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An Overview of Cognitive Radar: Past, Present, and Future

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INTRODUCTION

Since the dawn of humanity, nature has inspired creative endeavors in all facets of human intellect. In architecture and engineering, biomimetic design has been transformative. For hundreds of years, scientists studied birds to unlock the mysteries of flight. Artificial neural networks have been modeled from theories and observations on the function and structure of the neural synapses in the brain. Additionally, nature's masters of echolocation—bats and dolphins—can detect and track very small prey using sophisticated waveforms, which are varied dynamically through the encounter with the prey [1]. Indeed, it may be well argued that general artificial intelligence can not just match, but surpass, human intelligence, representing the holy grail of biomimetics.

The integration of some form of machine learning into engineering systems has often been referred to using terms such as "smart" or "intelligent." Yet, the description of what exactly makes a sensor "smart" is somewhat nebulous, ranging from sensors that (at a minimum) are networked and can communicate information so as to improve the operational efficiency, to sensors that have an on-board microprocessor for some form of embedded processing for optimal control of the measurement process [2], and to networked sensors that exhibit "distributed intelligence" with capabilities of self-monitoring, making decisions to automatically compensate for changes in their surroundings [3], [4]. Adaptive radars have the capability of changing the processing of received data as a function of time, while fully adaptive radars additional have the capability to adapt on transmit. As a result, "fully adaptive" has often been used synonymously with "cognitive" radar, although over the past 10 years, the term "cognitive" has become increasingly popular, perhaps in part because it evokes a vision of biomimetic artificial intelligence fully integrated into the sensing process, emulating human perception.

Formally, cognition is defined in the Oxford dictionary as "the mental action or process of acquiring knowledge and understanding through thought, experience, and the senses." Although there are many functions of the brain that enable human cognition, the cognitive neuroscientist Dr. Joaquin Fuster [5] has posited that there are five essential processes: 1) the perception-action cycle (PAC), 2) attention, 3) memory, 4) language, and 5) intelligence.

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The PAC is a circular flow of information—a feedback loop—from the environment to the senses (perception), and through motor structures back to the environment (action). Embodied in this cycle is the key idea that cognition is an *interactive* process, where the cognitive entity must respond or change its behavior in some fashion as a result of external stimuli.

In traditional fore-active radar systems, the information flow is one-way: The radar interrogates its surroundings by transmitting a fixed, predefined waveform regardless of any changes in the environment. Adaptive processing may be performed to receive, but results from such processing do not translate into the control of any radar function on transmit (e.g., there is no "action" only "perception"). Current research on cognitive radar aims not only at developing the adaptive hardware and analytical techniques necessary to enable two-way interaction of the radar with its environment for performance optimization, but also on leveraging advances in fields such as stochastic control, optimization, machine learning, and artificial intelligence (AI) to develop engineering analogs to a wide range of cognitive processes.

This article provides an overview of the evolution of cognitive radar, focusing on the crystallization of certain ideas that have led to a formal, technical definition of cognitive radar in the IEEE Standards. A survey of cognitive research trends over the past decade is provided to give insight on the techniques being developed for a wide range of radar applications. Finally, technical challenges to progress in cognitive radar design are discussed as motivation for future work in this field.

HISTORICAL CONTEXT

EARLY PIONEERS

The foundations of cognition in an engineering context date back to Norbert Wiener and his work in stochastic processes, communications, and control in the 1930s. Observing that *"the nervous system and the automatic machine are fundamentally alike in that they are devices, which make decisions on the basis of decisions they made in the past,"* [6] Wiener first coined the term *cybernetics* in 1948 as "the scientific study of control and communication in the animal and the machine." [7] Whereas artificial intelligence strives for computers to intelligently understand the world as an end goal in and of itself, cybernetics exploits this understanding to gain necessary feedback to achieve specific goals. In this way, it embodies a fusion of ideas from Shannon's information theory, originally designed to optimize the transmission of information through communication channels, systems theory and control, and biomimetics.

As the seeds of intelligent computing were being sown, the groundwork for modern methods in statistical signal processing and sequential detection was being laid [8]. Significant advances into the optimal design of sequences of experiments, hypothesis testing, and parameter estimation were made [9], [10]. Central to these works was the idea that the data collection process itself should be a closed-loop process, where a decision on how to collect subsequent samples is determined based on the analysis of prior samples. Early examples of such closed-loop data collections include that of Meier et al. [11], where dynamic state is treated as an adaptive measurement problem, and Athans [12], where an optimal closed-loop selection of measurements is determined in a Kalman filtering problem.

SENSOR AND RADAR MANAGEMENT

A broader, more comprehensive expression of this optimal experiment design problem is embodied by the term "sensor management," which first came into use in the late 1960s. The sensor management paradigm [13] represented the advent of a new generation of sensors, enabled by advancements in sensor and communication technologies in the 1990s, where previously fixed sensor operating parameters could now be adapted during the data collection process using software commands. Existing mathematical constructs for control of decision processes, such as Markov decision processes and multiarmed bandit decision processes, became important facilitators for the development of many approaches for sensor management that remain influential today.

As active sensors, radars have experienced similar, parallel developments, and are particularly well suited for integration of cognition as they possess multiple degrees of freedom via waveform agility and electronically steered antenna arrays. An early, fundamental radar signal processing algorithm that embodies principles of cognition is the least-mean-squares algorithm pioneered by Widrow et al. [14]. This approach enables an antenna array to adaptively form a main lobe, with its direction and beamwidth determined by a control signal, as well as place nulls so as to reject any unwanted signals or noise outside the main lobe, such that the mean-square error is minimized.

Ideally, radar resource management (RRM) can be best accomplished by optimal decision making and control of degrees of freedom (transmitter, receiver, antenna, and power) to maximize the performance of multiple radar functions (e.g., detection, tracking, and classification)—an inherently cognitive process. In the early 1990s, a number of benchmark problems were issued to enable the comparison of techniques that used the beam steering capabilities of phased array antennas to optimize the tracking in the presence of electronic countermeasures, while minimizing false alarms [15], [16]. This has generated a rich body of literature, with solutions involving a combination of multiple hypothesis tracking and interacting multiple model filtering for tracking (e.g., [17], [18]) to optimize performance measures such as signal-to-interference-plus-noise ratio (SINR), track sharpness, and detection threshold.

Increased adaptivity was a common feature of proposed solutions, which involved adaptive revisit time scheduling, adaptive selection of detection thresholds (e.g., constant false alarm rate detectors) [19], and adaptive clutter suppression with space-time adaptive processing (STAP) [20] for improved target detection (DET). Adaptive tracking techniques have varied the measurement times as well as signals used for track updates, based on measurements acquired by a tracker. This feedback loop is used to control the radar such that frequent measurements are made during unpredictable, or rapid dynamic maneuvers, while infrequent measurements are made during predictable periods or steady dynamics. Experimental radar systems, such as the U.K. Multi-function Electronically Scanned Adaptive Radar [21], U.S. Advanced Multifunction RF System, and Royal Canadian Navy Active Phased Array Radar, among others, have been used as a platform for demonstrating the new ideas being developed. Indeed, as early as 1990, researchers proposed future concepts for an intelligent radar that could learn from its environment [22], fusing artificial intelligence with prior knowledge to achieve improved optimization and data-dependent processing for resource management and remote sensing [23].

ENABLING PARADIGMS

Simultaneously, the concept of altering the intrapulse waveform modulation based on the measurements provided by the tracker was also beginning to be explored. This led to the development of methods for optimal waveform selection (e.g., [24], [25]) and adaptive extensions thereof (e.g., [26], [27]). The term *waveform diversity* [28], first introduced in 2002 by Dr. Michael Wicks [29], has become a focal point for research into cognitive radar and is defined in the IEEE Standard 686 as the "optimization (possibly in a dynamically adaptive manner) of the radar waveform to maximize the performance according to particular scenarios and tasks" including exploitation of multiple domains, such as "the antenna radiation pattern (both on transmit and receive), time domain, frequency domain, coding domain, and polarization domain." Examples include waveform selection from among multiple waveform classes, e.g., linear or nonlinear frequency modulation (LFM/NLFM), phase or frequency coding, and ultrawide band waveforms. It could also include adapting the parameters within a waveform class, such as changing the pulse repetition interval, bandwidth, or center frequency [30]. The work by Guerci [31], showed that the optimal waveform that maximizes the SINR arises as the solution to a generalized eigenvalue problem, while methods for imposing constraints on the waveform to make it suitable for practice are also considered.

Investigations into optimal radar waveforms date back to the inception of waveform design in the 1930–1940s, and include important milestones on LFM waveform design [32], the design of optimal coded waveforms to reduce sidelobes, mismatch loss, mainlobe broadening [33], [34], [35], improve pulse compression [36], and ambiguity function design for improved detection, [37] or target matched illumination [38]. In 1953, Dr. Philip Woodward published a seminal work [39] in which he introduced information theory in the context of radar detection, stating "the problem of reception is to gain information from a mixture of signal and unwanted noise," much of the literature has been concerned with "methods of obtaining as large a signal to-noise ratio (SNR) as possible on the grounds that noise ultimately limits sensitivity and the less there is of it the better. [While] valid ... [this] can be misleading, for there is no general theorem that maximum output SNR ensures maximum gain of information." Indeed, his book ends lamenting that "the basic question of what to transmit remains substantially unanswered."

Although this remains an open question, Woodward's work laid the foundation for subsequent information-theoretic waveform design approaches, including that of Bell [40], which proposed maximization of the mutual information between a random extended target and the received signal for optimal information extraction [41]. Dr. David Middleton's 1959 work on statistical communication theory [42] took a giant leap forward by developing a framework for "joint optimization of transmission and reception by choice of signal waveform." The approach developed was rooted in Bayesian decision theory and provided for system optimization through choice of waveform at the transmitter and minimization of a cost function, which provides for a value judgment of "error" and thus guides the decisions. Middleton's work thus provides a concrete analytical framework for implementation of the perception action cycle in a radar transceiver, which has served as groundwork for future milestones in cognitive radar research [43], [44]. However, Middleton also notes the difficulty in selection of optimality criteria and the assignment of costs accurately in an objective fashion. The cost may not be unique and reflects the "unavoidable uncertainty...that is the price we must pay for an inevitably incomplete knowledge of the world around us." In this remark, recognition that the *a priori* information gained from previous experience is highly likely to be inadequate is plain. Nevertheless, concludes Middleton, "the more uncertain our *a priori* data, the greater the expected cost of operation—we cannot avoid paying for ignorance."

Thus, complementary and equally essential as waveform diversity is the knowledge-aided signal processing paradigm, which, to put it simply, aims to exploit prior knowledge to improve the sensor performance. Originally proposed in the context of STAP to improve the adaptive suppression of clutter in nonhomogeneous clutter environments [45], prior knowledge of the interference environment was proposed for intelligent training and filter selection, as well as data prewhitening [46]. Prior knowledge in this example could take the form of a terrain map or even images from other sensors, such as hyperspectral imagers [47]. In 2002, the Defense Advanced Research Projects Agency (DARPA) initiated the Knowledge-Aided Sensor Signal Processing and Expert Reasoning Program to more broadly address the challenge of minimizing sensor deficiencies through exploitation of prior knowledge. Since then, this concept has been applied to numerous other radar problems, such as 2-D autofocus for spotlight SAR [48], tracking [49], ground moving target indication [50], and radar identification [51].

Perhaps unsurprisingly, both waveform diversity and knowledge-aided signal processing have analogs in the natural world. Bats have been reported to use many different waveforms (e.g., constant frequency, linear, and hyperbolic frequency modulation, multiple harmonics, and even other types of nonlinear frequency modulation) in pursuit of different activities, such as searching for prey, social calls for communications with other bats, and hunting—definitely a wonderful example of waveform diversity in a multifunctional active sensing system! Similarly, as humans, we are all aware of our own capacity to learn and thereby adapt our behavior as a result. Children will not touch a hot cup of coffee more than once, quickly learning that touching hot things hurt. We consult books, our friends, and remember past experiences when guiding ourselves to future decisions—and we would view doing so as "smart."

VISION FOR THE FUTURE

The crystallization of cognitive radar as a formal concept for next-generation radar reflects a conscious evolution in design that incorporates more and more features of human cognitive capabilities into the radar architecture to achieve increased autonomy and performance optimization in dynamically changing environments. It thus provides a vision for building upon the designs of existing radar systems, some of which may now in retrospect be recognized as having some cognitive characteristics. One hierarchy of human cognitive capabilities is given by Bloom's taxonomy, which originates from cognitive psychology and is shown in Figure 1. It may be argued that existing approaches map to only the lowest cognitive levels. While databases or prior measurements comprise "remembered" prior knowledge, most signal processing and machine learning algorithms represent methods used for "understanding." Knowledge-aided signal processing represents a higher level of cognition than adaptive processing as it does, to a certain extent, permit use of information in new situations.

An early expression of such a vision was given in 2003 with the introduction of the Sensors as Robots [52] concept: "As more knowledgeable and proven techniques are obtained, radar systems will begin to function as robots...

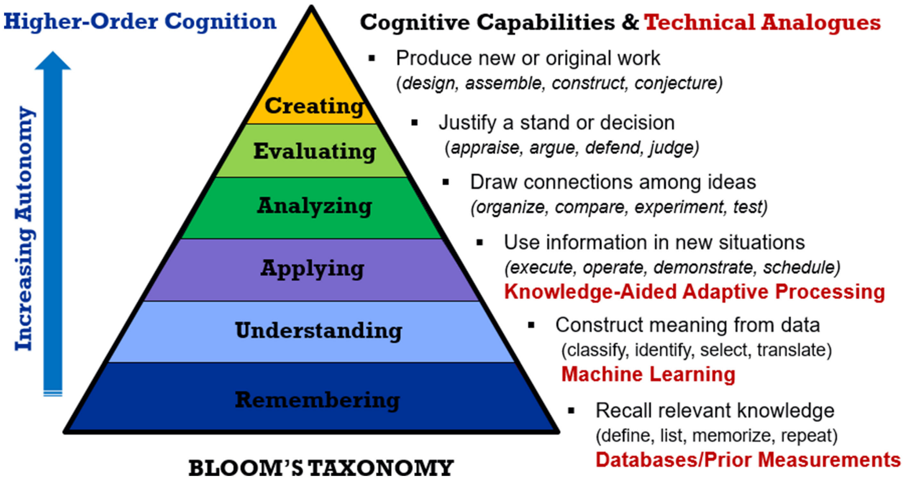

Figure 1.
Bloom's Taxonomy.

the final step will be autonomous operation of these sensors under the intelligent robot paradigm." [53] Whereas traditionally sensors have been a means for providing informational inputs to robots, this concept flipped the equation: now, sensors themselves would be autonomous, intelligent agents, "figuring out" how best to go about their tasks.

The term "cognitive radar" itself was first coined by Dr. Simon Haykin that same year [54], which drew heavily on ideas developed by Fuster in cognitive neuroscience. Haykin's work built upon past work in cybernetics, artificial neural networks, self-organized learning, and Bayesian decision theory to propose engineering analogs for implementation of four of the main cognitive features identified by Fuster: the PAC, memory, attention, and intelligence [55]. The parallels between the PAC envisioned by Fuster and that describing the operation of a radar transceiver for remote sensing may be observed from Figure 2. Both exhibit the common feature of providing for closed-loop feedback in the radar transceiver through interaction with the environment. Through the *perceptual hierarchy*, dynamic changes in the environment may be analyzed "bottom-up ... and lead to the processing of further actions, top-down through the executive hierarchy, toward motor effectors." [56] Note that there may be interaction and feedback along different levels of the perceptive and executive hierarchies. Hierarchy is reflected also in the cybernetics research of Jens Rasmussen [57], [58] in the 1980s, in which human behavior was described in terms of three levels: skill-based, rule-based, and knowledge-based. Skill-based behavior described subconscious yet efficient PACs, which, according to Bruggenwirth [59], maps to basic signal processing and generation units in a radar system. Rule-based behavior is applied by humans in familiar situations, and although consciously controlled, the action is reactive and thus results in procedures that have been learned over time. In radar, the parallel operation would be the procedures that have been prestored or hard-coded, based upon offline simulations and the analysis of prior experience. The highest layer is the knowledge-based layer, in which solutions to problems that arise in unfamiliar situations are derived using knowledge-based deliberation. In cognitive radar, a similar level of behavior would be implemented by search or inference

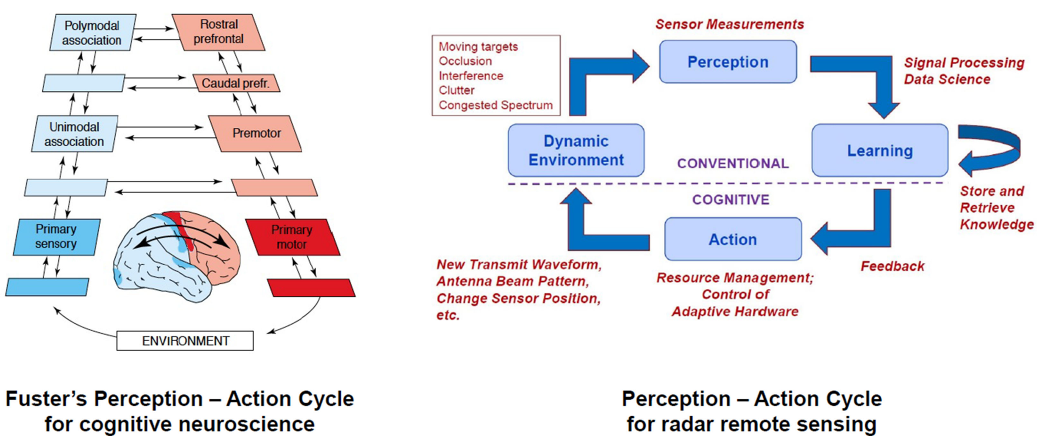

Figure 2.
Perception Action Cycle for Radar Remote Sensing.

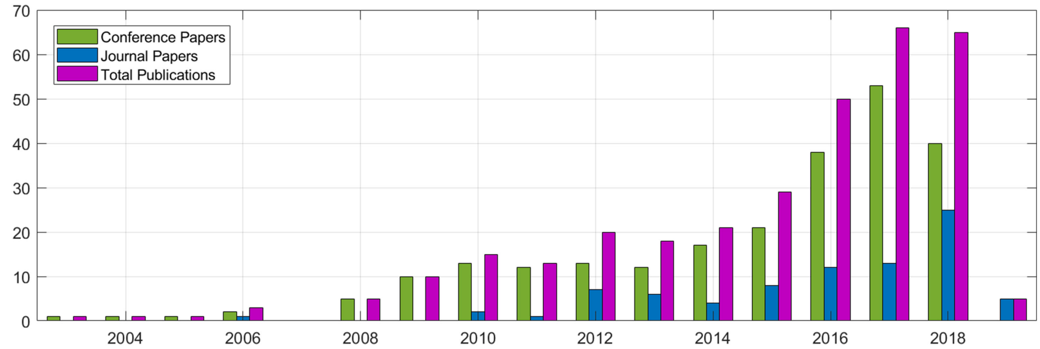

Figure 3.
Publications on cognitive radar (2003–March 2019).

algorithms that utilize all available knowledge derived from sensors, mission objectives, and memory.

CURRENT PROGRAMATIC THRUSTS

Haykin's work thus marked the beginning of concerted efforts into formulating and defining exactly what the architecture and characteristics of future cognitive radar systems would be like. The investigation into tangible implementations was in part spurred by the challenges imposed by an increasingly congested RF spectrum, while adaptivity on transmit and controlled illumination were being enabled by advances in electronics, embedded computing, adaptable RF components (amplifiers, filters), small, low cost, low-power RF transceivers, and software-defined radio platforms.

In the early 2000, two programs initiated by the U.S. Air Force Office of Scientific Research (AFOSR) and DARPA stimulated research that would serve as important precursors to cognitive radar: namely, the multidisciplinary University Research Initiative "Waveform Diversity for Full Spectral Dominance" Program and "Waveform Agile Sensing and Processing" Program. The aims of these programs were to devise methods for the optimization of radar performance under time-varying environmental conditions, including a capability to respond to unknown dynamic target parameters through waveform agility. Together, these two programs advanced the requisite mathematical foundations, incorporating the resulting theories into a systems design perspective.

Subsequently, AFOSR would take one step further in formulating the theories required for the PAC implementation by initiating the dynamic data driven application systems (DDDAS) program, defining the DDDAS concept as "the ability to dynamically incorporate additional data into an executing application, and in reverse, the ability of an application to dynamically steer the measurement (instrumentation and control) components of the application system." [60] Efforts are focused on four specific science and technology frontiers: 1) applications modeling, 2) advances in mathematical and statistical algorithms, 3) application measurement systems and methods, and 4) software infrastructures and other systems software. This is complemented by the U.S. Air Force Research Laboratory's program in Fully Adaptive Radar, led by Dr. Muralidhar Rangaswamy, which aims to close the loop on the radar operation at multiple levels in an attempt to bring to bear the sense-learn-adapt paradigm to maximize the system performance by making adaptive and optimal use of all available degrees of freedom. Significant advances from this program include: a) performance bounds for closed-loop radar tracking with controlled laboratory demonstration of this concept; b) a powerful modeling and simulation capability for generating training data for signal-dependent interference scenarios; c) signal processing algorithms for joint adaptive radar processing on transmit and receive; d) waveform design and optimization principles; e) convex optimization for adaptive radar covariance matrix estimation; f) ambiguity function analysis and Cramér-Rao bounds for distributed passive radar (which enable sensor geometry placement and illuminator selection for maximizing system performance); and, g) passive radar detection involving noisy reference channels with analytical performance guarantees. Most importantly, the modeling and simulation capability developed under this program has transitioned to a program under support from the Office of Secretary of Defense.

This intense research activity has resulted in a dramatic increase in publications over the past few years, as shown by Figure 3, which surveys publications in the IEEEXplore and SPIE Digital Libraries that reference cognitive or fully adaptive radar in their title or text. Much of this work is theoretical in nature and substantiated with simulation results; however, there are singular works (notably at Ohio State University [61], FFI [62] and ArmaSuisse [63]) that experimentally validate performance gains due to cognitive design. Cognitive radars face unique challenges to requirements specification and validation, as discussed in more detail in Section V. As enabling technologies mature, continued research will push forward the design of next-generation radar systems with ever increasing cognitive capabilities.

DEFINITION AND CLASSIFICATION OF COGNITIVE RADAR SYSTEMS

The increasingly common use of the relatively new term "cognitive radar" has resulted in some debate as to how a cognitive radar actually differs from other terms used—such as intelligent or smart radar, fully adaptive radar (FAR), and cognitive FAR—if at all; and what the technical requirements for describing a radar as "cognitive" are. Descriptions of cognitive radar that have been proffered include the following:

1) "Cognitive radar (CR), which differs from traditional active radar as well as fore-active radar by virtue of the following capability: The development of rules of behavior in a self-organized manner through a process called learning from experience that results from continued interactions with the environment." (Haykin et al. [55]).
2) "A system that is capable of sensing, learning, and adapting to complex situations with performance approaching or exceeding that achievable by a subject matter expert." (Guerci et al. [64]).
3) "While a fully adaptive radar may employ feedback and use prior knowledge stored in memory, a cognitive radar predicts the consequences of actions, performs explicit decision-making, learns from the environment, and uses memory to store the learned knowledge." (Bell et al. [44]).
4) "Cognitive radar is a radar system that acquires knowledge and understanding of its operating environment through online estimation, reasoning, and learning or from databases comprising context information. Cognitive radar then exploits this acquired knowledge and understanding to enhance information extraction, data processing, and radar management." (Charlish et al. [65] in 2017).
5) "A cognitive radar system follows the four principles of cognition: The perception-action cycle, memory, attention, and intelligence." (Farina et al. [66] in 2017).

As part of the work of the NATO SET-227 Task Group on Cognitive Radar, active between 2015 and 2019, and of which all the authors are a member, numerous discussions on the characteristics of cognitive radar were conducted, which highlighted the need for and insights on what a definition might look like. In 2017, Dr. Chris Baker and Dr. Hugh Griffiths spearheaded efforts to include a formal definition of cognitive radar in the IEEE Standard Radar Definitions 686 [67]: *"A radar system that in some sense displays intelligence, adapting its operation and its processing in response to a changing environment and target scene. In comparison to adaptive radar, cognitive radar learns to adapt operating parameters as well as processing parameters and may do so over extended time periods."*

From these definitions, it may be seen that there is general agreement in the cognitive radar research community concerning some common elements that must be present in a radar system for it to be classified as cognitive. These are the same characteristics identified by Fuster [5] within the context of cognitive psychology: the PAC, attention, and language. First, the PAC is the framework which provides for closed-loop feedback in the radar transceiver. If these functions were not to exist, then the ability to adapt based on the system's perception of the environment would be absent. Second, attention enables the radar to focus its resources on critical aspects of the observed scene. This is a characteristic that all multifunctional radars must possess as a resource management requirement. Finally, language may be viewed as the ability to encode data such that it is possible for the system to store, recall, and disseminate the information both internally and externally, but more broadly can embody any set of rules for communicating information, including internal messaging as part of decision making. As the storage and recall of information are essential to learning and decision making, without it the system would arguable be hindered from being responsive to any perception of outside stimuli.

The remaining two elements of Fuster's framework for cognition includes memory and intelligence, and are aspects regarding which designs begin to diverge. Here, memory alludes not just to physical storage devices, which could hold prior knowledge, but to memories of learned experiences gained during the course of extended periods of observations. Thus, memory can be said to function at varying levels: 1) as a fixed internal knowledge base, 2) as a dynamic knowledge base updated by an external source, and 3) as an online learning capable system. Similarly, intelligence may be characterized into varying degrees based upon 1) the complexity of the decision-making mechanism, and 2) capacity to plan long-term behavior. Conceivably, a radar operating at a high level of cognition would even be anticipative, planning based on its predictions of future outcomes.

Thus, an overarching classification scheme that would allow flexibility in the definition and identification of cognitive characteristics as recently been proposed [68], which relies on grading systems based on the degree of planning sophistication (P), decision mechanism sophistication (D), and memory sophistication (M). This taxonomy is depicted by the 3-D synthetic classification Space,

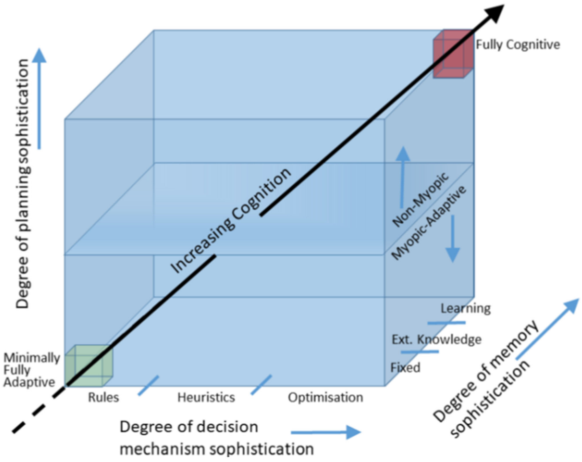

Figure 4.
3D Synthetic Cognitive Space. [68].

shown in Figure 4, and provides a means for acknowledging the cognitive aspects of existing radar systems, while providing a scale to identify the ways in which next-generation cognitive radar systems have advanced. While [68] Horne et al. also provided for a numerical scale to match this framework, it is not so much the numbers used, but the recognition that systems ought not be judged in a binary, black, and white fashion, that is significant.

TECHNIQUES AND APPLICATIONS

Over the past 15 years, research into cognitive radar design has spanned a wide range of applications, using many different techniques that draw on prior advancements in Bayesian decision theory, information theory, decision theoretic approaches (including fuzzy logic, rule-based systems, metaheuristic algorithms, and Markov decision processes), dynamic programming, optimization [e.g., maximization of SNR, convex optimization, and minimization of the Cramér-Rao Lower Bound (CRLB)], and game theory. Figure 5 shows a histogram of applications and techniques based on the 83 journal papers and 238 conference papers surveyed in Figure 3. A complete listing of this literature may be found in the Final Report of the NATO SET-227 Task Group on Cognitive Radar. This histogram reveals that while many applications are being considered, a few have been of great interest; namely, concepts for transceiver architecture and mechanisms for cognitive processes (ARCH), radar resource management (RRM), target detection (DET), localization/direction-of-arrival estimation (LOC) and tracking (TRK), radar networks (RN), and spectrum sharing (SS). Most works involve some form of waveform selection, optimization, and design (WD), while adaptive control of antenna beam pattern, design of adaptive RF components (ADPTHARD) as well as experimental testing (EXP) have also been explored.

Spectrum sharing has been a topic of focus due to the urgent challenges presented by a congested RF spectrum to military and civilian systems alike. The availability of frequency spectrum for multifunction radar systems is being continuously diminished. The growth of activities in civil communications and the emergence of new technologies and services that have a great demand for spectrum allocation induce a very strong pressure upon the frequency channels currently allocated to radars. In the VHF (30–300 MHz) and UHF (300–1000 MHz) bands, where for instance foliage penetrating radars are active, interference can come from broadcast and TV services. Recently, these bands have seen the introduction of the IEEE802.11ah and IEEE802.11af protocols for Internet of Things (IoT) and Cognitive Radio Technology, respectively. In the U.S., the National Telecommunications and Information Administration has devoted efforts on identifying frequency bands that could be made available for wireless broadband service

Application Codes

ARCH: architecture/general
RMG: resource management
DET: detection
TRK: tracking
EST: estimation
LOC: localization
PASSR: passive radar
RN: radar networks/MIMO
WD: waveform diversity
SAR: SAR imaging
SS: spectrum sharing
CC2: command & control
OTHR: over-the-horizon radar
LPI: low probability intercept
EW: electronic warfare
THR: threat assessment
BF: beamforming
NLR: nonlinear radar
REMS: remote sensing
HLTH: health
TRAN: transportation
TESTM: testing methodology

APPLICATIONS	TECHNIQUES																			
	CONCEPT	KA	BAYES	MARKOV	DYNP	CONVOPT	CS	OOPT	SINRMAX	IT	FUSION	FRFT	MODEUPT	MACHLRN	ITER	ADPTHARD	ANTENCON	GAME	EXP	TOTAL
ARCH	23		2	3	2			1		1				2		3	1		1	39
RMG	2		5	1	2			4					1	2				2	1	20
DET	5	7	6		2	2	2	8	7	4	2	1	1	3	4		1		1	56
TRK	4	1	21	3	3			13	4	4	3		4	3	1	3	2		12	81
EST	1	1	6	1			4	6	1	1				1	4	2				28
LOC	5		4			2	2	7					1		2	4	1		2	30
ATR	1		3	2			1	1	1	2			2	4	1					18
PASSR	5			1				4												10
RN	10	2	10			2	2	11	5	4	2		1	2	2	1	1	2	3	60
SAR	1	1					1	2					1						1	7
SS	6		1	5		1	10	10	7	5	1		2	6	3	7	1		12	76
WD	4	2	12	3	2	6		34	21	15	1	2	2	2	11	2			6	115
CC2	1												2		1				2	6
OTHR	2							1	1		1		2		1					8
LPI													1							1
EW	7					1	1	5	4	2			1	4		1	1	1	1	29
THR														2			1			3
BF			2					3		1			1							7
NLR	1																		1	2
REMS														1		1				2
HLTH			1						1		1									3
TRAN	1		1				1	2	1	1				1						8
TESTM																			1	1
TOTAL	82	14	74	19	9	14	24	112	53	40	11	3	22	32	30	24	9	5	44	

Technique Codes

CONCEPT: concept/general/ad hoc
KA: knowledge-aided
BAYES: Bayesian framework
MARKOV: Markov processes/models
DYNP: dynamic programming
CONVOPT: convex optimization
CS: compressive sensing
SINRMAX: SINR maximization
OOPT: other optimization methods
IT: information theory
FUSION: fusion
FRFT: fractional fourier transform
MODUPDT: model updating
MACHLRN: machine learning
ITER: iteration
ADPTHARD: adaptive hardware
ANTENCON: antenna control
GAME: game theory
EXP: experimental work

Figure 5.
Techniques and applications investigated in cognitive radar publications (2003–March 2019).

provisioning, resulting in allocation of 115 MHz of additional spectrum (1695–1710 MHz and 3550–3650 MHz bands) and a conflict with L-band (1–2 GHz) radars. An example is the air route surveillance radar used by the Federal Aviation Administration that shares the spectral band with wireless interoperability microwave access (WiMAX) devices. The majority of the LTE services, e.g., WiMAX LTE, LTE global system for mobile (GPS) are operative in the S-band (2–4 GHz), where they interfere with surveillance radars. In C-band, the spectrum has been eroded by allocation of the 5-GHz band to 802.11a/ac Wireless LAN Technology. X-band is still free from communication services interference, but when 5G systems become fully operative, even the Ka, V, and W bands will be dense.

Thus, in a near future, radars will likely be required to share their bandwidth with communication systems, where the latter ones, quite often, are the primary users. Yet, this problem cannot be addressed only by traditional modes of operation, such as antenna beamforming or interference cancellation on receive. Future systems require the ability to anticipate the behavior of radiators in the operational environment and to adapt its transmission in a cognitive fashion based upon spectrum availability. Radar cognition in this case is based on two main concepts: spectrum sensing and spectrum sharing. Spectrum sensing aims at recognizing frequencies used by other systems occupying the same spectrum in real time, while spectrum sharing tries to limit interference from the radar to other services and vice versa.

Furthermore, battlespaces of the future will not involve isolated geographical regions with limited technological resources, but will require seamless integration of networked ground-based, airborne, and space-based sensors at different levels, automated to find, identify, and track threats in increasingly complex and diverse environments. The challenge of spectrum congestion is one dimensional of this broader battlespace. Technological advancements have not just benefited modern society, but have also made it easier for adversaries to make their forces both mobile and elusive, such through use of small drones to attack a diverse set of tactical targets, previously not exposed to any threat. Both force protection and forward operations require pervasive, robust, and agile sensing that can optimize multiple missions in a dynamic environment. This operational requirement directly maps to the definition of what a cognitive radar strives to accomplish, and indeed, the generalized notion of a cognitive sensor network, empowered with multiple layers of hierarchical cognitive processing.

CHALLENGES

While the potential of cognitive approaches to enhance existing radar performance in almost all respects has led to great progress, full achievement of this potential faces several important challenges.

RESEARCH

Two key challenges to the research and development (R&D) of cognitive radars are the development of assessment and evaluation tools, as well as experimental testing methodologies. A common terminology for describing and comparing the characteristics of cognitive radar is needed. Although the ontology by Kreucher et al. [68] provides a graded framework for assessment, as algorithms and architectures advance, this will need to be further revised, detailed, and adapted. Furthermore, evaluation of cognitive radar algorithm performance requires quantitative metrics. This is not just vital for analyzing radar performance offline, but is also the basis for forming cost or reward functions on which online optimization is based. Although system performance will still be measured in terms of standard performance metrics—such as probability of target detection and false alarm, mean square error in tracking systems, and probability of correct classification in automatic target recognition systems—cognitive systems require additional metrics that quantify the gain in performance achieved at the cost of using system resources.

Common approaches fall into the categories of information-driven [69], task-driven, or quality-of-service (QoS). Information theoretic surrogates, such as mutual information and Bayesian information, can be very valuable in optimizing the waveform to increase the amount of information gained. However, when allocating resources, they tend to give a bias toward information rich tasks, such as tracking high SNR targets, which may not be the targets of most interest to the mission. Task-driven methods optimize each task using a performance measure that is specific to the task. This is effective in optimization of individual tasks; however, multiple-task performance measures, such as in a multifunction radar system, is a particularly difficult task. To this end, Mitchell et. al [70] provided some strategies for developing cost functions for executive processor optimization by combining performance and measurement metrics. QoS methods [65] circumvent the problem of combining task performance measures by combining and optimizing utilities, which represent the mission-relevant satisfaction that is associated with a task performance level, leading to mission relevant resource allocation. This issue of cost and reward function design remains more of an art than a science, and will continue to be a major research challenge.

A related, but unique, challenge to cognitive radar design is experimental testing, since the transmit waveform and settings are adapted during operation. With more sophisticated simulations, new development and qualification processes, including software-in-the-loop testing, can be developed and will contribute to cognitive radar validation. Evaluation on precollected data sets is no longer possible, except in limited cases where the data can be oversampled in some manner and then down-selected after the fact to emulate cognitive radar selection of parameters. For example, Bell et al. [71], the pulse-Doppler software defined radar (SDR) collected data at a high-pulse repetition frequency (PRF). The cognitive algorithm determined the number of pulses and required PRF (up to the actual PRF) and then downsampled the pulses to get the correct number of pulses at the desired PRF. A similar process was used by Oechslin et al. [72].

Thus, as of early 2015, the performance of advanced concepts for cognitive radar was only examined through simulation, or in the best case, using prerecorded data. There had been no reports of experimentally validated concepts, largely because the necessary hardware to test them had not been developed. However, this step is vital to establish the true performance potential of applying cognitive processing methods. In the last few years, cognitive radar testbeds have been developed at the Ohio State University (OSU) [61], Armasuisse [63], and FFI, [62] and real-time experimental evaluations have been reported by Smith et al. [61], [62], [70], [73]. Challenges in real-time experimentation involve repeatability of experiments, determining what is truth, determining metrics that can be obtained from the data and used for optimization, and timely computation. Robustness to modeling and computational errors has been largely ignored in the research to-date, but is a critical issue that has just begun to be investigated [74].

REQUIREMENTS DEFINITION

Inherent to the radar procurement process is the specification of the required radar performance. The typical approach is to define a number of worst cases and specify the performance that the radar should always achieve for these example worst cases. This approach is valid for noncognitive radar systems that do not reconfigure based on the current environment, as the single radar configuration that matches the worst acceptable performance may be utilized. But, for a cognitive radar, the worst-case scenario is unlikely to be selected as a solution, because this requirement specification does not warrant the additional development cost of cognition. Thus, using a limited set of worst-case scenarios does not make sense for cognitive radars, and an alternative approach is required. A related issue is that for a cognitive radar, the performance potentially depends on the amount of learnt or context knowledge available. To define a processing for requirements specification that considers learning and context, criteria weighing the importance of performance metrics, as well as quantification of the tradeoffs evaluated, will be needed to compare candidate solutions.

RELIABILITY OF PAST KNOWLEDGE AND LEARNING FROM EXPERIENCES

As the capabilities of radar transceivers advance to jointly sense, learn, and adapt on both transmit and receive, new opportunities and vulnerabilities will become part of the changing dynamics of electronic warfare (EW). While boosting sensing capabilities so that friendly systems can defend against jamming and other countermeasures, and leaving adversaries no place left to hide, cognitive radar nonetheless retains the risk that it could be beguiled into poor decisions, much akin to the human counterpart that has inspired its design. Thus, a cognitive radar requires a means for evaluating and ensuring the reliability of its knowledge sources: both sources of past knowledge, provided through access of databases, as well as knowledge learned through operational experience. This includes considering not only the possibility for deception, but also whether the validity of data degrades over time. Thus, understanding how to design a radar so that it can learn from past mistakes caused by poor decisions, and thereby enable it to gain the ability of making informed decisions in the future, will be critical.

LAWS AND REGULATIONS

Cognition in radar requires waveforms and circuits to be reconfigurable and optimizable in real time. However, an often overlooked operational constraint is the national and international laws governing operation. Naturally, the transmissions of radars and other devices are all regulated (e.g., ITU emission standard [75]). While radar transmissions should not exceed the limits imposed by regulation, unwanted emissions, due to nonlinearity in the transmitter and to the steep rise and fall times of the radar pulses, often occur [76]. Especially in cognitive systems, the dynamic reconfiguration of the transmission spectrum is not always easily implementable and may result in out-of-band (OOB) transmissions. This is primarily due to the nonlinear operational regime of the high-power radar RF circuitry (particularly for vacuum tube amplifiers), which causes nonnegligible spectral spreading outside the assigned radar band. This makes coexistence of communications and radar systems in close bands with narrow guard bands difficult [76]. Magnetron tubes, quite often used in legacy radar systems because they are inexpensive, have serious drawbacks in term of spectral purity. To reduce OOB emissions, bandpass filters are often used, though the cost of this improvement in spectral purity means a significant loss in the effective transmitted power. Solid-state-based amplifiers are much easier to control in terms of OOB, but cannot provide the high peak power of tubes and represent a minority of current operational systems.

An alternative short-term approach is to instead select from a predefined set of waveforms or waveform parameters. Many modern radars already have this capability, and a first step toward making cognitive radars a reality could be choosing among the set of allowable waveforms [29]. Alternatively, cognitive algorithms could also be implemented on passive systems [77]. Longer term, not only are technical solutions required to ensure cognitive radars can operate within regulatory bounds, but also new concepts and perspectives toward legal jurisprudence will be needed. The advent of artificial intelligence, across all engineering disciplines, has raised legal questions of responsibility of accountability of engineering systems capable of autonomous or semiautonomous decision making. How artificial intelligence will change jurisprudence on legal personhood and assignment of liability is a question that could drive the outcome of ongoing debates regarding banning versus regulating certain AI-based technologies, and indeed the future of cognitive radar design.

OPEN QUESTIONS

In addition to the technical and practical challenges described above, many open questions remain around cognitive radar design and implementation. Related to the issue of performance validation, for example, is the question of whether end users will accept fielding a sensor whose behavior is not exactly predictable. How robust will cognitive systems be? Or will system decision errors result in flamboyant failures far more severe than suboptimal performance metrics? Just as dealing with people can be frustrating, in the long run will the autonomy of radar systems truly lead to the benefits as the designers intended? As advances in real-time processing and adaptive hardware enable the physical construction of reconfigurable systems, trends in artificial intelligence will drive cognitive designs, necessitating human adaptation to the new and unique challenges posed.

CONCLUSION

Cognitive radar is an emerging technology that has been inspired by advancements in cybernetics, man–machine interaction, waveform diversity, knowledge-aided signal processing, and resource management. Although the term “cognitive radar” has just been around for about 15 years, it is perhaps best viewed, however, not as something that has suddenly been developed, but as the product of a steady evolution in design that aspires toward the achievement of cognition as seen in its counterparts in nature, such as exemplified by the sensing capabilities of bats and dolphins, or the intellectual decision-making of humans. This article has strived to provide a broad overview of recent progress and ideas in cognitive radar design, including challenges that will need to be addressed looking toward the future.

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