Cognitive Dynamic Systems: Radar, Control, and Radio

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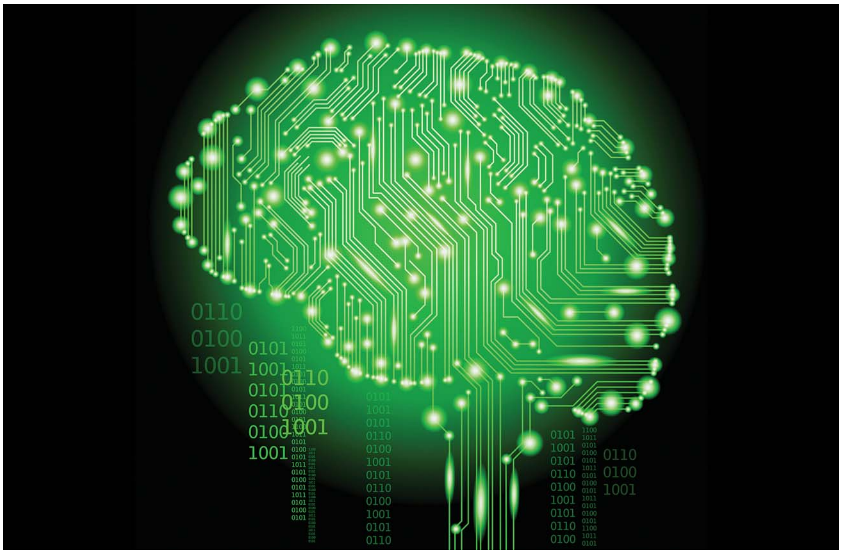

In this second Point of View article on cognitive dynamic systems, we will review the progress made and the way forward on this multidisciplinary integrative field. Specifically, we will address the following topics:

- brief historical notes on human cognition;
- advances made on cognitive radar of the monostatic kind;
- emergence of cognitive control for the first time, building on the new concept of a two-state model;
- the significant progress made on cognitive radio on several fronts.

I. INTRODUCTION

In February 2005, a classic journal paper on cognitive radio was published [1], which was then followed up with a seminal journal paper on cognitive radar that was published in January 2006 [2]. The publication of these two papers emboldened the author to write a predictive Point of View article on cognitive dynamic systems that was published in November 2006 [3]. There has been an exponential growth in cognitive radio, more so than in cognitive radar, in the past five years; hence, this update on where we stand on cognitive dynamic systems, looking ahead and addressing the emergence of cognitive control for the first time.

The article is organized as follows. Section II presents brief historical notes on human cognition. Section III, building on the historical notes, describes Fuster's paradigm for cognition as the framework of reference for cognitive dynamic systems. Section IV identifies two different classes of cognitive dynamic systems, viewed from an engineering perspective. Sections V, VI, and VII address three important engineering manifestations of cognition: radar, control, and radio, respectively. The article finishes with concluding remarks in Section VIII.

II. BRIEF HISTORICAL NOTES ON HUMAN COGNITION

With cognition being a characteristic of the human brain, it is natural that we consult neuroscience on what cognition stands for. Unfortunately, in the literature on neuroscience there is no unique definition for cognition; see, for example, Michael Gazzaniga's definitive edited volume *The Cognitive Neuroscience*, now in its fourth edition [4].

A large percentage of the information processing in the brain is performed in the cerebral cortex and it plays a key role in processes attributed to cognition by different researchers. Since the 1950s, Vernon Mountcastle's work on characterizing the columnar organization of the cerebral cortex has influenced research carried out in this

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field; he pointed out that cortical minicolumns are the basic functional units of cortex [5]. In 1978, based on the uniform appearance of the cortex, he proposed that all regions of the cortex may use a basic information-processing algorithm to accomplish their tasks. This algorithm must be independent of the nature of the information-bearing sensory input. In other words, all kinds of sensory inputs (i.e., visual, audio, etc.) are coded in a standard form and fed to this basic processing algorithm.

As a pioneer in computational neuroscience, David Marr followed a similar way of thinking that very few fundamental techniques are used by the cerebral cortex to process information for different tasks [6]. He was interested in developing a general computational theory for the brain based on biological evidences. However, in later years, he just focused on vision.

Following the same line of thinking and inspired by pioneering scientists who had put a great deal of thoughts and efforts into exploring what the essence of cognition is, Joaquin Fuster proposed the concept of "cognit" for knowledge representation in the cerebral cortex; moreover, he proposed an abstract model for cognition based on five fundamental building blocks, namely perception, memory, attention, intelligence, and language [7].

III. AN ENGINEERING PERSPECTIVE OF COGNITION

Hereafter, we refer to the five fundamental building blocks attributed to Fuster as *Fuster's paradigm*, which we adopt as the "frame of reference" for cognitive dynamic systems.

From an engineering perspective, we may describe the functions of these five fundamental building blocks of cognition as follows.

- The function of the perception–action cycle is to produce information gain about the environment by processing the received signal, with the amount of information gain increasing from one cycle to the next.
- The function of memory, from an information-processing perspective, is to encode the received signal, store the encoded information, and recall it when needed in response to some cue; for certain application, memory may also predict the consequences of action taken by some parts of a cognitive dynamic system.
- The function of attention is to provide for the effective and efficient utilization of computational resources in a cognitive dynamic system, so as to avoid the information-overload problem.
- The function of intelligence is to enable an algorithmic decision-making (control) mechanism in the cognitive dynamic systems to pick a strategy for optimal solution of a prescribed goal, confronted by environmental uncertainties and disturbances.
- Finally, language is intended to provide effective and efficient communication on a person-to-person basis as well as a group of persons.

Henceforth, language is outside the scope of this article and not considered further.

IV. TWO DIFFERENT CLASSES OF COGNITIVE DYNAMIC SYSTEMS

The way in which functions of the perception–action cycle, memory, attention, and intelligence are actually interpreted is dependent on the application of interest.

In particular, we may identify two distinct classes of cognitive dynamic systems.

- The first class embodies that application where the design of a cognitive dynamic system closely *mimics* the human brain, be it visual, auditory, or some other sensory kind; cognitive radar, a remote-sensory application, is a good example of this first class of cognitive dynamic systems.
- The second class embodies those applications where the design of a cognitive dynamic system is *motivated* by human cognition; cognitive radio, a communication application, is a good example of this second class of cognitive dynamic systems.

Stated in another way, in the first class, there is relatively "close" mapping of a cognitive dynamic system onto its human cognition counterpart. In the second class, now such mapping exists.

V. COGNITIVE RADAR

Fig. 1 shows the block diagram of a cognitive radar, where the two functional parts of the system, namely the perception–action cycle and distributed memory, feature prominently in the figure.[1]

Perception, performed in the receiver, operates on radar returns from an unknown target with a dual objective, reliable detection of the target, and its tracking behavior across time. In this article, we focus on tracking, which is treated as a state-estimation problem under the *Bayesian framework*.

To address the tracking problem, the traditional approach is to start with a state–space model that consists of a pair of equations: the system equation describes evolution of the state across time with system noise as the driving force, and the measurement equation describes dependence of the measurements on the state

[1]Comparing Fig. 1 for cognitive radar of a monostatic kind with Figure 4.7 in Fuster's book [7], we see a reasonably close resemblance between them. One other noteworthy point: in engineering, a block diagram flows from left to right; on the other hand, in neuroscience, it flows in a bottom-up fashion. Fig. 1 follows the latter convention.

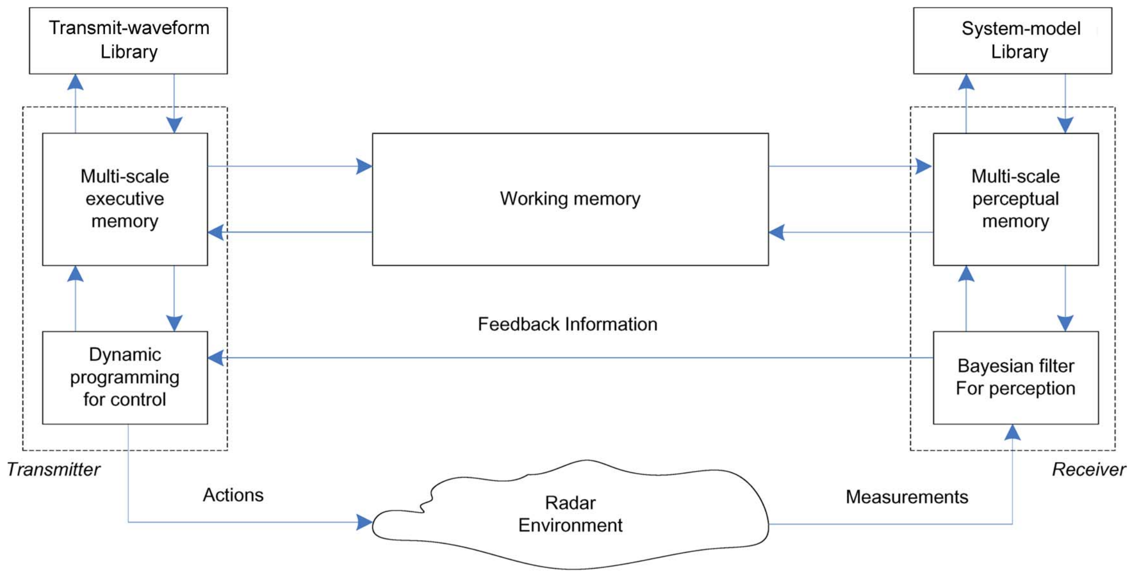

Fig. 1. ***Block diagram of cognitive radar.***

corrupted by measurement noise. Typically, but not always, the state–space model is nonlinear, which requires approximating the optimal Bayesian filter in some sense. Hereafter, we look to an approximate Bayesian filter to preform perception of the environment, which is naturally performed in the receiver. The perception–action cycle requires that the receiver be linked to the transmitter. In a monostatic radar, where the receiver and the transmitter are collocated, such a requirement is relatively straightforward to handle. Accordingly, the receiver is also responsible for computing feedback information about the radar environment and then supplying it to the transmitter for action in the environment. With state estimation playing the role of perception in mathematical terms, it is logical to formulate the feedback information using the state-estimation error vector. For the feedback information, we may use the Fisher information metric or the Shannon entropy, depending on the application of interest [8]. Next, turning to the transmitter, its function is to control the receiver indirectly through illumination of the environment. Here again, with optimal control in mind, we may look to Bellman's dynamic programming as the method of choice. However, when dimensionality of the state–space, action–space, measurement–space, or combination thereof, is high, which is typically the case in tackling difficult tracking problems, we have to resort to approximate dynamic programming for mitigating the curse-of-dimensionality problem. Thus, in light of what we have just described, the perception–action cycle embodies four functional blocks: approximate Bayesian filter for environmental perception in the receiver, linkage for feedback information from the receiver to the transmitter, approximate dynamic programming for receiver control performed in the transmitter, and finally, the state–space model of the radar environment. The perception–action cycle may therefore be viewed as a closed-loop feedback control system, which, in physical terms, is clearly visible in Fig. 1.

Next, we turn to the requirement that a cognitive radar must learn from the experience gained through continued interactions with the radar environment. This requirement is satisfied by equipping the radar with a multiscale memory system, one part of which resides in the receiver, another part resides in the transmitter, and the two of them are reciprocally coupled in the manner described in Fig. 1. The part of memory that resides in the receiver is called perceptual memory. From a practical perspective, it is desirable for the perceptual memory to have a multiscale structure. In the neural network literature, this kind of structure is referred to as features of features. Basically, through a learning process, the first layer of the perceptual memory extracts the important features that characterize the incoming measurement vector. Naturally, these features act as the input to the second layer of the perceptual memory, which, in turn, goes on to extract the features of features that characterize the original measurement, and so on for the third layer of perceptual memory. The idea behind such a learning process is summed up as follows. The perceptual memory of Fig. 1 is reciprocally coupled to the so-called system-model library; this library consists of a grid of points, with each point representing a different set of values of the nonlinearity describing state transition and system-noise covariance in the system equation. It is assumed here that the library provides a set of all possible discrete values of the system equation in the state–space model that could arise in practice. Accordingly, the perceptual memory may be viewed as an *associative memory* of the heterogeneous kind, the objective of which is to correlate each grid point in the system-model space to a corresponding point in the measurement space.

The part of the memory that resides in the transmitter is called the executive memory, whose structural composition follows a similar format to that of the perceptual memory. Note also that the executive memory is reciprocally coupled to another library called the transmit-waveform library. Each grid point in this second library represents, for example, a different combination of chirp rate and Gaussian pulse duration: two parameters that define the transmit-waveform vector. In a manner similar to the perceptual memory, the executive memory may be viewed as an associative memory of the heterogeneous kind, except for differences in terminology: feedback information and transmit waveform play the role of measurements and system-model library, respectively.

In order to exploit the full capability available in having the perceptual memory and the executive memory is to have them reciprocally coupled together. This reciprocal coupling is achieved by means of the *working memory*, as shown in Fig. 1; typically, the working memory functions for a relatively short time within each perception–action cycle, so as to attend to the consequences of actions taken by the radar. With all the three kinds of memory viewed as a whole, we thus have an integrated system that enables all the information-processing steps performed in each cycle of the perception–action cycle mechanism to proceed in a synchronized (coherent) fashion across time. This self-organized synchronous behavior is another cardinal characteristic of cognitive radar.

Examining the block diagram of Fig. 1, we see that both the perception–action cycle and memory occupy distinct physical places of their own within a cognitive radar. However, this is not so when it comes to attention. Rather, memory-based attention manifests itself across the cognitive radar through "algorithmic" mechanisms. Specifically, we have perceptual attention in the receiver and executive attention in the transmitter. In a tracking problem, for example, the so-called explore–exploit strategy plays a key role in formulating an algorithm for the executive attention. To illustrate, suppose that a grid point in the waveform library was picked for illuminating the environment in the previous perception–action cycle. Then, in the current cycle, that particular grid point performs the role of a "center" point within a cluster, embodying the set of grid points that lie in the immediate neighborhood of the center; this step constitutes the exploration phase. The cluster of grid points so obtained is passed on to the controller for action in the environment.

Considering intelligence, here again we see that intelligence does not occupy a distinct place of its own in cognitive radar. Rather, intelligence manifests itself artificially through algorithmic mechanism that is driven by the combination of attention, memory, and the perception–action cycle. Specifically, given the cluster of grid points identified in the exploration phase and the feedback information computed in the receiver the controller selects the optimum transmit waveform by minimizing a prescribed cost function, and with it exploitation phase of explore–exploit strategy is completed.

Thus, the computational effort involved in a global search of the transmit-waveform library is replaced with a local search. Typically, with the execution of this strategy being relatively short from one perception–action cycle to the next, we expect evolution of the local search for the selection of a transmitter waveform to be relatively smooth, which is yet another cardinal characteristic of cognitive radar.

In a target-tracking application, for example, the practical benefits gained from the use of cognitive radar may be summed up as follows [9]:

- *significantly* improved speed of convergence;
- *equally significantly* improved tracking accuracy;
- *smooth transition of the transmit waveform* from one perception–action cycle to the next.

Moreover, the most important benefit to be gained by the use of cognition is risk control (management), which is enabled by an intelligent choice of the decision-making mechanism in the transmitter for a prescribed goal of interest, confronted by environmental uncertainties and disturbances, which are physically not implementable in the internal libraries of the cognitive radar.

VI. COGNITIVE CONTROL

Fig. 2 shows the block diagram of a cognitive control system,[2] where the right-hand side of the figure is referred to as perceptor and its left-hand side is referred to as controller [10].

For *reinforcement learning* to function as the controller in Fig. 2, we have to think in terms of a two-state model of the environment, composed as follows:

- state–space model, which describes evolution of the target state, given the incoming measurement;
- entropic-state model, which accounts for, in probabilistic terms, all the unknown environmental uncertainties and disturbances in the environment.

Estimation of the target state and computation of the entropic state are both performed in the perceptor.

[2]In a historical context, our discovery of cognitive control came out of work being done on cognitive radar, in which cognitive control is embedded. Nevertheless, cognitive control and cognitive radar are two different manifestations of human cognition, each with its own domain of applications.

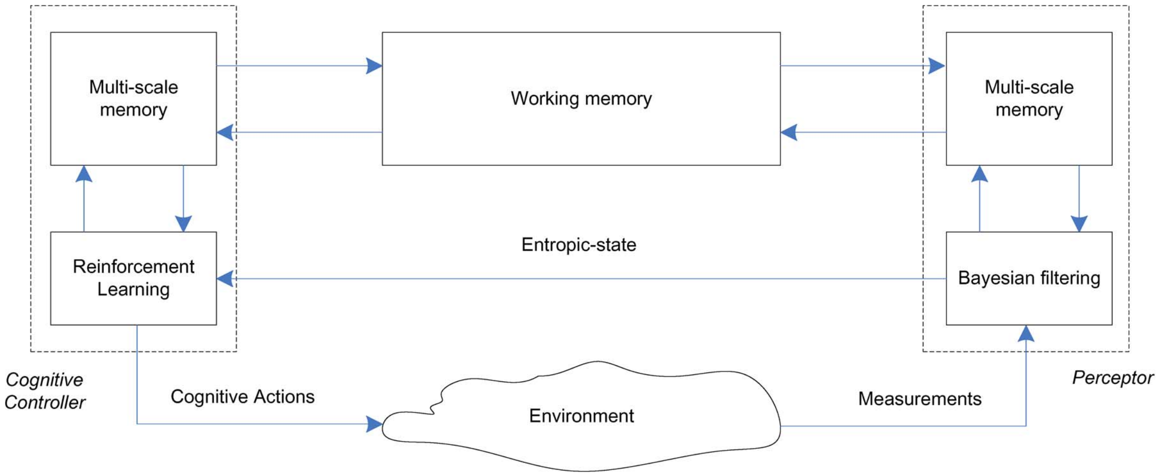

Fig. 2. ***Block diagram of cognitive controller.***

Moreover, the feedback information passed on to the controller is simply the entropic state.

With this two-state model in mind, the cognitive controller depicted in Fig. 2 functions with much less computational complexity on two accounts:

- the reinforcement learning machine (agent) controls the perceptor;
- to accommodate this controlling action, in turn, the reinforcement learning machine has "direct" access to the entropic state.

In control-theoretic terms, we may therefore restructure the cognitive controller of Fig. 2 in the equivalent simplified form shown in Fig. 3, according to which the perceptor may be viewed as an "agent." Most importantly, insofar as the action of the controller is concerned, the simplified diagram of Fig. 3 is in perfect accord with the reinforcement learning literature [11].

At first sight, the block diagrams of Figs. 1 and 2 for cognitive radar and cognitive control look essentially similar, except for the two libraries in cognitive radar. This should not be surprising because they are both motivated by human cognition. However, they differ in their respective practical applications. Moreover, the two-state model described for the first time for cognitive control applies equally well to cognitive radar.

VII. COGNITIVE RADIO

The term cognitive radio was coined by Mitola and Maguire [12], in which the visionary idea of cognitive radio was introduced for the first time within the software-defined radio (SDR) community. Subsequently, Mitola elaborated on the so-called "radio knowledge representation language" in his own doctoral dissertation [13]. Continuing on, in a short section entitled "Research issues" at the end of his dissertation, Mitola went on to say the following:

> "How do cognitive radios learn best? merits attention: The exploration of learning in cognitive radio includes the internal tuning of parameters and the external structuring of the environment to enhance machine learning. This thesis does not attempt to answer these questions, but it frames them for future research."

Then, in [1], detailed exposition of signal processing, control, learning and adaptive processes, and related game-theoretic ideas that lie at the heart of cognitive radio were presented for the first time. As depicted in Fig. 4, three fundamental cognitive tasks in the perception–action cycle of cognitive radio were identified in that paper:

1) radio-scene analysis of the environment, which is performed in the receiver;
2) dynamic-spectrum management and transmit power control, both of which are performed in the transmitter;

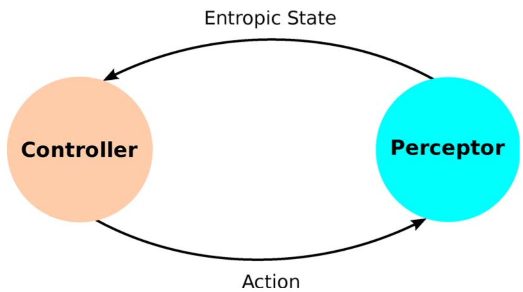

Fig. 3. ***Simplified form of the cognitive controller, realized by exploiting the notion of entropic state.***

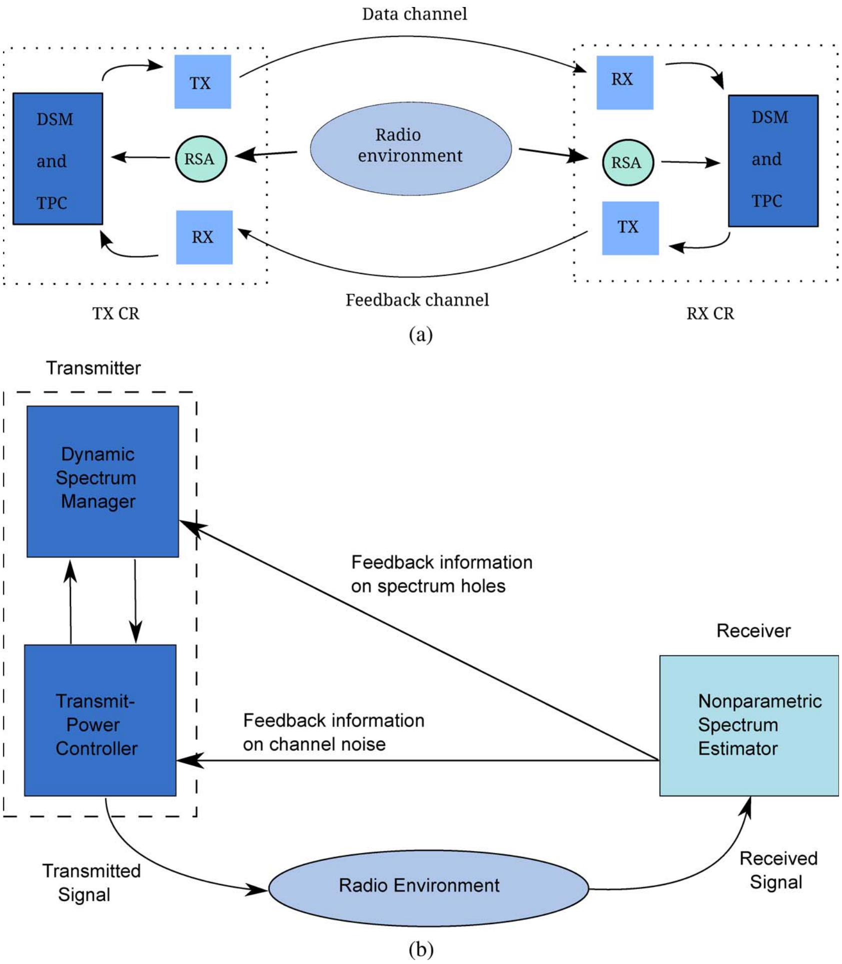

Fig. 4. ***(a) Directed-information flow in cognitive radio. DSM: dynamic spectrum manager; TPC: transmit-power controller; RSA: radio-scene analyzer; RX: receiver; TX: transmitter; TX CR: transmitter unit in the transceiver of cognitive radio; RX CR: receiver unit in the transceiver of cognitive radio. (b) Perception--action cycle of a single cognitive radio unit, where the transmitter and the receiver are located at different points in space.***

3) global feedback, enabling the transmitter to act in light of information about the radio environment fed back to it by the receiver.

As mentioned previously, for a dynamic system to be cognitive under Fuster's paradigm, it has to embody the four fundamental building blocks: perception, memory, attention, and intelligence. Perception is achieved by using nonparametric spectrum estimation for perception in the receiver. The dynamic spectrum manager has the practical means to dynamically choose and assign a set of appropriate links for communication to each cognitive radio unit by learning the underlying environmental communication patterns. Experimental knowledge thus learned about the communication patterns of the primary users in a radio network and, to some extent, those of other secondary users in the local neighborhood, is stored in memory and updated from one perception–action cycle to the next. Furthermore, in response to an input from the bottom-up link in Fig. 4(b), the dynamic spectrum manager focuses its attention on subbands with lower interference levels. In so doing, communication over the newly found cognitive radio link is maintained, bypassing the congested subbands. As with human cognition, intelligence in cognitive radio builds itself on the processes of perception, memory, and attention; intelligence is facilitated by global feedback and local feedback.

In what follows, we briefly describe the three fundamental cognitive tasks identified above, together with related issues.

A. Radio-Scene Analysis

Radio-scene analysis, embodying spectrum sensing, is a key enabling function of cognitive radio. Simply put, the objective of spectrum sensing in cognitive radio is to identify (detect) *spectrum holes* that represent subbands belonging to primary (legacy) users, which are not employed at a particular point in time as well as space. Spectrum holes are a spectral resource that is essential to cognitive radio, as they provide the very means for their utilization by secondary (cognitive radio) users for as long as these holes remain available.

Among all the fundamental tasks in cognitive radio, spectrum sensing is by far the most exhaustively studied in the literature. Specifically, we may mention three approaches.

- *Energy detection*, which provides a reasonably satisfactory performance at low computational complexity [14]–[16]; however, this approach to spectrum sensing is model dependent in that it requires information about noise variance at the receiver input, which makes it nonrobust.
- *Cyclostationarity*, which is based on the use of classical Fourier transform theory of stationary processes with an important modification: the introduction of the so-called parameter α (having the same dimension as frequency) in the statistical characterization of cyclostationary processes that involves modulation [17]–[20]. Robustness of the second approach depends on how well the parameter α is chosen.
- *Multitaper method* (MTM), which provides a nonparametric approach to power

spectrum estimation [21]. The attributes of MTM include spectral accuracy, easy-to-quantify tradeoff between bias and variance, regularization, and robustness [8], [22]. In mathematical terms, MTM is rather demanding. However, in computational terms, its implementation may be achieved relatively fast, using the fastest Fourier transform in the west (FFTW), described in [23]: with the use of such a tool, it can be implemented in microseconds, given prescribed library values of the *Slepian sequence* that are at the heart of the MTM.

As with energy detection, MTM can be applied to detect spectrum holes, using a hypothesis-testing approach. For the first time in [24], closed-form analytic formulas are derived for the probabilities of spectrum-hole detection and false alarm, which are particularly applicable for the sensing of primary users with relatively narrow bands. Moreover, in that paper, superior performance of the MTM detector over the energy detector is demonstrated for single sensors as well as multiple ones.

B. Dynamic Spectrum Management

Dynamic spectrum management (DSM), aimed at the distribution of available spectrum holes among secondary (cognitive radio) users, is one of the most challenging problems for several reasons [25]:

- DSM is equivalent to the graph-coloring problem that is NP hard;
- it is a time-varying problem;
- its dimensionality can assume relatively high values, depending on the density of secondary users.

Despite its optimal property, we therefore find that the traditional centralized approach to solve the DSM problem is not only expensive but also unscalable. Consequently, we are compelled to find a decentralized approach that can achieve a satisfactory suboptimal solution. In other words, suboptimality of the DSM is a tradedoff for scalability.

In [26], a self-organizing DSM scheme inspired by human brain is described. This novel approach tries to find the best subbands for each cognitive radio user by applying the idea of *self-organizing maps*.[3] These maps constitute a special class of neural networks, the main goal of which is to adaptively transform an incoming signal pattern of arbitrary dimension into a 1-D or 2-D discrete map in a topologically ordered manner in accordance with Hebb's postulate of learning [27].

In the Hebbian-based self-organizing DSM technique, the goal is to increase spectrum utilization as high as possible. To achieve this goal, the cognitive radio network continuously tries to complement the space-occupancy pattern of the legacy network, as follows:

> The spectrum-usage pattern of the cognitive radio network is matched to a particular pattern of underutilized subbands in the legacy network that has the least or, better still, no activity at all.

The compelling reasons for the use of such an approach to solve the DSM problem are summarized here.

- First, the Hebbian learning process is a time-varying, highly local correlational learning rule; it provides a good match for DSM that is also a time-varying and localized problem in its own way.
- Second, the algorithm is computationally very simple to implement.
- Last and most importantly, the cognitive radio network operates in a decentralized manner, with the complexity depending on the density of cognitive radio units and not their total number; hence, unlike the centralized approach, it is scalable.

[3]The original self-organizing map used in the DSM is the so-called Tsigankov–Koulakov model, in recognition of its two originators [26].

C. Transmit Power Control

Transmit-power control (TPC), reciprocally coupled to the dynamic spectrum management, is also performed in the transmitter. Its purpose is to control the power transmitted by each cognitive radio user so as to maintain it at a prescribed level low enough not to interfere with a legacy user; moreover, the control is performed in a robust manner. Such a procedure is described in [28], which is based on the following four pillars:

- *game theory*, with emphasis on the Nash equilibrium involving rational players [29], which is a predictive concept well suited for modeling nonstationary processes exemplified by spectrum holes;
- *information theory*, wherein the topic of particular interest is iterative waterfilling [30]; the iterative features of interactive waterfilling include relatively fast rate of convergence, implementable in a decentralized manner (and therefore compatible with the Hebbian-based self-organized DSM described in Section VII), and the efficient use of orthogonal frequency-division multiplexing [31];
- *optimization theory*, in which the practical issue of interest is robustification of the iterative waterfilling algorithm so as to guard against unavoidable uncertainties in a radio environment [28];
- *control theory*, wherein use is made of variational inequality and projected dynamic systems for transforming the iterative waterfilling game into a new representation, namely an ordinary differential equation (ODE) framework for cognitive radio networks that is convenient for analysis of the network behavior [28].

VIII. CONCLUDING REMARKS

Reflecting back over the past five years, the integrative field of cognitive dynamic systems has consolidated, in that we now know how to apply the fundamental principles of cognition to build new generations of engineering systems. However, the progress made has been varied, with cognitive radio extensively enriched, cognitive radar much less, and cognitive control just about to emerge.

Following the order in which these three different engineering manifestations of cognition have been discussed in this article, here is a summary of their individual status.

- *Cognitive radar*, research into which is still in its early stages of development. Nevertheless, the block diagram of Fig. 1 clearly shows the distinct physical locations of the perception–action cycle and memory in a cognitive radar system, the two of which in turn, drive the algorithmic mechanisms responsible for attention and intelligence. The way in which these four building blocks of cognition are realized in cognitive radar provides the basic framework for deeper studies into it. In particular, we need to go beyond a single target in a Gaussian noise environment and start tackling more difficult practical problems involving multiple targets in the presence of ground clutter or sea clutter. Looking further ahead, the grand challenge is to work on a ground-breaking application where cognitive radar can make a significant difference on the world stage. Two such challenges are the deployment of a cognitive network of inexpensive radars for weather forecasting[4] and the deployment of inexpensive surveillance radars across the Great Lakes in North America for national security.
- *Cognitive control*, comparatively speaking, is very much in its fancy. Fig. 2 depicts how a cognitive control system can be structured for the first time in the literature. In this structural composition, as expected, the perception–action cycle and memory feature prominently; as usual, attention and intelligence (driven by perception and memory) manifest themselves algorithmically. In constructing this figure, clever use is made of the two-state model of the system, with the traditional state–space model accounting for a target in the environment and the new idea of entropic state accounting for all the unknown uncertainties and disturbances in the environment. This two-state model is the cardinal characteristic of cognitive control. Moreover, it is equally applicable to cognitive radar on account of the control exercised by the transmitter via the environment.
- *Cognitive radio*, research into which has been growing exponentially since its inception over a decade ago. Whereas cognitive radar and cognitive control mimic the human brain in their respective ways, cognitive radio is inspired by the brain. Nevertheless, the principles of cognition are equally well realized in building cognitive radio, albeit in ways entirely different than it is in cognitive radar and cognitive control. In any event, from a commercializable practical perspective, it is regrettable that despite the advances that have been made on so many fronts, cognitive radio is yet to make a difference in the wireless world. Hopefully, with ever increasing interest in femtocell networks [33], [34], cognitive radio may find its proper niche in the world of wireless communications, hopefully in the not too distant future. ■

[4]In [32], the use of a meteorological network of inexpensive radars has been proposed for the purpose of weather forecasting and the prediction of severe storms, covering the whole of the United States. The use of cognition in such a network makes it all the more powerful.

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