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A view on radar and communication systems coexistence and dual functionality in the era of spectrum sensing

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ABSTRACT

In this paper, we discuss the state of radio frequency (RF) coexistence and how it benefits from dynamic spectrum sensing. We categorize coexistence of radar and communications in terms of their cooperation and non-cooperation in using the spectrum as well as their roles as primary, secondary, and dual users of the frequency bands. We describe the ways the radar can alter its parameters in response to the sensed spectrum through the completion of the cognitive perception-action cycle. The paper takes a broad view of the field and puts in context coordination of the two RF services through co-design, dual function, signal as well as system of opportunities. We present possible future research directions which will enable further innovations and progress in spectrum sharing and RF interference avoidance and mitigation.

1. Introduction

The radio frequency (RF) congestion and competition for bandwidth is underscored in Fig. 1, which depicts coexistence of several RF users, including radio telescopes, telemetry, wireless communications and radar. In particular, radar and communication systems require frequency bandwidth to deliver high performance and meet their individual functionalities. Whereas bandwidth plays a fundamental role in radar target detection, localization, and classification, it also provides high data rate and improves quality of service in communications. The fact that the entire frequency spectrum cannot be fully, or in a major part, given to either system, has traditionally invoked the concept of dividing the spectrum into agreeable sharing strategies where each system is allocated with known fixed frequency bands [1,2]. Metaphorically, sharing in this sense is like sharing an apple, each person has their own fixed portion from the start. Using a set theory analogy, this type of sharing is equivalent to having the number of sets equals to the number of RF services and sensing where each set represents a specific bandwidth. The sets are mutually exclusive, and their union represent the total available bandwidth.

Spectrum sharing in an “apple-like” or a fixed set sense is not a coexistence. It is inefficient, does not address the growing demand of bandwidth from the wireless communications industry, and does not accommodate the growing number of RF services and sensing for terrestrial and extra-terrestrial RF activities. This has given rise to sharing in a different sense where each system is entitled to use all frequency bands within a large spectrum bandwidth. To this end, and in broad terms, an RF system can be given the “right of way,” when it is considered a primary user, or required, as secondary, to “yield” to other users; both situations are conducted within the framework of cooperative and non-cooperative coexistence. An emerging area in non-cooperation radar sharing considers autonomous solutions for real-time spectrum access in dynamic environments [3]. These dynamic spectrum access (DSA) strategies utilize supplemental information in the form of spectrum sensing data, thus allowing the radar to tailor its parameters in order to autonomously respond to the dynamic environment. Implementation of this strategy suggests specialized waveform design (waveform diversity) via the perception action cycle (PAC) of cognitive radar models [4,5].

This paper presents the “opinion” of the authors on the current state of research and trends in RF coexistence of radar and communication systems and their dual functionality in the era of spectrum sensing. While there could be different opinions and perspectives from the research community, we attempt to use common definitions and terminologies and capture the main thrusts, highlight the trade-offs and interplay of the underlying objectives and constraints, and link past with present and future radar aided by spectrum sensing. Our opinion of the current standing of this area and its future outlook is influenced by our individual and

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Fig. 1. Spectrum sharing is a challenge for legacy radar incapable of accepting and avoiding interference from commercial RF systems.

combined knowledge in active RF sensing as well as our awareness of, and exposures to, key contributions to advances in spectrum sensing and its application to radar.

This paper's focus is on the radar coexistence paradigm that is built on spectrum sensing. We classify radars according to their primary, secondary, and dual user roles. We also consider DSA for a radar network and delineate the offerings and challenges of coordinating the spectrum findings of multi-function sensor nodes. We show how waveform design impacts coexistence and guides the trade-off between multiple performance metrics. Understanding this trade-off is key to selecting radar waveforms and undertaking actions based on the conditions of the target and spectral environments [5–7]. We examine how to autonomously operationalize this selection process using the PAC for real time DSA. Motivated by the sensing paradigm, we discuss multi-function sensor nodes that are capable of spectrum sensing, communications, and radar. In particular, we provide a concise review of joint radar and communication systems where the two RF systems are housed on the same platform [8,9]. We briefly discuss mode priority for switching between radar and communication functionalities and summarize the main strategies for embedding communication signals in the radar's beams and pulses; a process that defines dual function radar communication (DFRC) systems. From an over-arching perspective, we present an ontology to combine cognitive functionalities into a network of multi-function sensor nodes. This functionality requires control at the "meta" level, hence the emerging topic of metacognitive radar is discussed for advanced adaptation in disparate environments [3,10]. We take the opportunity of writing this paper to also summarize our vision of software defined radar technology and its impact on spectrum sharing. Throughout the paper, we emphasize the concepts rather than analysis and use illustrative figures instead of equations or mathematical formulas.

The paper is organized as follows. Section 2 discusses non-cooperative radar coexistence and delineates the radar's role as a primary, secondary, or dual spectrum user. It puts in context dynamic spectrum sensing in aiding radar to coexist without interference to, or from other, occupants of the spectrum. Section 3 presents cooperative coexistence and provides different strategies for coordination between radar and communication signals. It includes dual function systems and puts passive radar under the auspices of cooperative coexistence. Section 4 views coexistence from a radar network perspective and from the perspective of networked sensors for event monitoring and information integrations. Section 5 focusses on waveform design and diversity in reaction to sensed spectrum information. It confirms the abilities of the radar to quickly respond to fast time-varying spectrum by changing its settings and parameters. Section 6 expands on one emerging co-operative coexistence, namely DFRC systems and summarizes different possible strategies for embedding communication signals in radar beams and pulses. Section 7 discusses the emerging over-arching approach of metacognition which guides and coordinates the execution of different possible responses of the radar to spectrum occupancy. Section 8 presents key open problems in this field which are poised to contribute to further progress in RF coexistence via sensing.

2. Non-cooperative radar coexistence

Fig. 2 considers categories of radar coexistence which occurs when a radar occupies the same frequency band as other RF systems, or devices, not necessarily at the same time [1,7,11–20]. The primary RF systems of consideration are commercial communications systems, but may include unlicensed, government, or other military RF systems. As depicted in the figure, in the broadest terms, radar coexistence can be cooperative or non-cooperative. In this section, we use Fig. 2 to describe non-cooperative coexistence and also refer to it in the next section when addressing cooperative coexistence. Both sections focus on the different forms of RF coexistence and different levels of collaborations between radar and communications. Non-cooperative radar coexistence approaches attempt, as the word implies, to mitigate mutual interference without a direct exchange of information with other RF systems. The user categories considered for non-cooperative radar spectrum access models are primary, secondary, and dual role. Although the following sub-sections describe each model in detail, the primary focus of this paper is the radar's role as a secondary (Section 2.2) and dual (Section 2.3) user. These two roles require the exploration of waveform diversity and cognitive radar models for possible future spectrum sharing applications that involve both radar and communication systems.

2.1. Radar as the primary user for non-cooperative coexistence

The first block on the left under the non-cooperative coexistence of Fig. 2 grants the radar, as the primary user, exclusive rights to the frequency allocation for all time. This legacy approach was originally adopted by regulatory groups that assigned specific frequency allocations with rigid rules for spectrum access [1,2,12,13]. With the growth of the wireless communications industry over the past decade, new spectrum policies have been implemented that grant secondary and unlicensed users spectrum access to these restricted bands [1,21–28]. Radar frequency allocations are prime candidates for spectrum sharing since their bands are underutilized and wide (i.e., radar bandwidths are typically larger than that of commercial communications systems). These policies have allowed commercial RF systems to share the underutilized spectrum as secondary or unlicensed users, which has promoted the development of technology for DSA [29,30]. For this type of sharing, modifications to radar transmissions are not required since the radar remains as the primary user; however, the radar must employ techniques to mitigate mutual interference at its receiver. Common techniques utilize temporal, frequency, and spatial degrees of freedom, separately or in combinations, and apply filtering, beamforming, and joint-domain analysis for effective interference suppressions [31–34]. Interference removal conducted in the frequency domain is achieved by filtering and assumes that communication signals have narrowband characteristics [35]. Interference suppression in the spatial domain requires multi-sensor radar platforms to null the communication signals by proper beamforming [36]. The optimum beamformer seeks to maximize signal-to-interference and noise ratio (SINR) and it adapts its coefficients to respond to dynamic interference environments [37–41]. However, interference nulling becomes challenging if there is an insufficient number of degrees of freedom or the interference lies in the main beam [42]. In the case of a wide-band interference that assumes a clear time-frequency signature,

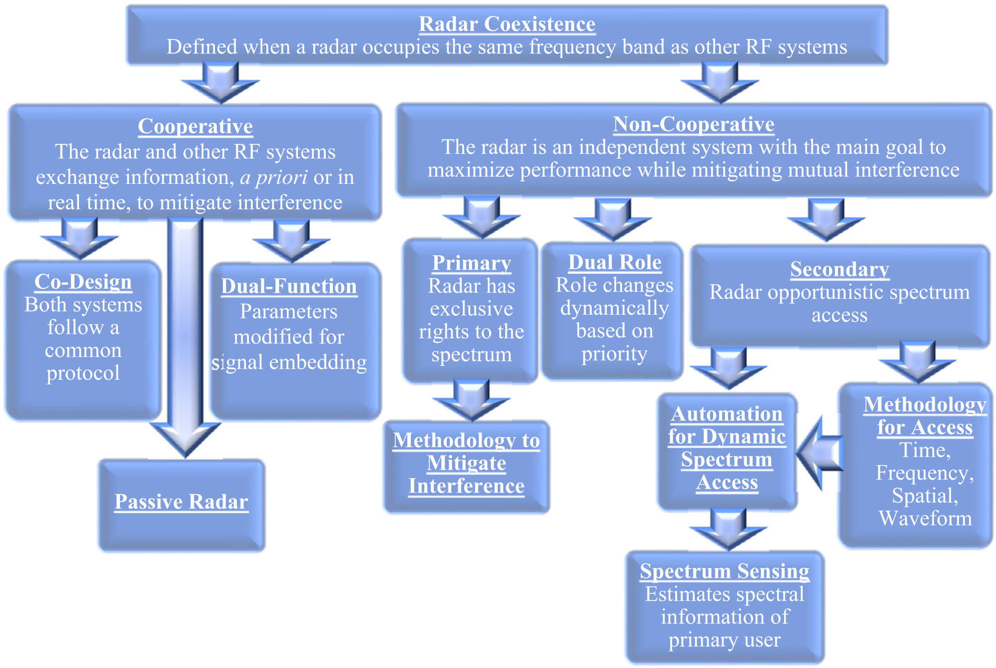


Fig. 2. Radar coexistence definitions and terminology. Radar coexistence covers a broad range of applications mainly dependent on user status and the cooperative / non-cooperative design strategy.

then a joint-variable signal representation in time and frequency is effective in revealing the interference's instantaneous frequency and enabling its removal without sacrificing much of the bandwidth [43,44]. It is noted that there is a difference between typical anti-jam methods and communication interference mitigation techniques. The former recognizes that the jammer can employ highly nonstationary and unstructured signals within a wide class of waveforms that could be multiplexed and are unknown to the radar receiver, which makes it difficult to sense in different transform and signal representation domains. Digital communication signals, on the other hand, are defined by finite alphabets and have known statistical, spectral, and constellation properties that can be readily discerned. Signal identification and automatic modulation classification is an emerging field that greatly benefits from strides made in machine learning as well as advances in spectral sensing, most notably through software defined radio (SDR) technology [45–48].

2.2. Radar as the secondary user with dynamic spectrum access

Recent global regulatory practices have focused on spectrum auctions to simultaneously earn revenue and promote the proliferation of commercial communication systems. For example, in the United States, the Advanced Wireless Service (AWS) 3 auction of service licenses raised over $41 billion, while the more recent C-band auction of service licenses in the 3.7–3.98 GHz band raised over $81 billion to promote 5G [22,23]. Auctions in Germany grossed €5 billion for mobile networks frequency bands, while commercial operators in the United Kingdom have paid annual amounts of nearly £200 million for continued voice and data services [14]. These regulatory actions have prompted a possible role-reversal of the radar's user status; hence, the radar becomes the secondary user, as depicted in the right block under non-cooperative coexistence of Fig. 2. As a secondary user, the radar attempts to access the spectrum and mitigate mutual interference [3,7,20,49–52]. This requires the radar to modify both its transmitter and receiver for opportunistic spectrum access in order to establish effective and efficient coexistence.

Radar strategies to exploit opportunistic spectrum access encompass the frequency, time, spatial, and waveform (code) dimensions. Time-frequency (TF) access considers an intelligent frequency hopping model to maneuver into unoccupied frequency allocations at the appropriate time [3,7,20]. This model could simply react to the primary user or use memory to predict its frequency location. The spatial dimension considers both angle and geo-spatial models. The former uses digital beamforming to null radar transmissions in the direction of the primary user [52], while the later uses geographical position information to avoid operation in the same area as the primary user [53]. The research area of waveform diversity has examined a variety of spectrally compliant waveform approaches that tailor the radar's transmissions to mitigate mutual interference [4]. One approach considers adding notches into the radar waveform to coexist with narrowband emitters and to maintain a wide bandwidth [50,51,54–56], while others consider Multiple-Input, Multiple-Output (MIMO) radar transmissions to mitigate mutual interference [49].

Autonomous implementation of opportunistic spectrum access is critical for real-time adaptation in dynamic spectral environments. Automation requires adjustments to radar operation in order to sense the electromagnetic environment (EME) and implement a radar strategy for DSA [3,57]. The goal of DSA is to provide both systems with the sufficient bandwidth to meet their respective objectives. Radar, as the secondary user, carries the burden of avoiding interference and accessing available frequency bands. In essence, the radar must be cognizant of causing interference to the communications and to cease transmission in the bands where communication signals are detected. The research area of cognitive radar offers several models for autonomous feedback and control that have been exploited for radar spectrum sharing [58]. In particular, the PAC model offers a means to autonomously change the radar's behavior and waveform in dynamic spectral environments to effectively share the spectrum and mitigate mutual interference [19]. "Perception" develops an understanding of the spectrum whereas "action" is everything that follows as a response of such understanding which includes learning, deciding and adapting. Execution of the PAC is a key consideration for effective spectrum

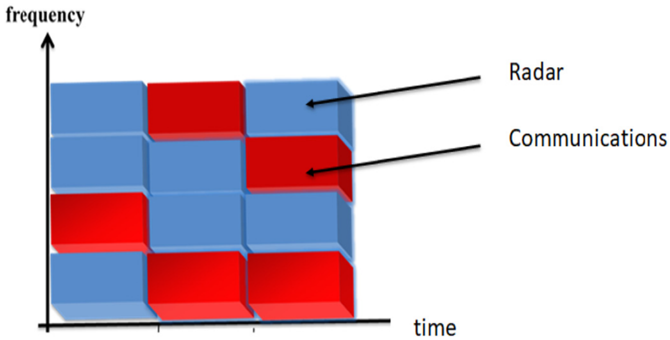


Fig. 3. Example of spectrum sharing and DSA between radar and communication systems. Both systems access a frequency allocation for a time, then vacant for the others use. (For interpretation of the colors in the figure(s), the reader is referred to the web version of this article.)

sharing. The PAC must be *fast* enough for radar to adapt to dynamic interference, but *slow* enough for radar to maintain the coherent processing interval (CPI) (to prevent clutter modulation) and complete the action (learn, decide, adapt) process [3]. The PAC must therefore be merged with radar operations since both functionalities are necessary in order to mitigate mutual interference and accurately process target information [59].

Spectrum sensing is used to develop an accurate perception of the EME, provides a supplemental evaluation of the spectrum, enhances knowledge of the primary user (i.e., the communication system) from the physical layer perspective, and informs the radar of occupied and unoccupied frequency allocations [29,60], namely center frequencies and frequency extents. The sensed information can be used, fused, or discarded by the radar as it sees best to maintain or optimize performance. During sensing, the radar halts its transmission and implements passive sensing of the spectrum; however, it is possible to conduct spectrum sensing from a different platform or in isolation. It should be noted that spectrum sensing can be implemented in cooperative models, or used by radar with a primary user status; however, this sensing may not be necessary depending on the scenario under consideration. Cognitive radar approaches that implement spectrum sensing have been shown to effectively share the spectrum with communication systems in real-time (sub millisecond) [3,56,57,59,61–63]. Radar spectrum sensing is a paradigm shift for effective non-cooperative spectrum sharing and is a key theme of exploration examined in this paper.

The DSA strategy considered in the development for cognitive radar is based on a joint time-frequency approach. This approach implements energy detection for spectrum sensing in order to determine the band occupancy and the "clean" frequency allocations for effective spectrum sharing. Energy detection has several advantages including low complexity processing (to support real time cognitive radar operations), the capability to detect multiple emitter types (i.e. radar transmissions, communication signals, etc.), and requires minimal *a priori* information that supports online learning methods. However, energy detection approaches typically require higher signal-to-noise ratios (SNRs) compared with other signal detection methods. This joint time-frequency approach has been effectively implemented on SDR platforms for autonomous, real time coexistence with commercial communication systems [3,57,59,61,63].

An illustration of DSA is depicted in Fig. 3, where the primary communications user is in red and the secondary radar is in blue, with red and blue boxes non-overlapping. Using the set theory parallels discussed in Section 1, the sets remain mutually exclusive but can partition the space differently and dynamically, allowing any frequency within the total bandwidth to be a member of one set at one time. This type of spectrum sharing between radar and communications is also metaphorically, and in layman's terms, like two persons, A and B, sharing a house, which defines the total bandwidth. Each person is entitled to use all rooms (frequency bands), but only one person can be in one room at any given time (see Fig. 4). In this respect, if Person A is always given the first choice of the room, i.e., primary, then Person B becomes secondary. As Person A cannot be in all the rooms all time, this type of sharing in RF coexistence defines and promotes dynamic access to the underutilized spectrum.

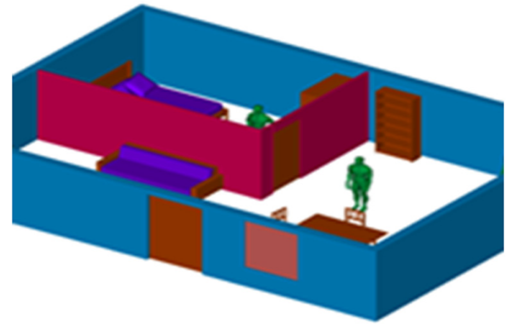


Fig. 4. Analogy of spectrum sharing with two people sharing a house. Each person can use all rooms, but only one room is occupied at a given time.

2.3. Dual-role radar spectrum sharing

The dual-role of the radar is described by the center block under the non-cooperative coexistence of Fig. 2. In this context, dual-role sharing considers non-cooperative approaches where the radar and communications devices are separate, stand-alone systems; otherwise, a ground-up cooperative co-design model could offer solutions as will be discussed in the next section. Recent developments in cognitive and adaptive signal processing make it possible for radar to switch its roles between the primary and secondary user in real-time in order to support more effective equal-sharing strategies between all users. This role-reversal is becoming necessary due to recent government regulatory practices to enable wireless device usage across the spectrum. Dual role spectrum sharing, in general, is a subject not typically explored within the literature, although models do exist. The "spectrum commons" model considers spectrum sharing where no one system is given priority over the other [1]. Unlicensed users fall into this category due to their low powered emissions. Hence, these devices are designed, developed, and operated without the knowledge of the primary user and effectively share the spectrum without modifying their behavior for coexistence. A major challenge with extending this approach to devices with high output power is the risk of mutual RF infringements and enforcement of policies to prevent users from causing interference (a challenge for spectral regulatory agencies). However, with the evolution of machine learning, adaptive signal processing, and reconfigurable component technologies, it may be possible to extend similar approaches for radar.

Facilitation of impromptu sharing by the radar requires narrowband access to the wideband spectrum in order to mitigate mutual interference, which requires the radar to develop an understanding of the spectrum, its users, and available frequency allocations in order to synthesize waveforms via waveform diversity approaches to maximize SINR. The trade-off for radar is a decreased bandwidth resulting in a degraded range resolution, which is acceptable subject to the conditions of the environment and the radar mode of operation [7,60]. For example, consider a search and track radar (primary user) with linear frequency modulated (LFM) transmissions that operates in a fixed, wideband channel in the presence of secondary and unlicensed users [64]. The radar can sacrifice bandwidth while maximizing its SINR (and mitigating mutual interference) while searching for a target; thus, radar becomes the secondary user. Once the target enters the scene, the radar switches its role to the primary user and begins to increase bandwidth as the target distance decreases. The radar can then ascertain more information about the target over time by becoming "greedier" with its spectrum allocation priorities. Hence, the radar shares the spectrum when possible but dominates the spectrum if necessary.

3. Cooperative radar coexistence

Cooperative coexistence requires a joint radar communication operation where both systems exchange information, *a priori* or in real time, to mitigate interference. Cooperative coexisting services can be separate systems, requiring synchronization and coordination, or can be integrated into a unified platform where full synchronization is readily assumed. Cooperative models have been shown to improve joint performance and the spectral efficiency for both systems, but incur an extra cost in design complexity compared with non-cooperative models. Two main categories can be recognized under cooperative coexistence, as illustrated in Fig. 2. The block on the right describes DFRC [8,9]. DFRC system requires that one or more existing radar parameters are modified for communication signal embedding (hence the "R" before "C"). If communications is the primary operation in dual-function systems, then "R" would follow "C", as in DFCR. Section 6 includes discussions on different forms of the DFRC systems.

The other category is represented by the block on the left and describes co-design which is a cooperative coexistence strategy that assumes both systems play a role in the design and follow a shared protocol for operations. Many models consider the radar and communications operations as separate systems [65]; however, it is possible that the operations are part of the same platform (although the systems remain disparate). Co-design models attempt to better balance the operations of both radar and communications and can emphasize a radar centric or communication centric functionality [49]. It is also possible for models to include additional sensor modalities, other than radar and communications, which provides multi-function operations and processing. Models that favor radar centric functionality within the design include protection regions [66–68], signaling methods (beacon signals) [28], spectrum access systems (SAS) [25,27], and waveform designs [52,69–71]. Protection regions represent geo-graphical areas surrounding the radar to prevent radiated emission by commercial communications systems. Developing these geo-graphical areas require an understanding of how susceptible the radar is to the transmissions of the secondary commercial systems. Radio environmental maps and power allocation methods have been proposed to aid the communications system (secondary user) in mitigating interference to the radar (primary user) [67]. Similar applications consider signal methods that require the radar to radiate a beacon signal informing the communication systems that it is permissible to transmit. More recently FCC co-design approaches consider a SAS for the Citizens Broadband Radio Service (CBRS) at 3.5 GHz to promote spectrum sharing for commercial RF systems. The SAS implements a three-tiered architecture that facilitates the spectrum usage of commercial priority access and general authority access systems with an incumbent user (radar in this context). Co-design approaches can also form separate radar and communication beams on the same platform via aperture partitioning or spatial multiplexing [70,71].

The third category in Fig. 2 casts passive radar as a cooperative coexistence strategy. Passive radars [72–74] share the same underlying strategy as dual-function systems in the sense that one of the RF services is completely dependent on the presence of the others. Passive radar has seen significant progress over the last decade in diverse applications, including border crossing and patrol. Being passive means that the radar does not use its own signal or transmitter but has its own receiver. In essence, passive radar refrains from any kind of RF emissions irrespective of the frequency bands being available or not. Without a dedicated transmitter, the radar exploits third party transmitted signals which are referred to as "signals of opportunities." The radar assumes ubiquitous presence of these signals in the operating region and, therefore, does not perform spectral sensing. Signals of opportunities include analog television signals, FM radio signals, cellular phone base stations, digital audio broadcasting, digital video broadcasting, terrestrial high-definition television transmitters, and the Global Positioning System (GPS) [75,76]. Since passive radar does not have control over the emitted power, its direction, or the signal waveform and bandwidth, the signal ambiguity function, Doppler, and spatial resolutions are limited, rendering performance in terms of detection and localization of targets and the estimation of their parameters rather challenging [77]. A combination of passive and dual function modes is discussed in Section 6.

The different coexistence categories shown in Fig. 2 can morph into the four tiles of Fig. 5 thereby summarizing the key methodologies of cooperative and non-cooperative spectrum sharing. This figure partitions coexistence into cooperative and non-cooperative as well as divides it according to the radar's role. So, horizontal movement signifies the radar priority while vertical movement signifies the coexistence type. Cooperative coexistence with radar as the primary user (upper-right) highlights DFRC and other co-design methods used by communication systems to mitigate interference to the radar. Cooperative approaches with radar as the secondary user (upper-left) highlights waveform co-design, passive radar, and DFCR. Non-cooperative coexistence with radar as the primary user (lower-right) shows techniques employed by radar to mitigate interference from communications systems, while radar as a secondary user (lower-left) requires deployment of opportunistic spectrum access techniques to mitigate interference to communication systems.

4. Multifunction RF sensor nodes for radar networks

The proliferation of wireless communications technologies and SDR platforms have also paved the way for networked radar to replace existing legacy systems with fixed frequency allocations. Hence, the concept of a single, high-powered radar platform is evolving into a network of multifunction RF node capable of sensing, radar, communications, and other sensing modalities (cooperative) while sharing the spectrum with multiple non-cooperative co-existing configurations of commercial wireless devices (non-cooperative). The confluence of these sensor modalities provides additional domain knowledge of the environment for enhanced performance and situational awareness [17,78]. The advantages of networked radar include a wider surveillance area, lower power emissions resulting in a smaller spectral footprint, and performance improvement (for example, multiple radars examine the same target from different locations for enhanced tracking performance) [79]. Other advantages are gleaned when each node is also capable of providing DSA. Specifically, the network can [29,80]: 1) provide a more robust estimate of the spectrum by using the aggregated spectrum sensing information processed at each node; 2) coordinate DSA activities of each node to avoid self-interference between nodes; and 3) allocate resources dynamically so that some nodes survey the spectrum while others concentrate resources on targets in an advantageous manner.

The network of multifunction RF nodes provide the capability of both cooperative and non-cooperative coexistence strategies and signifies a paradigm shift from traditional designs to the next generation radar system. The operation of the node requires proper resource management in order to mitigate the overhead involved

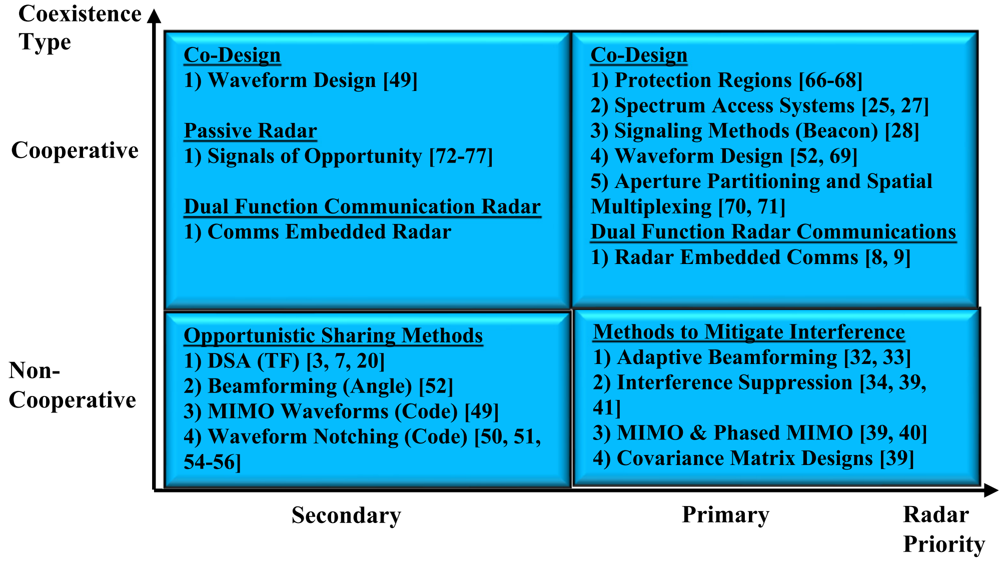


Fig. 5. Summary of coexistence categories with highlighted methodologies.

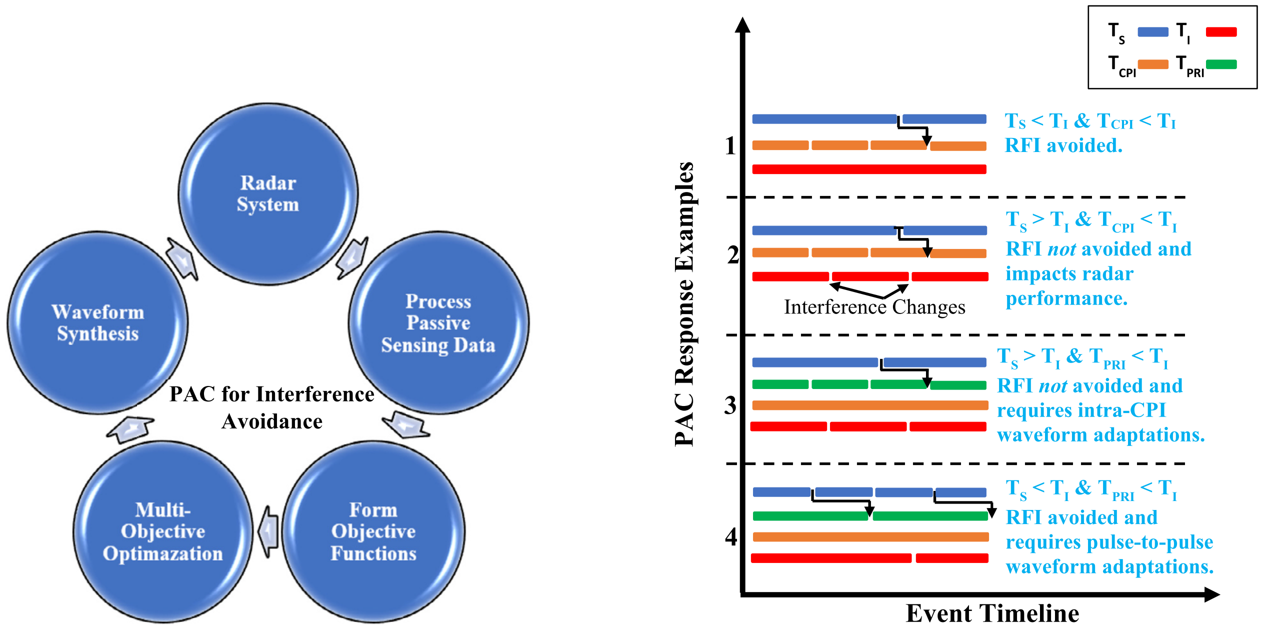
with determining a particular function. Cognitive radar offers solutions to regulate the selection of sensor functionality and to identify the optimal frequency allocation for narrowband DSA in crowded wideband channels [3]. It is noted that the timeline of the PAC is challenged in a networked environment where appropriate coordination between nodes is required by interweaving communications between sensing and radar functions, or by implementing beamforming or other spatial techniques for simultaneous operations. Similar to the discussion above, the priority of communications and radar functions must first be determined by a decision process in order to allocate the appropriate resources needed for operation. For example, in a radar network, if targets are not present in the scene, then resources can be allocated for node synchronization and communications of information garnered by individual nodes. Otherwise, when information is required for radar targets, resources must be devoted to radar with communications and information sharing becoming a secondary consideration.

The merger of multiple RF modalities with radar functionality has been explored extensively within the literature and follows the co-design discussion in Section 3. Early research conducted for the Knowledge Aided Sensor Signal Processing Expert Reasoning (KASSPER) and Airborne Intelligent Radar System (AIRS) programs evaluated adaptive algorithm and filter bank selection in different operating environments based on different environmental conditions to enhance target detection and tracking [81,82]. Radar performance is improved by using certain features in the environment to estimate clutter statistics, which can be used to select effective constant false alarm rate (CFAR) processing algorithms for a given terrain (sea, mountains, etc.) and weather conditions. These programs established a framework for leveraging different environmental sensor information (atmospheric and position) for the real-time improvement of radar performance. More recent research on joint radar, communications, position, navigation, and timing (PNT) consider unmanned aerial system (UAS) for air traffic management, collision avoidance and automated landing [83].

Multi-function RF capability has also been explored for the Internet of Things (IoT). The IoT is a merger of sensor technologies as is eloquently described by [84]: the IoT "can be defined as an integration of wired and wireless communication technologies, sensors and actuators that allow users to control and monitor objects (things) through the Internet, which also cooperate among themselves." Radar will play a big role in the IoT as a complimentary sensor for a variety of emerging applications that include wireless human sensing for vital signs of respirations and heartbeats, man-machine interface and touchless device RF control for smart homes using hand and arm gesture recognitions [85], fall and abnormal gait detections, wastewater management [86], air traffic monitoring [87], and personalized healthcare (amongst others). Government radar spectrum sharing applications with commercial communications will be split between a dichotomy of cooperative and non-cooperative coexistence approaches. In many cases, government radars will be independent networks and separate from the commercial communications infrastructure (like 5G and the IoT). Furthermore, the explosion of wireless technologies, from both the private and government sectors, will ultimately result in over-crowding of the frequency spectrum from both licensed and unlicensed users. Thus, non-cooperative approaches for DSA will continue to serve as a means to effectively and efficiently share the spectrum.

5. Waveform diversity for radar coexistence

Radar waveform synthesis and diversity for DSA are dependent on many factors including the measured interference in the EME and the target scene. From a DSA temporal and frequency diversity perspective, there must be a means to change the radar waveform by primarily modifying the center frequency and bandwidth so as to maximize performance while mitigating interference. Following the discussion in Section 2, the trade-off between the radar's performance criteria must therefore be examined in order to achieve effective coexistence. In particular, this trade-off is assessed for the radar's two principal metrics, namely, SINR and bandwidth. One possible solution for this trade-off assessment is to apply the spectrum sensing, multi-objective optimization (SS-MO) approach outlined in Fig. 6a [7,60,64,88]. The model uses spectrum sensing and optimization for waveform diversity. The spectrum of the EME is estimated via passive sensing using the same aperture as the radar. This passive collection process must be synchronized with radar operations one of two ways. The first requires sensing in a spatial direction different from radar transmissions; otherwise, additional processing is required to remove the radar transmission from the sensing estimate. The other collection process considers interleaving radar and sensing operations in time, which is useful for radar systems that cannot support spatial scanning (or the scanning process is too slow to adapt to the dynamic environment). The model considered in this development is generic to



(a): High level perception action cycle used to adapt radar waveforms in the presence of interference. This model considers tuning the center frequency and bandwidth to jointly maximize SINR and bandwidth.

(b): Comparison of PAC response time to dynamic interference. Ideally, the PAC is faster than the dynamic RFI. Intra-CPI waveform adaptations results in clutter modulation and additional processing is required for mitigation.

Fig. 6. The SS-MO radar model for waveform diversity in dynamic interference environments. Waveform adaptation relies on the PAC.

support both approaches. The spectral estimate is next used by the optimization process to identify an unoccupied frequency allocation. The goal is to (ideally) examine every possible combination of frequency allocations the radar can use to determine the best trade-off between SINR and bandwidth. For example, the radar could transmit over a narrowband channel represented by a single frequency bin. This results in high SINR but poor range resolution. The other extreme selection results in operations over the entire wideband channel for enhanced range resolution; however, this choice leads to co-channel mutual interference with other wireless devices operating in the environment. Multiple sub-bands (within the wideband channel) should therefore be examined to determine the optimal frequency allocation for radar.

The block diagram in Fig. 6 illustrates that the objective functions of this process are formed using SINR and range resolution. The SINR for a particular sub-band is estimated using the standard radar range equation (RRE) after pulse compression:

$$W_i = P_R \tau \beta_i / \Gamma, \tag{1}$$

where τ is the radar pulse width, P_R is the radar receive power, β_i is the bandwidth of sub-band i within the overall bandwidth B of the wideband channel, and Γ is an estimate of the noise and interference power within the spectrum based on passive sensing measurements of the spectral environment via a spectrum sensing energy detection approach. We also define f_i as the center frequency of sub-band i. The passive sensing information forms a power spectrum, via the fast Fourier transform (FFT), of the wideband channel in order to identify the frequency allocations that contain interference. The power spectrum is processed to examine sub-bands within the wideband spectrum, where each sub-band is delineated by a single frequency bin. The radar receive power is defined as

$$P_R = P_t G^2 \lambda^2 \sigma N_P / [(4\pi)^3 R^4], \tag{2}$$

where P_t is the radar peak transmit power, G is the transmit and receive antenna gain, λ is the wavelength of the carrier frequency, N_P is the number of pulses within a CPI, R is the arbitrary range to target, and σ is the target radar cross section (RCS). The variables $\{P_t, \sigma, N_P\}$ are adjusted based on target classification results. For example, slower moving target could require additional pulses on target, while low RCS targets could require higher power transmissions and/or additional pulses on target. Classification of the target type allows for better selection of the RCS, thereby resulting in a more accurate SINR estimate.

The second objective function is simply defined as the bandwidth, $Y_i = \beta_i$, where the range resolution $\Delta_R = c/(2Y_i)$ can then be estimated as required and c denotes the wave propagation speed. The goal of the optimization process is to then find the optimal solution, $x_i^* = \{\beta_i^*, f_i^*\}$, such that the objective functions $\{W_i(x_i^*), Y_i(x_i^*)\}$ are maximized subject to $W_i \geq W_{min}$ and $Y_i \geq Y_{min}$, where W_{min} and Y_{min} are the boundary conditions (constraints) for minimum SINR and bandwidth (respectively) allowable for radar operation, and x_i^* is the decision variable representing the bandwidth and center frequency of the optimal sub-band. The boundary conditions achieve a minimal performance capability for radar operations. It is possible that these constraints can change as environmental conditions evolve. For example, as discussed above, the minimal bandwidth requirement for radar differs depending on whether a target is present in the environment; therefore, the lower bound for the bandwidth can be adjusted to best fit the radar's operational requirements. Once the optimal sub-band is selected by optimization, the decision variables (i.e. center frequency and bandwidth) are used by the radar to synthesize a new waveform. Multiple pulses of this newly formed radar waveform are then transmitted into the EME. The feedback and control process of Fig. 6a repeats via the PAC of the radar and follows a sense, decide, and adapt operation loop. Sensing is dependent on the spectrum conditions via passive spectrum sensing (i.e. formation of Γ) and the target scene via radar operations (i.e. variables $\{P_t, \sigma, N_P\}$). The waveform parameters are determined by optimization (i.e. decide), while adaptation requires synthesis of the radar waveform.

The time-frequency waveform diversity approach of Fig. 6 determines the optimal sub-band solution for cognitive radar in the presence of RF interference (RFI); however, such a solution comes at the cost of latency and computational complexity. The processing times for the added operations are defined as follows: T_{P} is the passive collection and processing time; T_{D} is the optimization processing time; T_{W} is the waveform synthesis processing time; $T_{\mathrm{s}} = T_{\mathrm{P}} + T_{\mathrm{D}} + T_w$ represents the PAC response time to RFI; T_{CPI} and T_{PRI} are the radar's CPI and pulse repetition interval (PRI) respectively; T_{I} is the rate at which the RFI changes. The PAC response time occurs on a pulse-to-pulse, dwell-to-dwell, intra-CPI, CPI-to-CPI, or scan-to-scan basis. The more agile solution (e.g. pulse-to-pulse) allows the radar to respond to fast-changing interference thereby mitigating mutual interference at the cost of clutter modulation [3,89,90]. Clutter modulation occurs when waveform modifications are initiated within the CPI and introduces a coupling between the range and Doppler dimensions. It causes mainlobe and sidelobe modulation effects that spreads energy throughout the range-Doppler image, masks true targets locations, and increase false alarms. Solutions to clutter modulation require additional processing thereby further hindering the reaction time of the radar to interference. Less agile solutions (e.g. scan-to-scan) maintain the traditional coherence processing of radar waveforms, but cannot keep up with fast-changing interference. Once again, a trade-off exists between the rates at which the radar should adapt to dynamic interference.

In fast changing interference environments (small T_{I}), alternative low complexity spectrum sensing and decision processing algorithms are required. The latency bottleneck in Fig. 6b resides in the computational complexity of the optimization procedure. This complexity is based on a brute-force search of the solution space that results in $O(N^2)$, where N is the length of the FFT. Genetic algorithms can replace the brute-force search and significantly reduce the computational complexity with a minor performance loss [88]. Other techniques, namely the fast spectrum sensing (FSS) approach [7], refines the information in the power spectrum to minimize the number of sub-bands evaluated in the optimization process. This process effectively reduces the size of the data input to the brute-force MO procedure resulting in a decreased computational complexity of $O(N)$ while maintaining the same level of the original performance. Refinement of the information to the complex decision process is crucial for operationalizing cognitive and multi-function radar (a key take away from these experiments). In more recent development, FSS replaced the optimization process to select the widest frequency allocation available in the spectrum and was integrated onto the Field Programmable Gate Array (FPGA) of a software defined radar (SDRadar) platform to enhance the radar's reaction time to interference [57,59]. It was shown that the radar can sense the spectrum, decide on a center frequency and bandwidth, transmit and receive one radar pulse within 164 μs (pulse-to-pulse adaptation) [3]. The results in [91] illustrate that this methodology establishes coexistence with commercial 4G Long Term Evolution (LTE) emissions. This DSA approach constitutes a fast *reaction* to interference and the PAC follows a sense, decide and adapt process.

The reaction approach is sufficient for DSA applications with interference changing at rates slower than the PAC response time (i.e. $T_{\mathrm{S}} < T_{\mathrm{I}}$). Other approaches for DSA include prediction and machine learning [61–63,92], which adds learning and memory to the sense, decide, and adapt process of the PAC. The prediction and machine learning approaches are capable of anticipating interference in time in order to more accurately avoid interference. The prediction approach is based on a stochastic model that quantifies interference activity as an alternating renewal process. In particular, statistics are gathered for each sub-band which measure the average time (and variance) the interference remains active and inactive in the sub-band. Measurements that correspond to a high inactivity result in a reduced risk of generating mutual interference. Machine learning for DSA considers a Reinforcement Learning approach that models the EME and target scene as a Markov Decision Process (MDP). The goal of this approach is to find a policy that selects actions given observed states, where policies can be indirectly identified using function approximations via deep neural networks or a Q-learning framework. Both techniques support online learning (thereby requiring minimal *a priori* information) and pulse-to-pulse waveform adaptions with a response rate of $T_{\mathrm{S}} < 500$ μs. It is also possible to tailor notches into the transmission waveform in order for the radar to maintain a wide bandwidth for operation in the presence of narrowband interference [55,56]. The notching approach can be combined with prediction to "hop" the notch at the appropriate time in order to maintain coexistence on a pulse-to-pulse basis with $T_{\mathrm{S}} = 451$ μs [3,63]. Finally, reconfigurable RF front-end circuitry can be used to manage amplifier matching for multiple radar configurations [93]. In particular, high-power tunable matching networks have shown the capability to optimize the power added efficiency (PAE) of the transmit power amplifier which results in spectral containment and increased output power to maximum the radar's detection range.

6. Communication for multi-function sensor nodes

Existing research in the integration of a multi-function sensor node considers the DFRC systems. RF convergence of technologies is a fast-growing research area within the radar community. This approach has recently emerged as a viable option to address the spectrum contention paradigm. The DFRC system approach epitomizes the ultimate harmonious solution where the two systems are integrated and housed on the same platform [8,9]. This has given rise to the concept of "system of opportunity," in lieu of "signal of opportunity" that underpins passive radar. In a system of opportunity, communications are provided with a means to use the entire radar platform, including its frequency bandwidth and waveforms, and most important, antenna array and beamforming. The DFRC system approach predicates on the fact that a common aperture and frequency spectrum between radar and communications leads to low Size, Weight, and Power (SWaP) consumption requirements [94]. In defense applications, sharing the aperture and spectrum between radar and military communications moves away from independent systems and dedicated components and allows for integrated command and control systems and integrated sensor management. In commercial applications, the fusion of multiple sensor technologies onto the same platform benefits the infrastructure needed for future wireless communications applications, such as the IoT. In Fig. 7, we show a DFRC system to the left where the radar beam pattern is used for sending communication symbols through sidelobe modulations. The right part of Fig. 7 depicts a co-design case using the same platform where separate radar and communication beams can be formed by aperture partitioning or spatial multiplexing [70,71].

It is evident from the above description that a typical DFRC systems recognizes radar as the primary function [95,96]. The communications in this model does not sense the environment and is not considered secondary, as in DSA. Rather, it acts as a "guest" on the radar and, in this respect, can capitalize on the resources of the radar infrastructure while striving not to disturb radar operations and missions. These resources include large bandwidth, multi-sensors, high power and high-quality hardware and digital beamforming [97]. The communications in DFRC systems can be for the sole purpose of supporting the radar network [98,99] where multiple nodes need to share information about their operations and radar parameters, including scheduling data, target range-Doppler maps and target tracking trajectories, as well as specifics of the

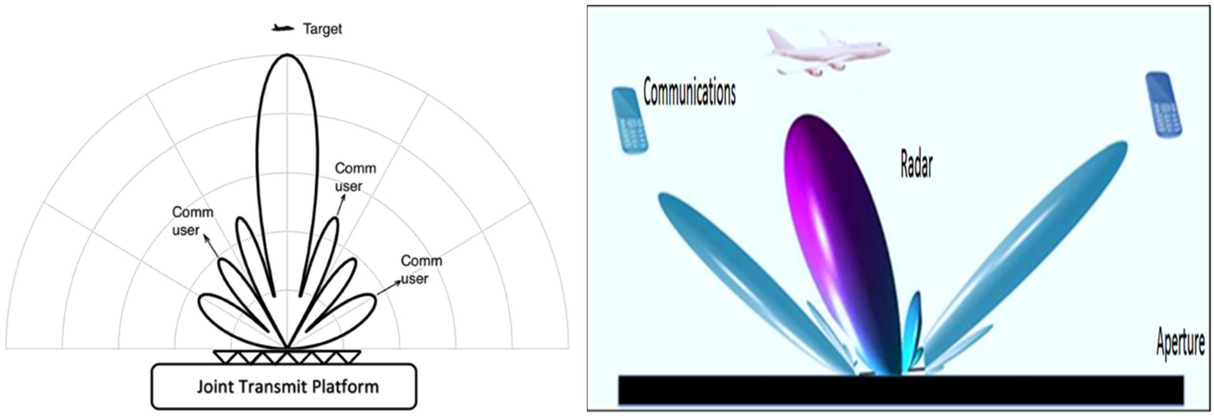


Fig. 7. Left, DFRC System (Common beam), Right, Co-Design via Aperture Partitioning or Spatial Multiplexing Beams.

surrounding clutter and interferences in the field of view [100]. In this case, one system function, namely communications, becomes an integral part of the other, radar, and is considered essential for its successful execution and completion. A DFRC system can also use the radar platforms as a downlink, communicating information irrelevant to radar but important to other RF spectrum users [101,102]. In this scenario, communication receivers can be stand alone, stationary or mobile, nodes. These nodes can communicate with the DFRC system in the uplink [103]. The uplink, however, causes interference with the radar receiver and, as such, requires effective interference mitigation techniques to separate target returns from the received communication signals [104].

A DFRC system can implement one of many strategies which embed communication signals in the radar waveforms or the radar beam pattern. In the former, embedding of information may occur along the fast-time or the slow-time dimension [8,105,106]. Fast time signal embedding amounts to modulating the radar pulse with a stream of communication symbols within each PRI and, therefore, lends itself to a high data rate embedding strategy. Cognizant of the impact of transitioning between alphabet symbols of different amplitudes and phases on spectral widening, fast time embedding prefers continuous phase modulation communication signals so as not to spread the radar power outside its allocated spectrum bandwidth. Certainly, continuous phase modulation (CPM) comes with associated processing complexities in transmitter modulation and receiver demodulation. Under this embedding strategy, since the DFRC system significantly changes its pulses over different PRIs, clutter modulation occurs over the radar CPI. This modulation presents a challenge to moving target indication (MTI) or Doppler filter processing for weak target detection and must therefore be properly minimized or removed in post-processing [105]. In slow-time signal embedding, only one symbol is sent over a PRI. Embedding in this case is accomplished by changing the radar pulse complex amplitude according to the symbol embedded, which is referred to as "pulse scaling" rather than "pulse modulation" that defines fast time embedding. This embedding strategy, though it professes slow-data rate, does not suffer from clutter modulation since this complex scaler can be removed at the radar receiver prior to coherent processing.

In an attempt to increase the data rate for slow-time signal embedding, one can resort to a code-shift keying (CSK) strategy where the radar uses few or a myriad of waveforms instead of a single pulse [107,108]. These employed waveforms are typically orthogonal phase coded or frequency hopping signals, each represent a communication bit stream. As an example, if the radar has in its possession 64 different phase coded sequence signals, then each sequence would correspond to a communication stream of 8 bits. The CSK strategy does not mitigate the clutter modulation problem, but it exploits advances made in waveform design and diversity.

The code-shift keying strategy has also been extended and generalized for MIMO DFRC system platforms. The spatial degrees of freedom combined with the use of multiple orthogonal waveforms have enabled designing a variety of methods, referred to as index modulation, to represent the communication data stream [109]. From the MIMO radar perspective, as long as the waveforms remain orthogonal and the receiver knows which transmit antenna emits which waveform, the radar detection and resolution performance is invariant to the different antenna-waveform pairing. As such, each waveform-antenna assignment can represent an index, i.e., one communication symbol [110]. This strategy can be combined with slow-time symbol complex multiplication for increased data rate. Index modulation strategy also includes selecting different transmit array configurations for different communication symbols. This strategy exploits fast antenna switching technology which can rapidly switch some of the array antennas on and off in real time.

A different signal embedding strategy in DFRC systems is to use the radar beamformer sidelobes. When the communication receiver angular position is known, the corresponding beamformer sidelobe can change in amplitude or phase according to the communication symbol. In this regard, the radar waveforms are kept intact without any alterations. Further, the radar main beam exhibits no, or negligible changes. Sidelobe signal embedding can also take advantage of waveform diversity to increase the data rate. Such an increase would depend on the number of employed orthogonal waveforms as well as the communication symbol constellation size.

An important variant of co-design is a hybrid active-passive mode of operations [111–113]. This mode consists of a transmitter serving both functions with separate radar and communication receivers. In this case, the radar is considered passive, needing both direct and surveillance channels to the transmitter and target, respectively, as shown in Fig. 8 for MIMO configurations [112]. However, in this case, the transmitter is cognizant of both radar and communication objectives and allocates power and bandwidth resources to achieve optimum performance trade-offs. The transmitter uses a portion of its total system power to broadcast the radar waveform and the remaining portion to transmit an information signal. Both orthogonal and non-orthogonal cases of signal transmissions can be considered. In the former, signal transmissions are scheduled optimally using divided resource elements. In the latter case, the transmitter broadcasts radar and communication signals using the same resource elements. The tradeoff analysis involves solving an optimization problem, where the objective is to maximize SINR at the passive radar receiver while ensuring

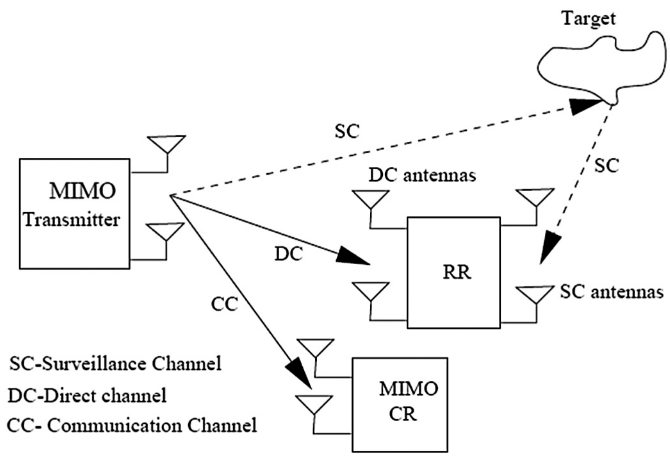


Fig. 8. Distribute system with a transmitter serving both functions with separate radar and communication receivers. The transmitter is cognizant of both radar and communication objectives and allocates power and bandwidth resources to achieve the optimum performance trade-off.

that the information rate for the communcations receiver is above a certain threshold value.

7. A combined ontology

The evolution of DFRC to the multi-function sensor node for advanced sensing and autonomous operations requires the implementation of the PAC at multiple levels within the individual node and throughout the network. Each node must first have the capability to autonomously perform DSA for a particular spectral environment by implementing a cognitive radar technique well suited to the observed environment. In dynamic or non-stationary scenarios, it can be shown that the performance of the cognitive radar technique can degrade as the ambient environment changes. For example, consider a radar implementing a cognitive radar strategy for DSA in a 5G environment. The introduction of a random frequency-hopping signal in the 5G environment could lead to a "cognitive loss [114]" of the strategy resulting in a degradation of radar performance. Ideally, each sensor node would have multiple cognitive radar techniques at its disposal in order to select the most advantageous, or optimal, technique available for different environments. These techniques form a "tool-box" of capabilities that would ideally be matched to a particular environment in order to maximize radar performance and mitigate mutual interference. Selection of the right tool at the appropriate time is of key importance and requires a high-level decision process with its own PAC that runs separate to the PAC of the cognitive radar technique; hence, a learning process is needed for cognitive radar.

The above "meta" approach serves as a watchdog to protect radar performance in dynamic environments and is referred to as the metacognitive radar (MCR) engine [3,10,115–117]. The MCR engine simultaneously monitors the spectrum and radar performance in order to implement the most effective cognitive radar technique in a fast-changing dynamic environment. This model requires a hierarchy of PACs that are designed to adapt on different timescales. For example PAC models operating on longer timescales provide the capability to identify cognitive loss, while PAC models operating on shorter timescale (pulse-to-pulse) have the capability to respond quickly to events in the environment.

For DSA, the MCR engine first classifies the spectrum through observations of the EME via spectrum sensing, then selects a set of potential cognitive radar techniques (similar to the ones discussed in Section 3) that are expected to result in higher radar performance. Reinforcement learning is next used to explore radar performance of the potential techniques, where the technique that performs best over time is selected, or exploited, for radar operations. Both radar performance and the spectrum are continuously monitored. Degradation of radar performance within a noticeably different RF environment cues the MCR engine to explore new cognitive radar techniques and the process repeats. Implementation requires multiple PACs as depicted in Fig. 9. As shown by the decision timeline, the MCR operates over a longer time period in order to monitor the cognitive radar technique and select alternative, and potentially more effective, solutions for performance improvements. Once selected by the MCR engine, the cognitive radar technique modifies waveform parameters used for radar operations over a different PAC timeline. This process is analogous to a puppet master manipulating and introducing new marionettes into a changing storyline of a play in order for the characters to better adapt to the changing scene.

The MCR engine is not limited to the non-cooperative DSA approach, but should be expanded to include generalized coexistence strategies. This expansion is necessary as the proliferation of wireless devices continues to expand, thus resulting in primary, secondary, and unlicensed users attempting to occupy the same frequency allocation at the same time. This "over-utilized" spectrum scenario is the doppelganger of its under-utilized counterpart, each resulting in an ineffective spectrum sharing scenario. Implementation of other coexistence strategies provide additional degrees of freedom to the sensor node, which include digital beamforming for spatial coexistence and the implementation of orthogonal waveforms that mitigate mutual co-channel interference between the sensor node and ambient RF emitters. These strategies are complementary to the time-frequency DSA approach. The architectures of the MCR engine must therefore be expanded to identify over-crowding scenarios, where DSA is less effective, and explore alternative approaches for coexistence.

The MCR engine for a single sensor node can also be extended to the entire network of nodes. A network MCR model is therefore used to oversee the flow of information throughout the network, the assignment of node type (radar, comms, or sensing functionality), and the evolving target and environment scene. Within this model, each node serves as an intelligent agent capable of independent DSA in addition to cognition at the network level. This hierarchy of cognition can coordinate the operation of each node more effectively in order to maximize performance at the network level compared with standard networking approaches. For example, consider a network of sensor nodes operating in a fast-changing environment and target scene. The goal for the network MCR engine is to select the optimal modality for each node, where some nodes are better suited for radar operations while others are better suited for passive sensing. The networked MCR model could implement reinforcement learning to optimize the modality of each node in the network in order to maximize network performance. As the environment and target scene evolves, the modalities of each node can be reassigned using the exploration / exploitation strategy of the reinforcement learning model. Implementation of the MCR model could be considered for both centralized and decentralized configurations; however, more resources are required for the non-centralized approach to synchronize learning throughout the network.

8. A lens on the future of software defined radar

The premise of spectrum sensing in radar technology emerged in response to the need of sharing and coordinating the occupancies of the various frequency bands. This response has created a new paradigm for radar systems as they strive to meet their objectives and maintain desirable performance. With spectrum sharing, the radar needed to "rethink" its spectrum usage and its role as the primary user which assumes exclusive rights to the spectrum. In-

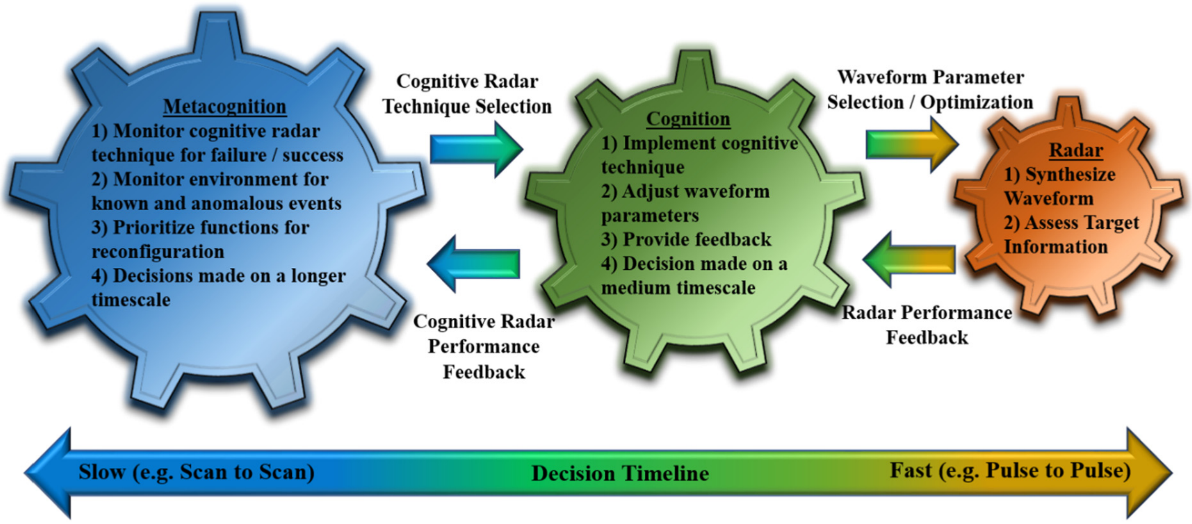


Fig. 9. Metacognitive radar simultaneously monitors for "cognitive loss" and changes in the spectrum. Once a loss or change is observed, the MCR Engine explores alternative strategies to increase overall radar performance.

creased wireless device usage, coupled with recent policy changes to promote sharing, has changed the dynamic of how radar coexists as the primary, secondary, or an equal sharing partner.

Spectrum sensing for aiding radar presents a form of cognition which is tailored to feedback knowledge of available frequency bands to immediate decisions on radar parameters within the current PAC. We project that ongoing investigations on improving the radar response time to acquire knowledge will continue to be a focus of research for the foreseeable future. Such improvement will not only lend itself to a gain across all radar functions, but also will enable optimization-based design tradeoffs most suitable for instantaneous priorities and minimally acceptable performance.

Spectrum sensing can inform beamforming, especially in wideband signal platforms. A dictionary of band occupancies provided by spectrum sensing at any given time can influence optimum array design in terms of array configuration, i.e., topology, and coefficients. If the radar is a secondary user of all bands, then operations will proceed only in interference-free environments. This suggests that interference covariance matrix estimation for interference nulling is no longer fundamental to beamforming. However, if the radar has both primary and secondary roles, in essence yielding in some bands while allowing its operations to proceed in others, then covariance matrix estimation becomes necessary in the latter bands. This enables optimum SINR MIMO configuration design, sparse or otherwise, which incorporates waveforms, antenna locations and array coefficients, across all bands.

Along the same vein, the radar operation can assume a hybrid active-passive mode which is a first step towards distributed multifunction sensor nodes. In this mode, both free and occupied spectrum bands can be used by the radar, which becomes a signal opportunist in the bands occupied by the primary users and thereby presents itself as a passive sensor. On the other hand, for the designated bands, the radar becomes active, using its own transmitter and waveforms. In this regard, spectrum sensing would inform the radar of the passive and active bands for its operation. But for this approach to work, spectrum sensing must also provide real-time information of the signal structure within the occupied bands as well as direct channels to the emitters. There are many open problems under such an approach for which fusing of the target information gleaned from the active and passive bands becomes the leading undertaking.

The overarching approach of metacognition will continue to gain thrusts. It provides a high level of flexibility to select among strategies of responses according to current needs and the means for radar to adapt in disparate, dynamic spectral environments. It also provides a foundation to explore multiple PACs that monitor the target scene and spectrum over near, mid, and long term timelines. This foundation allows for the simultaneous monitoring of multiple target and spectrum events from different sources of information (time, frequency, waveform, and spatial) while managing the resources necessary to take appropriate actions. The capability for radar to self-monitor its perceptions and actions increases situational awareness thereby establishing a means to assess the quality of real time automation. The metacognitive approach therefore constitutes the first step towards overcoming the pitfalls of cognitive radar [118] and establishing trust of autonomous systems within the RF user community. Metacognition can involve adjusting other radar parameters in addition to waveform, such as array configurations and adaptive beamforming weights.

Metacognition can also be realized in DFRC systems. Different communication embedding strategies have different levels of complexity and impact the radar differently, where for example, a trade-off exists between clutter modulation and changes in the radar ambiguity function. These strategies are also viewed differently from the communication receiver perspective in terms of achievable Bit Error Rate (BER), complexity, synchronization, and the underlying demodulation assumptions. One can think of a cognitive DFRC where one strategy can be most preferred over others for a given time. For example, in a radar network, when the radar communicates its scheduling information, a slow data rate can be accommodated, whereas when communicating the target range-Doppler map, high data rate becomes beneficial. Also, for strong clutter, the DFRC system can elect to avoid clutter modulations and fast-time signal embedding, which becomes more suitable in ground to air rather than air to ground target scene interrogations.

As RF technologies continue to evolve, the classic legacy radar system that relies on its primary user status, high power transmissions, and single frequency allocation to dominate the spectrum is coming to an end. Advanced networks that require multifunction sensor nodes will replace these legacy radars in order to support a wide variety of RF applications. The hardware to support this radar evolution already exists today in the form of advanced software defined radar platforms, single board computers, and hardware accelerators. This hardware provides a means to collect information from multiple channels and process this information to a usable form. The concept of metacognition can then be implemented in such a platform at the network level in order to guide the flow of information to each node and provide the high-level decision process necessary to select the operational mode of each node. This capability can be used to address a multitude of radar applications that occur in multiple environments.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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