure pattern recognition approach.
Bayesian Non-Parametric Clustering Results using Gibbs Sampling

Fig. 5. Pattern discovery and clustering results of multiple cumulants vectors before normalization using Dirichlet Process Gaussian Mixture Model. $\mu$ denotes the mean vector of each Gaussian component and $P_i$ denotes the transmit power level where $P_1^2 : P_2^2 : P_3^2 : P_4^2 = 2.5 : 5 : 5.3 : 4$ when overall average SNR is 10 dB and the number of samples is 100.

[10]. Fig. 5 demonstrates that four modulation types as well as the channel idle status can be specified automatically, along with which the transmit power information can also be cognized. This may be explained by the fact that the energy information in the first dimension is considered to expand the scale of the estimated HOS values such that the clustering and classification could be more easily achieved. The spectrum occupancy information can be obtained in the meanwhile as long as the current multiple cumulants vector is assigned to the nearest cluster to the origin. Furthermore, the modulation preference of the user is understood from the prior probability of each component. In reality, DPGMM shall update the number of active clusters and the mixture probability density function adaptively if new sample feature vectors are fed into the training database.
C. Example 3: Learning and Prediction for Spectrum Environment

In the last example, we utilize machine learning techniques, e.g., non-stationary Hidden Markov Model (NS-HMM), to predict channel environment for cognition of multi-channels spectrum occupancy. Due to energy and hardware constraints, secondary user may not be able to perform spectrum sensing at all channels. This problem can be relieved by predicting the channel occupancies before each sensing time slot starts. As modeled in [14], [15], the state of different channels and the time PU spends dwelling on a state are assumed to be independent. Moreover, the state transition probability of a licensed channel is time-varying and could be a function of the duration of a channel state. Consequently the dynamics of channel states form a discrete-time non-stationary Markov chain [14].

The multi-channels spectrum sensing based on learning and prediction can be performed with three steps. Primarily, the parameters of the learning model are estimated by the historical information embedded in the observations database from the previous examples. As in [14], Baum-Welch algorithm is extended to estimate the parameters of the NS-HMM model, where the received signal strength serves as observations. Subsequently, given a new observation the channel occupancy of the next time slot can be predicted using the learning model, and meanwhile the probability of vacancy state of each channel can be ordered from high to low. Then the secondary user is able to efficiently perform spectrum sensing in accordance with the order and update the channel state database with the true channel state detected. Throughput is set as an evaluation criterion of the proposed sensing strategy for variable rate service cognitive radios whose information bits transmitted per time slot are variable. The mean throughput can be derived in terms of the mean error prediction probability and the probability of vacancy state for objective channels in closed form [15]. Simulation results in Fig. 6 illustrates that the multi-channels spectrum sensing and prediction based on NS-HMM achieves better performance in terms of throughput, compared with random selection of license channels. Besides the enhancement of spectrum sensing efficiency, the learning and prediction of channel occupancy can also be utilized to foresee the traffic flow of cellular networks consist of certain PUs and SUs at certain spectrum sub-bands. Hence the network congestion may be detected in advance. Moreover, transmit state of different users at the same time slot can be cognized so that the synchronous transmit cooperation
IV. SUMMARY AND PROSPECTS

In this article, we introduced the concept of enhanced multiple parameter cognition architecture for future wireless communication systems whose efficacy are verified by the three examples. We systematically discussed current challenges and various usage scenarios of cognitive cellular systems, and presented three stages of the cognitive architecture that addresses these challenges in a more intelligent and adaptive way. Examples demonstrated that the cognition in multiple parameter space can be rather different from conventional single parameter identification, revealing fundamental insights in the new characteristics of the proposed cognition paradigm.

As illustrated in Fig. 2, multiple parameter cognition has prompted a compromising but necessary way towards the ultimate goal of cognitive networks, i.e., full cognition. More parameters from across the layers in Fig. 1 are supposed to be coupled and organized to reinforce the
cognition efficacy under this architecture. For prior-sufficient cognitive conditions, estimation and detection techniques are preferred for their optimality while practical improvement on the computational efficiency need to be studied when parameters of greater dimensions are taken into account. For prior-deficient cognitive conditions, which is more common in realistic setup and remains by far an open research field, more recognition and learning techniques are worth trial because of the intelligence and low-complexity introduced. Apart from the cognition strategies, more investigations ought to be proceeded concerning the strategies for joint wireless resource allocation and network performance optimization, e.g., interference management, dynamic spectrum access, ultra-dense deployments, etc., based on the multiple parameters obtained.

REFERENCES

[1] S. Singh and P. Singh, “Key concepts and network architecture for 5G mobile technology,” Int. J. of Scientific Research Eng. & Tech. (IJSRET), vol. 1, no. 5, pp. 165–170, Aug. 2012.
[2] C.-X. Wang et al., “Cellular architecture and key technologies for 5G wireless communication networks,” IEEE Commun. Mag., vol. 52, no. 2, pp. 122C-30, Feb. 2014.
[3] J. Mitola and J. Maguire, “Cognitive radio: making software radios more personal”. IEEE Personal Commun., vol. 6, no. 4, pp. 13–18, Aug. 1999.
[4] Y. Huang, H. Jiang, and H. Hu, “Design of learning engine based on support vector machine in cognitive radio,” in IEEE Int. Conf. on Computational Intelligence and Software Engineering, Wuhan, China, Dec. 2009, pp. 1–4.
[5] B. Lo and I. Akyildiz, “Reinforcement learning-based cooperative sensing in cognitive radio ad hoc networks,” in IEEE Int. Symp. on Personal Indoor and Mobile Radio Communications, Instanbul, Turkey, Sept. 2010, pp. 2244–2249.
[6] V. Tumuluru, P. Wang, and D. Niyato. “A neural network based spectrum prediction scheme for cognitive radio,” in IEEE Int. Conf. on Communications, Capetown, Southafrica, May 2010, pp. 1–5.
[7] J. Li, F. Gao, T. Jiang, and W. Chen, “A new spectrum sensing strategy when primary user has multiple power levels,” to appear IEEE GLOBECOM, 2014. Available at [http://arxiv.org/abs/1311.5681](http://arxiv.org/abs/1311.5681).
[8] J. Guo, G. Zhong, and D. Qu, “Multi-slot spectrum sensing with backward SPRT in cognitive radio networks”. in IEEE International Conf. on Wireless Communications & Signal Processing, Nanjing, China, Nov. 2009, pp. 1–5.
[9] In the Matter of Unlicensed Operation in the TV Broadcast Bands, ET Docket No. 04–186, Notice of Proposed Rulemaking, FCC OET, May 2004.
[10] A. Swami and B. Sadler. “Hierarchical digital modulation classification using cumulants,” IEEE Trans. Commun., vol. 48, no. 3, pp. 416–429, Mar. 2000.
[11] B. Dulek, O. Ozdemir, and P. Varshney, “Modulation discovery over arbitrary additive noise channels based on the Richardson-Lucy algorithm,” IEEE Signal Processing Lett., pp. 756–760, Apr. 2014.
[12] A. Dandawate and G. Giannakis, “Asymptotic theory of mixed time averages and kth-order cyclic-moment and cumulant statistics,” IEEE Trans. Inf. Theory, vol. 41, no. 1, pp. 216–232, Jan. 1995.
[13] G. Rasmussen. “Dirichlet process Gaussian mixture models: choice of the base distribution,” J. of Comp. Science and Tech., vol. 25, no. 4, pp. 653–664, July 2010.
[14] X. Chen, H. Zhang, A. MacKenzie, et al. “Predicting Spectrum Occupancies Using a Non-Stationary Hidden Markov Model,” IEEE Wireless Commun. Lett., vol. 3, no. 4, pp. 333–336, Apr. 2014.
[15] Z. Ye, Q. Feng, and K. Shen. “Spectrum environment learning and prediction in cognitive radio,” in IEEE International Conf. on Signal Processing, Communications and Computing, Xi’an, China, Sept. 2011, pp. 1–6.