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Grand Challenges in Radar Signal Processing

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INTRODUCTION

Signal processing for radar systems is a vast and fascinating discipline that covers numerous techniques and touches on many application areas. The history of radar began more than one hundred years ago, in 1904, when Christian Hülsmeyer demonstrated the first experimental radar in Cologne, Germany (Griffiths et al., 2019). The banks of the River Rhine at Cologne's Hohenzollern Bridge were the scene of this important invention. Later, in 1920, Guglielmo Marconi also observed in his experiments radio detection of targets, but it was not until World War II that the dynamic development of radar emerged. It has since then evolved into an indispensable all-weather, long-range sensor. Military and security applications have always been the main drivers of radar development. However, more recently, radar has become a key technology for civilian applications including air, maritime, and ground traffic control, in addition to urban sensing and indoor monitoring. Radar not only affects our present time worldwide, but also shapes our future.

According to its acronym RAdio Detection And Ranging, the classical radar mission is to detect and locate objects (Skolnik, 2002). With the advent of coherent pulse radar, velocity measurements have become possible by exploiting the Doppler effect (Chen and Ling, 2001). In contrast to camera images and many other sensors, radar is able to provide quantitative data on range and speed. Today specialized radars measure range as well as azimuth and elevation angles, enabling target detection and localization. Through Synthetic Aperture Radar (SAR), Inverse SAR (ISAR), or Interferometric SAR (InSAR), a 3D image of an object can be obtained (Melvin and Scheer, 2012; Richards, 2014). In recent years, passive radar systems have been gaining considerable and increasing attention for both target detection and ground imaging (Lombardo and Colone, 2012; Blasone et al., 2020). Applications of radar techniques span from ocean current monitoring to Earth digital elevation mapping, from automotive to biomedicine, from industrial monitoring in IoT scenarios to through the wall imaging (Amin, 2010), from the detection of vital signs and discerning the activities of daily living (Amin, 2017) to UAV monitoring (see Theodoridis and Chellappa (2013) and Theodoridis and Chellappa (2017) for a broad overview of many radar signal processing techniques and applications). There are also many key radar applications in agriculture, forestry, soil moisture monitoring, geology, geomorphology and hydrology, oceanography, land use, land cover mapping, and archeology.

Radar has a long history, and judging from the growing applications of active sensing, it has an illustrious and bright future. Future radar systems should effectively support a massive variety of applications with novel hardware solutions and innovative signal processing techniques. Several grand challenges inherent to future radar systems are outlined in the following.

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GRAND CHALLENGES IN RADAR SIGNAL PROCESSING

Sparse Sensing and Sparse Array Design in Radar

Sparse sensing, or compressed sensing (CS), has been successful in solving the problems of target detection, estimation, and classification in radar applications. It combines nonlinear reconstruction algorithms and pseudorandom linear measurements to solve underdetermined linear equations that define many inverse problems (Potter et al., 2010). In their study (Ender, 2010), Ender describes the application of CS techniques for pulse compression, radar imaging, and air space surveillance with array antennas. Over the last decade, CS and sparse signal reconstruction methods have been widely applied to tackle traditional radar problems, e.g., high-resolution target Direction of Arrival (DOA) estimation (Fortunati et al., 2014), as well as emerging problems, e.g., spectrum sensing in cognitive radar (Aubry et al., 2019). More recently, sparse sensing was combined with machine learning to solve the problem of missing or limited data (Cheng et al., 2020; Weiß et al., 2020). Optimization methods with sparse regularizations and constraints have been applied in both phased arrays and multiple-input multiple-output (MIMO) radar platforms for efficient radar aperture design under a given number of frontend receivers. Sparse array design with different objective and cost functions have benefited from recent advances in convex optimizations and semidefinite quadratic programming (SQP) (Xu et al., 2015). Global optimization methods, like particle swarms or simulated annealing, have been applied for array design with flexible antenna placements. Another successful design approach is the cyclic algorithm (CA) that optimally matches the designed and desired beam patterns via iteration (Roberts et al., 2011). A sparse antenna array has several advantages in the high-resolution thinned configurations for phased array and multi-input multi-output (MIMO) radar (Roberts et al., 2011). Whereas structured sparse arrays, such as Nested and Co-prime arrays, seek to increase the virtual aperture and available degrees of freedom to handle more sources than physical antennas (Wang et al., 2018), unstructured sparse array design can be time-varying and is guided by the knowledge learned from the sensed environment (Elbir and Mishra, 2020). Research into the design of sparse arrays is an area that is indeed catalyzing a growing interest in the scientific community.

Radar Waveform Optimization

Waveform optimization for system parameter estimation is an emerging topic in signal processing with applications in radar and remote sensing. In radar, waveform adaptation in different domains, such as spatial, temporal, spectral, and polarization, is aimed at dynamically improving system performance (Aubry et al., 2013). Such capability is enabled by new computing architectures, high-speed and off-the-shelf processors, arbitrary digital waveform generators, solid-state transmitters, and modern phased arrays with multiple transmit and receive channels, etc. Waveform optimization improves radar detection, classification, identification, localization, and tracking (Gini et al., 2012; Cui et al., 2020). New optimization methods and techniques are currently under investigation to deal with challenging radar waveform designs involving practical constraints, such as constant modulus, spectral constraints, waveform similarity, and finite or discrete-phase alphabet.

Cognitive Radar

Cognitive radar is a recent and growing research area that offers substantial benefits for defense and civilian radar systems (Haykin, 2006). Although many research efforts have focused on perception-action cycles, few of them have demonstrated the learning component (Guerci, 2010; Farina et al., 2017; Charlish et al., 2018; Greco et al., 2018; Bruggenwirth et al., 2019) and many aspects of the field contain open problems. A radar that can perform online learning to execute better actions and adapt its operational parameters based on its situational awareness can have potential benefits. Additionally, cognition is typically investigated for a single radar system. However, the distribution of perception-action cycles over multiple radar nodes, at different operating levels, starting from signals and multiple radar functions to the mission level, have a huge research potential. Cognitive radars should take advantage of all the available degrees of freedom and sources of diversity including location, frequency, code, beam patterns, revisit time, PRF, and polarization when choosing future actions (Geng et al., 2020; Yan et al., 2020). These actions should be cognizant of low-observable targets, drones or swarms of UAVs, dense and contested spectrum use, and adversarial activities. The most relevant enabling technologies for the future development of cognitive radar are adaptive waveform design, numerical optimization, RF System-on-Chip (RFSoC), all-digital radar arrays, machine learning, and deep learning.

Machine Learning for Radar

Machine learning (ML) has achieved great results which are attributed to major investments of many countries as well as massive cooperation among members of the international scientific community. In particular, the use of ML techniques has made it possible to improve the performance of some signal processing techniques based on traditional approaches and to overcome their intrinsic limitations. Following the success of using ML techniques in many engineering fields, the radar community has also begun to apply ML techniques to solve classic radar problems and to address traditional challenges from a new perspective (Carotenuto and De Maio, 2021). As already mentioned, ML is one of the enabling technologies for new cognitive radar systems, moreover there has already been an extensive development of signal processing algorithms based on ML that have found application in various fields related to radar systems. Some traditional applications have benefited most from the use of ML. In particular, radar imaging and classification is an area where ML has contributed significantly. In particular, in the scientific literature, we can find many applications of ML to solve problems related to the processing of radar signals, e.g., for the recognition and classification of radar emitters, processing and classification of radar images, noise suppression in the radar image, automatic target recognition (ATR), target detection, anti-jamming techniques, adaptive waveform design, dynamic antenna array selection, cognitive electronic warfare (CEW), reconstruction from measurements with missing data, high-resolution Direction of Arrival (DOA) estimation, and many others [see Zhu et al. (2017) and Lang et al. (2020)] for an exhaustive and comprehensive analysis of the state of the art of ML and especially deep learning (DL) applications in the radar and remote sensing fields). The proposed algorithms include conventional machine learning based on feature engineering combined with appropriate classifiers, such as support vector machines (SVM), decision trees (DT), random forest (RF), and empowerment methods. They also include automatic feature learning such as deep learning (e.g., deep belief networks (DBN), autoencoder (AE), convolutional neural networks (CNN), recurrent neural networks (RNN), generative antagonist networks (GAN)) (Lang et al., 2019). In general, it is now recognized that a higher degree of automation improves radar environmental awareness, irrespective of the type of application considered. The adaptivity of the radar, both on transmit and receive, should be "intelligently" regulated through accurate environmental awareness made possible by ML. This area of research has experienced an exponential growth in the last 10 years and is continuing to expand; the timeliness of these topics is confirmed by the flurry of academic activities and the fast-growing number of publications (Ma et al., 2019).

Coexistence of Radar and Communication Systems

In recent years, there has been an explosive growth in wireless communications, especially for applications in the Industrial Internet of Things (IIoT). On the other hand, radar technology has evolved in the direction of ever-increasing functionality. A modern radar system must be able to dynamically change the transmission waveform and operating frequency band, depending on the specific information collected in real time from the surrounding environment (Blunt et al., 2010). Due to the rapidly growing demand on finite spectral resources, the desire for better and more flexible use of the spectrum is also increasing (Aubry et al., 2015). On the other hand, commercial wireless industry strives for greater access to the spectrum and has eyed and sought use of the frequency bands traditionally assigned to radar systems, which has led to the so-called problem of "spectrum erosion" (Griffiths et al., 2015; Blunt and Perrins, 2018). As part of the search for efficient resource sharing and new technological solutions, it has recently been recognized that the competition for bandwidth between radar and communication systems can be alleviated by jointly and optimally designing the two systems, realizing them on a single platform (Blunt et al., 2010; Aubry et al., 2015; Hassanien et al., 2016). In this respect, the platform is not just a radar or communication system, but a multifunctional system whose waveforms and operations support multiple activities and tasks simultaneously (Chiriyath et al., 2017; Wang et al., 2018). The topic of dual-function radar communication systems has attracted the interest of theoretical researchers and practitioners from both the radar and communication scientific communities (Cohen et al., 2018; Zheng et al., 2019). The design of joint dual-function radar communication systems is a timely and relevant research topic and requires new ideas and technological solutions (Rahman et al., 2020; Mazahir et al.). Research underway focuses on established and emerging areas such as cognitive spectrum sensing for resource allocation in communication systems, adaptive waveform design for modern radar systems, and MIMO radar and communication system designs, to name a few. Examples of open problems and methods can be found in two recent special issues, one of the *IEEE Trans. on AES* devoted to Spectrum Sharing (Blunt et al., 2019) and the other of the Elsevier *Digital Signal Processing* journal devoted to the Co-operation and Joint Design of Communications and Radar Systems in a Crowded Spectrum (Amin et al., 2020).

Radar for Advanced Driver Assistance Systems

Radar technology is one of the enabling technologies for advanced driver assistance systems (ADASs) and highly automated driving (HAD). In recent years, we have witnessed a leap in new systems and new signal processing techniques tailored to the field of automotive radar (Waldschmidt et al., 2021). Although current automotive radar technology is still based almost exclusively on the principle of frequency modulated continuous wave (FMCW) radar, modern automotive radars are expected to be more flexible and to allow for adaptive selection of waveform parameters as well as dynamic use of transmit and receive channels. This flexibility calls for multipurpose radar sensors, which can perform functions ranging from adaptive cruise control to automated parking. Additionally, the implementation of advanced autonomous driving functions requires that radar sensors work in symbiosis with lidar and cameras. All this justifies the growing research and development in the field of automotive radar systems in both industry and academia. For example, the use of SIMO (single-input multiple-output) and MIMO (multiple-input multiple-output) radar systems has provided automotive systems with the capacity for spatial filtering to achieve the necessary spatial resolution for obstacle Direction of Arrival (DOA) estimates (Engels et al., 2017; Zhang et al., 2020). Problems related to target blindness, snow, rain, and near-field detection are also still relevant and require further investigation. One of the great challenges in automotive radar concerns adaptive filtering for the mitigation of interference at various radar sensors (on the same vehicle or on different vehicles) (Alland et al., 2019). This problem will be increasingly important in the near future, given the increasing number of vehicles equipped with radar sensors in heavy traffic situations. In addition to the coexistence of multiple radars in a crowded traffic environment, spectrum sharing with communication systems is also a major concern (Kumari et al., 2018). Other challenges and opportunities evolve around the phenomenology of the sensed signals, system architecture, circuit technology, automotive SAR imaging, object identification, and advanced signal processing techniques (Saponara et al., 2019). An increasing role of machine learning is also expected in signal processing algorithms for detection and classification in automotive radar (Khomchuk et al., 2016; Seyfioğlu et al., 2018; Schumann et al., 2020; Waldschmidt et al., 2021). The automotive radar community is at the forefront of technologies that promise to provide fully autonomous driving cars, and several automotive radar industry groups (GM, Hertzwell, Zendar, Toyota, etc.) are investing heavily in solving these problems.

Radar for Biomedicine and e-Healthcare

The civilian or dual-use applications of radar sensors are experiencing an enormous growth, thanks to the maturation of millimeter wave technology which allows for reliable low-cost radar sensors. Among the areas that have benefited most from these developments are undoubtedly those of health monitoring and biomedicine. Indeed, intelligent healthcare systems are undergoing a rapid transformation from the conventional specialist and a hospital-focused style to a distributed patient-centered system. Some technological developments have encouraged this rapid evolution of intelligent healthcare systems, including those related to radar technology and machine learning techniques. These technologies, together with 5G and Internet of Things (IoT), are crucial for the evolution of future smart health services. There are a plethora of applications of radar sensing in biomedicine. For example, radar imaging techniques are becoming a promising alternative, or at least complementary techniques, to existing imaging modalities for detecting breast cancer and monitoring response to treatment (Song et al., 2019). Although many excellent results have already been achieved, there are still several outstanding challenges, such as the low signal-to-noise ratio, tissue heterogeneity, and low resolution. Radar-based remote monitoring of human vital signs and activities is also an application area that has sparked great research interest due to its potential applications in patient health monitoring in hospitals, elderly homes, rehabilitation centers, and care facilities (Amin et al., 2016; Li et al., 2018b; Seifert et al., 2019; Mercuri et al., 2021). However, there are still many open problems related to the low signal-to-noise ratio, high aspect angles, obstacles, dynamic environments, discrimination of very similar activities, non-focal motion, and the large and time-varying nature of human activities. Overcoming the challenges in healthcare and biomedical applications requires further advancement of the state of the art in statistical signal processing and machine learning techniques (Maitre et al., 2020).

Micro-Doppler Radar

A moving point-like target introduces a frequency shift in the narrowband radar return due to the Doppler effect. However, in the real world, any target has a complex structure, the body is not fully rigid, and any structural component of the target may not follow an ideally straight-line motion. As a result, the motion contains a component called micro-motion, which includes the effect of vibration, rotation, and acceleration. Micro-motion and its induced micro-Doppler effect were introduced to characterize the movement of a target (Chen and Ling, 2001). Thus, extraction and analysis of radar micro-Doppler characteristics have become an active research area. Micro-motion can be observed in many applications, such as rotating propellers of a fixed-wing aircraft, rotating rotor blades of a helicopter, engine-generated vibration in a vehicle, rotating antenna on a ship, swinging arms and legs of a walking person, flapping wings of a bird, and the heartbeat and respiration of a person (Chen, 2014). Over the past few years, it has been proven that micro-Doppler characteristics can be exploited to extract a signature of a target and because of this, it found applications in many areas such as enhanced target detection, characterization, and tracking. Modern high-resolution radars, equipped with advanced signal processing algorithms, have a better capability to extract micro-Doppler features, which allow classical problems such as non-cooperative target detection and classification to be solved in a more efficient way (Clemente et al., 2015; Ritchie et al., 2016; Fioranelli et al., 2020). This also paves the way for new applications, such as human activity monitoring (Amin, 2017; Shrestha et al., 2020), urban and indoor surveillance (Pastina et al., 2015; Seyfioğlu et al., 2018), healthcare (Li et al., 2018a; Lang et al., 2019; Seifert et al., 2019), automotive applications (Khomchuk et al., 2016; Duggal et al., 2020), and manufacturing (Zeintl et al., 2019; Izzo et al., 2020). A recent book (Fioranelli et al., 2020) covered the latest developments in radar micro-Doppler signatures and non-cooperative recognition of moving targets and identified a number of ongoing research areas, among which passive radar approaches for healthcare, multimodal sensing for assisted living using radar, small drones and bird signatures extraction, and micro-Doppler signature extraction and analysis for automotive application were mentioned.

CONCLUSION

New radar technologies and applications are discovered and proposed almost every day; however, there still exists challenges and gaps that need to be addressed. In this editorial article, we have outlined some important challenges in radar signal processing, but the list is certainly not exhaustive. For example, distributed signal processing methods to exploit all the information available within an interconnected and spatially diverse multi-platform system is certainly a research area of growing interest. In fact, the *IEEE AES Magazine* is organizing a special issue devoted to "Multi-Platform and Multi-Functional RF Systems (MPRFS) and (MFRFS)" that will be published at the end of 2021. Another application area, not mentioned above, concerns the application of new radar technologies and methods for advancing atmospheric and climate science. This is a traditional research area where the use of machine learning techniques, possibly integrated with traditional statistical signal processing methods, promises new frontiers. Additionally, areas of increasing research interest include terahertz and mmWave radar, software defined radar (SDR) and low-cost radar, and quantum radar. Finally, advances in radar sensing technologies will pave the way for effective Internet of Things (IoT) and industrial IoT (IIoT) solutions, therefore affecting many aspects of our daily lives. The progress toward low-cost sensors, hardware architectures, and signal processing algorithms will further push the use of radar technology into new civilian application areas.

AUTHOR CONTRIBUTIONS

The author confirms being the sole contributor of this work and has approved it for publication.

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