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The Rise of Radar for Autonomous Vehicles

Signal processing solutions and future research directions

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Automotive radar is the most promising and fastest-growing civilian application of radar technology. Vehicular radars provide the key enabling technology for the autonomous driving revolution that will have a dramatic impact on everyone's day-to-day lives. They play a central role in the autonomous sensing suit because of the significant progress in the radio-frequency (RF) CMOS technology that enables high-level radar-on-chip integration and thus reduces the automotive radar cost to the level of consumer mass production. However, this would not be sufficient without high spatial resolution performance, which can be obtained by multiple-input, multiple-output (MIMO) and cognitive approaches at a lower cost.

The uniqueness of automotive radar scenarios mandates the formulation and derivation of new signal processing approaches beyond classical military radar concepts. The reformulation of vehicular radar tasks, along with new performance requirements, provides an opportunity to develop innovative signal processing methods. In this article, we first revise conventional techniques for signal processing in automotive radar. Then, we emphasize the limitations of the historically driven conventional processing approaches in practical roadway scenarios and present alternative signal processing solutions. Finally, we propose several future research directions to enhance vehicular radar performance.

Introduction

Autonomous driving is one of the megatrends in the automotive industry, and a majority of car manufacturers are already introducing various levels of autonomy into commercially available vehicles. Autonomous conveyances need to substitute for a human driver in both sensing and decision making. The main task of the sensing suite in autonomous vehicles is to provide the most reliable and dense information on the vehicular surroundings. Specifically, it is necessary to acquire information on drivable areas on the road and to report all objects above the road level as obstacles to be avoided. Thus, the sensors need to detect, localize, and classify a variety of typical objects, such as vehicles, pedestrians, poles, and guardrails. Since the major benefits

Digital Object Identifier 10.1109/MSP.2019.2926573
Date of publication: 9 September 2019

 1053-5888/19©2019IEEE

of autonomous vehicles are expected in urban environments, the variety of obstacles' appearance and the short response time required pose the major challenges to the sensing suite. Comprehensive and accurate information on vehicle surroundings cannot be achieved by any single practical sensor. Therefore, all autonomous vehicles are typically equipped with multiple sensors of multiple modalities: radars, cameras, and lidars.

Because cameras resemble human driver vision, they can be the most natural sensors for autonomous driving. They are low in cost and have a small form factor, providing dense and rich information on the environment, along with the color and texture of objects. However, cameras have significant shortcomings: they are sensitive to illumination and weather conditions, have to be mounted behind an optically transparent surface, and do not provide direct range and velocity measurements. On the contrary, radars are robust to adverse weather conditions, are insensitive to lighting variations, provide long and accurate range measurements, and can be packaged behind optically nontransparent fascia.

The first attempts at automotive radar applications were reported a few decades ago [1]–[3]. However, the mass deployment of radars in commercial vehicles began only recently. The autonomous driving megatrend is the major factor in automotive radar mass production. The technological progress of the 77-GHz RF CMOS with integrated digital CMOS and further packaging advances enable low-cost radar-on-chip and antenna-on-chip systems. The continuously shrinking vehicular radar form factor enables novel on-platform integration possibilities and, consequently, new applications [4].

Historically, automotive radars were classified into long-range radars (LRRs), short-range radars (SRRs), and side-blind zone radars (SBZAs) [5]. This was driven by a variety of applications and performance requirements, such as operation range, field of view (FOV), and object of interest. Thus, LRR is mainly used for adaptive cruise control and, therefore, is required to detect, localize, track, and classify vehicles at longer ranges, with a narrow FOV. SRR needs to provide information on a vehicle's surroundings at ranges of up to 100 m, with an FOV of more than 120°, where the reference target can be any object above the road level. The simplest automotive radar, SBZA, is required to detect only objects within the lanes adjacent to the host vehicle.

The reduced radar size and advanced capabilities have opened the door for completely new radar application segments. Thus, ultrashort-range radar (USRR) was recently introduced for autonomous parking and side-looking applications at a wide FOV of 120° and ranges of up to 30 m [6]. The multimode radar [7], where the same hardware configures its operation (antenna configuration, waveform, radar echo processing, and so forth) to various operational modes, is another automotive radar trend.

Vehicular radars are required to provide sensing capabilities starting from zero range and, therefore, are continuous wave (CW) and, because of low-cost requirements, employ linear-frequency modulation (LFM) ([8, Ch. 16]). Other waveforms, such as phase modulation [9] and step frequency [10], were also introduced for automotive radars.

The most dramatic transformation of the vehicular radar system is now occurring because of its role shift from a sensor that detects to one that images [5], [11]. Autonomous driving requires high-resolution sensing capabilities, and thus automotive radars must provide high-resolution information on the vehicle environment in the range–Doppler–azimuth–elevation domains. Range resolution is inversely proportional to the radar bandwidth. In 77-GHz radars, the available bandwidth is 4 GHz, which provides sufficient range resolution. Doppler resolution is limited by the coherent observation time and depends on the transmitted waveform, receiver processing, and target dynamics. Angular resolution is contingent upon the antenna aperture and thus is determined by the number and geometry of the transmit and receive channels, limited by the radar cost and packaging size.

Automotive radars are required to operate in dense urban environments with distributed objects. Therefore, the applicability of conventional superresolution methods, such as multiple signal classification (MUSIC) and minimum-variance distortionless response (MVDR) [12], relying on spatial sparsity, is limited. The requirements for high-angular resolution in both azimuth and elevation, using a small number of channels, turns the MIMO radar concept [13] into an attractive alternative to the full sensor array. Thus, the majority of state-of-the-art automotive radars use some variant of MIMO radar.

In automotive radar applications, a novel interpretation of the target and clutter notions is required because all of the dynamic or static objects above the road level are targets of interest, and detailed information on them is needed for autonomous driving. This operational scenario poses additional challenges for the radar processing and limits the applicability of conventional radar techniques to automotive radar.

This work overviews the conventional fast LFM–CW automotive radar signal processing flow, emphasizes its limited applicability to vehicular radar scenarios, and proposes a few novel approaches for key performance improvements. In particular, novel range–Doppler processing, detection, clustering, and dynamic range (DR) enhancement methods are required, specifically designed for high-resolution automotive radar. Thus, one of the challenges in vehicular radar operation is the discernment of small objects (e.g., child pedestrians) as well as large ones (e.g., semitrailers). Conventional implementation of detection methods, such as constant false-alarm rate (CFAR), are suboptimal in the automotive environment since objects occupy multiple range–Doppler–azimuth–elevation cells. Therefore, novel detection methods for target recognition that use information from adjacent range–Doppler cells are required.

High-resolution automotive radars can generate multiple detections from the same object. Thus, data association methods are required. Detections originated by the same object have similar properties and, therefore, can be associated into clusters. Data similarity is determined by specific criteria and metrics, such as distribution in the range–Doppler–azimuth–elevation space.

Automotive radar operation challenges

The main role of the sensing suite in autonomous driving is to be a substitute for human driver vision and thus provide reliable information on a moving vehicle's surroundings to enable a prompt reaction to the dynamically changing scene and threats to the vehicle being driven. The autonomous sensing capabilities are well beyond those of human eyes, compensating for the limited artificial intelligence in comparison with human cognition.

The radar, along with cameras, plays a central role in autonomous vehicles oriented toward mass production. Automotive radars have multiple advantages over cameras and lidars, such as long operation ranges, immunity to lighting and weather influences, ability to operate behind optically nontransparent fascia, and direct measurement of targets' radial velocity. Therefore, radars have been given a key role in autonomous vehicles. Both the advantages and challenges of automotive radars stem from the properties of their associated electromagnetic waves and their wavelength, which is determined by regulations. The main issue for automotive radar systems is to provide high-resolution information about multiple dynamic targets in an extremely cluttered automotive scene with a high update rate.

Figure 1 shows a typical urban scenario as an example of the automotive radar challenges described in this section. The radar is required to perceive this scene of a vehicle passing near a pedestrian. To achieve this task, high-resolution sensing in range–Doppler–azimuth–elevation and a sensitive detector, followed by clustering, tracking, and classification algorithms, are required. This section describes the major challenges of the vehicular radar that determine its design guidelines.

Scene variety

Many automotive radar challenges stem from the requirement to operate across a variety of scenes, ranging from urban and metropolitan to rural and freeway environments. These settings are characterized by a wide spectrum of targets and infrastructures, varying by radar cross section (RCS), velocity, and motion pattern: road debris, animals, pedestrians, vehicles, bridges, and so on. As a result, an automotive radar needs to be designed to detect, localize, track, and classify everything from slowly moving children and animals in parking lot scenarios to fast-moving vehicles on freeways. Consequently, the necessity to support this wide range of velocities challenges the waveform design in terms of chirp duration, duty cycle, and frame size. Moreover, the tradeoff between Doppler ambiguity, maximal range, and range resolution makes demands upon the automotive radar system design.

The large variety in target size, ranging from small RCS targets, such as on-road debris, to large RCS structures, such as bridges, requires a high DR. Another reason for the high DR requirement is the simultaneous detection of far and small targets and close and large objects. As a result, a high DR dictates the required effective number of bits (ENOB), limiting the sampling rate. The cost of the analog-to-digital converters (ADCs) increases with the DR according to $\text{DR} = 6.021\ \text{ENOB} + 1.763$ dB [14].

Operation in typical urban scenes is characterized by a large number of targets that create a continuum of radar echoes across the FOV, which poses a computational complexity challenge to the detector and the beamformer processing algorithms. Moreover, when designing a high-resolution radar, typical automotive radar targets are spatially distributed and can be observed as a superposition of multiple point reflectors, complicating the detector design. In addition, the superposition of multiple point scatterers is observed by the radar as a single target with a highly variable RCS.

For typical autonomous scenarios, the radar is required to provide high-resolution 4D information regarding the host vehicle's surroundings. These data are then used to identify obstacles above the road level. Thus, high angular resolution in elevation is required to recognize any obstacle 10 cm above the road surface. Identification of the drivable path further requires the detection of overhead objects, such as bridges and signs, that may interfere with the moving vehicle. Finally, the automotive radar needs to support a variety of active safety features, under a wide spectrum of operational conditions, that challenge the optimization of the radar parameters.

In dense urban environments, the vehicular radar experiences multipath from the surrounding surfaces. The multipath effect increases estimation errors and generates ghost targets, which are considered to be false alarms [15]. Multipath mitigation involves processing with additional computational complexity.

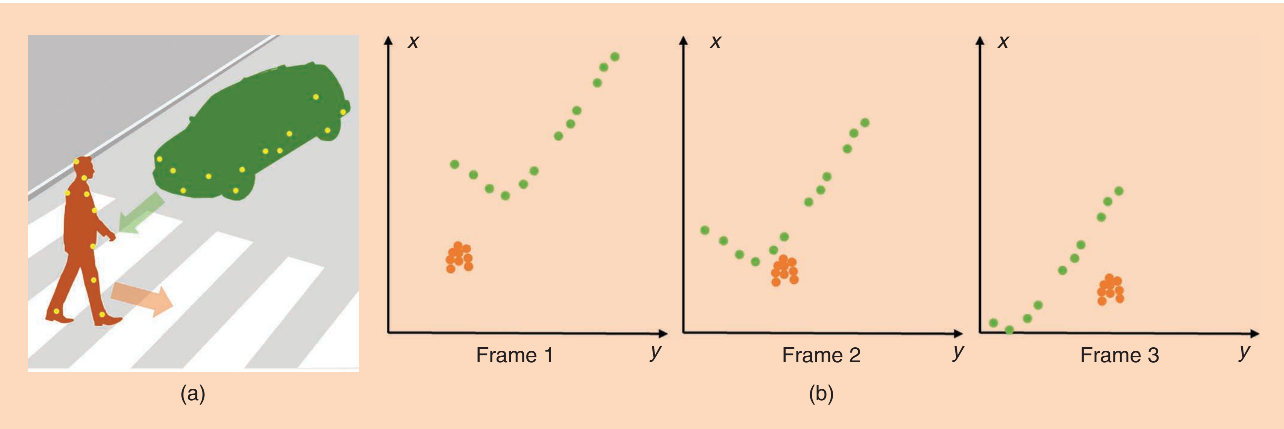

FIGURE 1. An example of the urban environment, demonstrating some of the automotive radar challenges. (a) A vehicle passing near a pedestrian. Each target consists of several detections, generating a point cloud. (b) Adjacent point clouds of a pedestrian and vehicle, over several frames.

High resolution

Autonomous driving requires information on all obstacles surrounding the host vehicle above the ground level. Thus, an automotive radar needs not only to localize the surrounding objects but to provide information on their extent (and, preferably, shape) and classify them. These tasks require high resolution in range, Doppler, azimuth, and elevation to attain lidar-like performance. The high-resolution requirement increases the computational complexity of radar signal processing and requires the development of computationally efficient algorithms to provide real-time (or low-latency) solutions to the high-dimensional and extensive data.

The range resolution is given by $\Delta R = c/2B$, where B is the transmitted signal bandwidth. In LFM signals, $B = \tau b$, where b denotes the chirp slope, and τ is the chirp duration. The Doppler resolution is given by $\Delta D = 1/\mathrm{TOT}$, where TOT is the time on target. The TOT is limited by the overall maximal allowed system latency and by the maximal coherent integration interval, determined by the target's radial velocity V as follows: $\mathrm{TOT} < \Delta R/V$. Beyond this limit, an increase in TOT does not contribute to the target intensity or to Doppler resolution because of the target migration to other range cells.

Figure 2 shows a scenario in which the target's dynamics exceed this limit, creating the range migration phenomenon. The Doppler information in a typical fast LFM automotive radar is extracted via an additional fast Fourier transform (FFT). High Doppler resolution requires a long integration time, and low Doppler ambiguity necessitates a high chirp rate, resulting in a large number of chirps during the observation time. Therefore, high resolution in the range–Doppler domain needs the implementation of a large 2D FFT. Conventionally, in automotive radars, the FFT is performed by dedicated processing accelerators. The implementation of a large 2D FFT increases the processor cost, requires a larger on-chip fast memory, and challenges the heat dissipation design.

A high angular resolution in azimuth and elevation requires a large antenna array aperture and thus a large number of transmit and/or receive channels. Therefore, computational resources are demanded to process the generated data. In addition, the need for a large antenna aperture challenges its integration in the automotive platform and drives the system cost as the number of transmit and receive channels increases.

Clutter

The operational environment of automotive radar differs from that of conventional military radars in the sense that all objects above the ground level are targets that need to be detected, localized, and classified. In automotive radar, any obstacle above the ground level is considered to be a threat, if located in the planned driving path of the host vehicle. Therefore, the conventional clutter returns are actually targets of interest. Typically, clutter returns are weak because of low aspect angles and high operational frequencies. However, ground returns from a close proximity to the host vehicle determine the requirements for antenna sidelobe levels in elevation since road echoes received through sidelobes can be stronger than echoes from far and weak targets at the antenna main beam.

In scenarios with a moving host vehicle, static clutter echoes from the road are received at different Doppler shifts, which is a function of the road angle $D = V\cos\theta\cos\varphi$, where V is the host vehicle speed and θ and φ are the elevation and azimuth, respectively, of the clutter return. The detection of weak and far targets within strong Doppler-spread clutter challenges the automotive radar detector design. Figure 3 illustrates a scenario of a target adjacent to clutter, where the target is a pedestrian and clutter originates from a fire hydrant, potentially masking the target.

Interference

One of the future challenges of automotive radars is interference mitigation [16], [17]. Vehicular radar is subject to three types of interference: self-interference, cross interference from other radars on the same vehicle, and interference from other vehicles' radars. Self-interference originates from strong radar echoes reflected by the vehicle platform, painted fascia, and the radome itself. These echoes mask short ranges of the automotive radar and thus degrade the detection performance on close targets. In addition, they contribute to increasing the probability of false alarms and reducing the radar DR, as the self-interference often determines the saturation limit. Furthermore, the computational complexity increases because of the requirement for mitigation algorithms.

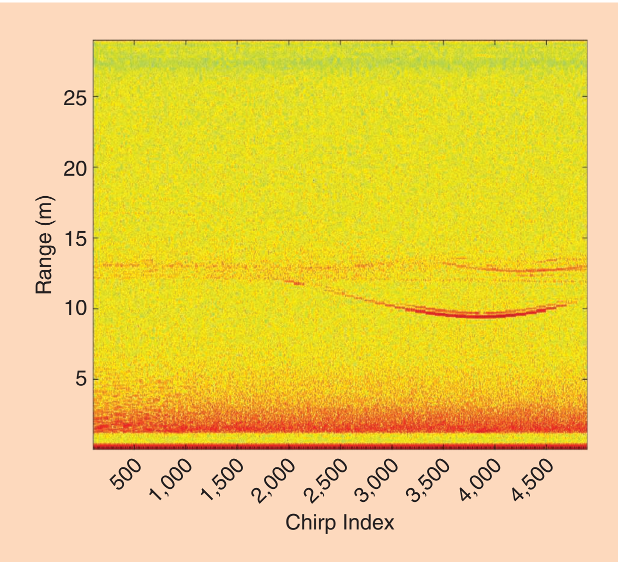

FIGURE 2. A range–chirp map showing target migration in a range over a long observation time.

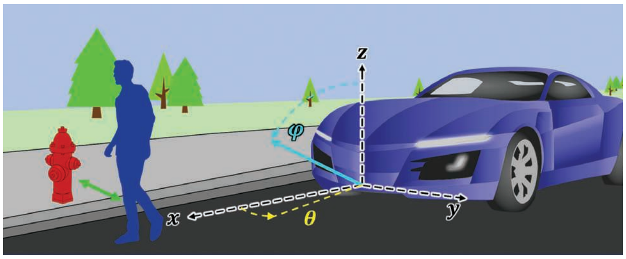

FIGURE 3. A cluttered roadway scenario.

Autonomous vehicles need surround coverage, which is achieved by mounting multiple radars around the vehicle. The radars have overlapping FOVs, which might cause mutual interference. The interference is both direct and reflected from targets. Thus, innovative algorithms for interference mitigation are required.

When most vehicles are equipped with automotive radars, multiple interferences are to be expected between radars of adjacent vehicles. Direct and reflected interference sources are expected to occur in dense-traffic scenarios, where the level of interference depends on the distance between radars, beam pattern, orientation, waveform, and the signal processing scheme. Interference sources increase the probability of false alarms, create ghost targets, and can mask true targets. Mitigation schemes will increase the computational complexity.

State-of-the-art automotive radar technology

State-of-the-art vehicular radar is designed to address automotive environment challenges. This is reflected in the radar's hardware, system design, waveform, antenna, and processing chain.

Concept

To tackle the automotive environment issues, as described in the "Automotive Radar Operation Challenges" section, the following technologies have been commonly adopted for vehicular radars: CW–LFM MIMO, high carrier frequency, solid state, CMOS, and RF integrated circuit. Pulse-Doppler radars have minimal detectable range (blind range) since the radar's receiver is turned off during the transmission interval. Automotive radars are required to detect targets at close proximity (starting from zero range), making the pulse-Doppler radar operation concept inappropriate for vehicular applications. Another advantage of CW operation is the low transmission peak power, which is important for operation in close proximity to the general public and which is strictly regulated by health authorities. Pulse-Doppler radars conventionally operate with up to a $D_{\mathrm{dc}} = 10\%$ duty cycle, and, therefore, to achieve the required average power $P_{\mathrm{avg}} = P_{\mathrm{peak}} D_{\mathrm{dc}}$, they need to transmit higher peak power P_{peak} compared with CW radars. The latter have modulated signals to obtain a target's range information. The LFM waveform is the most common CW modulation scheme since it has high range resolution and allows simple and low-cost fabrication.

State-of-the-art automotive radars have adopted the MIMO operation concept to achieve high angular resolution at a wide 2D azimuth–elevation FOV, with a high update rate. The MIMO vehicular radar illuminates the entire FOV with a wide and static transmit beam, where the angular information is obtained using the MIMO scheme at the receiver [13]. Common alternatives of direction-of-arrival (DOA) estimation are scanning phased array and monopulse (see [8, Ch. 1]). Scanned-based DOA estimation and monopulse are infeasible in automotive radars because of the low update rate and low angular resolution.

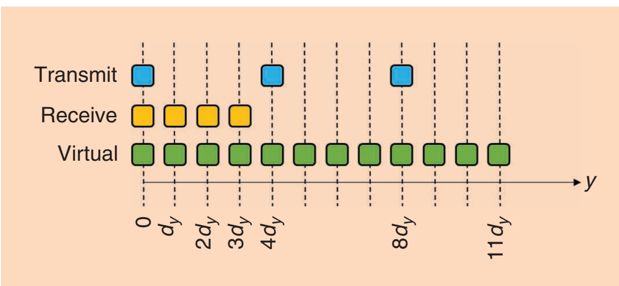

FIGURE 4. A MIMO radar antenna array.

High angular resolution, determined by the antenna beamwidth at a wide FOV, can be achieved via a multibeam beamforming. Analog beamforming implementation requires multiple circuitries for each generated beam, followed by multiple samplers. The large number of beams prohibits its analog implementation, which becomes complex, expensive, and cumbersome.

An alternative approach is digital beamforming, where each antenna element is sampled, and digitally steered beams can be obtained via a discrete Fourier transform [18]. In digital beamforming, there is no physical constraint on the number of beams, which is limited only by the computational power. This process is applicable at the receiver in a single-input, multiple-output system. In a MIMO system, this concept is extended from physical elements to virtual elements by transmitting orthogonal signals and decoding them at each receiver element [13].

FOV

Autonomous driving requires surround coverage of the host vehicle to provide reliable information about the static and dynamic obstacles that can be threats for the vehicle. The requirement of a low-cost system motivates the widest possible azimuth FOV. MIMO radar provides a wide FOV while obtaining narrow beams and a high angular resolution. This is achieved by the effect of virtual sensors. Each combination of receive and transmit elements generates a virtual element, with signal properties determined by the unique transmitter–target–receiver path, as conceptually shown in Figure 4. The MIMO virtual antenna aperture is larger than that of a conventional phased-array antenna, providing higher angular resolution.

Regulated by the authorities, automotive radars are implemented at a high carrier frequency band of 76–81 GHz. The radar antenna size decreases, and the angular resolution, determined by the ratio between the antenna aperture and the carrier frequency, increases with the carrier frequency. Therefore, a higher operational frequency allows smaller and lighter automotive radar implementation, attaining higher angular resolution.

The Doppler resolution ΔD improves linearly with increasing carrier frequency f_c,

$$\Delta D = \frac{c}{2 f_c} \frac{1}{\mathrm{TOT}}. \tag{1}$$

The higher operational frequency provides a larger available spectrum bandwidth for a transmitter with a constant fractional bandwidth [19]. Therefore, the range resolution increases at a higher carrier frequency.

High carrier frequency poses a technological challenge to fabricate high-quality and low-loss RF components. Thus, the performance of RF components in terms of noise figure, phase noise, antenna gain, and efficiency typically degrades with increasing carrier frequency. Moreover, free-space path loss grows as the carrier frequency increases, resulting in shorter radar detection range (see [8, Ch. 1]).

Automotive radars are expected to be manufactured in high volumes, far greater than conventional military radars. Therefore, certain techniques and materials, e.g., solid-state CMOS, which meet both mass production and low-cost requirements, will be implemented. The most challenging aspect of radar mass production is antenna calibration, which conventionally is a long and costly process, inapplicable to mass production. Efficient innovative methods are required for fast and accurate calibration.

Waveform

Motivated by the requirement of high angular resolution, state-of-the-art automotive radars adopt a MIMO approach, which requires orthogonal waveform generation. The simplest way to achieve a waveform's orthogonality is time-division multiple access (TDMA), where the number of TDMA cycles N_{Tx} equals the number of transmit antennas. For the LFM–TDMA–MIMO automotive radar, the pulse repetition interval is $T_{\mathrm{cyc}} = T_{\mathrm{c}} N_{\mathrm{Tx}}$, where T_{c} is the chirp period and is equal to the chirp duration. The range resolution and maximal unambiguous Doppler velocity are $\Delta R = c/2bT_{\mathrm{c}}$ and $D_{\mathrm{unamb}} = (c/2f_{\mathrm{c}})(1/T_{\mathrm{cyc}})$, respectively. The overall $\mathrm{TOT} = N_{\mathrm{cyc}} T_{\mathrm{cyc}}$, determined by the number of cycle repetitions N_{cyc}, upper-bounds the update rate of the radar detections $\mathrm{FPS} \leq 1/\mathrm{TOT}$ and defines the Doppler resolution as $\Delta D = (c/2f_{\mathrm{c}})(1/\mathrm{TOT})$. Additional approaches for obtaining nearly orthogonal signals have been derived [20], and similar approaches can be adopted for automotive applications.

Conventional vehicular radars are designed for a specific set of active safety features, and, therefore, radar waveform parameters are optimized for this particular array of operational conditions. Thus, an LRR is required to provide long ranges for fast-moving targets (a short chirp duration for increasing the maximal unambiguous Doppler) with lower range resolution. In turn, an SRR operates at shorter ranges, with higher range resolution and smaller unambiguous Doppler. Since the optimal waveform is scenario and mission dependent, the development of a radar that adapts the waveform according to the instantaneous radar mission and environment is required.

Processing chain

When operated in dense urban environments characterized by multiple objects, the transmitted automotive radar signals are reflected back from the targets and clutter and then received and down-converted as a mixture of multiple radar echoes accompanied by additive receiver noise. The main task of the vehicular radar signal processing chain is to suppress the additive noise and detect, isolate, and classify these multiple mixed echoes from different objects that are prominent and separable in the 4D spectral domain of range, Doppler shift, and 2D DOA. Conventionally, the automotive radar processing chain performs this task by employing multiple integrations along the different dimensions [7].

In the presence of M targets, the baseband data model at the kth chirp and the nth antenna receiver with a single transmitter is given by

$$x_{n,k}(t) = \sum_{m=1}^{M} A_m s(t-\tau_m) e^{j2\pi f_{\mathrm{d}m} k T_c} e^{j2\pi f_c \Delta\tau_{m,n}} + v_{n,k}(t), \quad (2)$$

where $s(t)$ is the transmitted signal and A_m, τ_m, and $f_{\mathrm{d}m}$ are the amplitude, time delay, and Doppler shift of the mth target, respectively. The time-delay difference $\Delta\tau_{m,n}$ denotes the delay difference between the antenna array origin and the nth antenna for the mth target, and $v_{n,k}(t)$ represents the additive receiver noise.

Stretch processing is performed by multiplying the received signal with the conjugated transmitted signal. For an LFM signal $s(t) = e^{j\pi b t^2}$, one obtains

$$\tilde{x}_{n,k}(t) = x_{n,k}(t) s^*(t) = \sum_{m=1}^{M} \tilde{A}_m e^{-j2\pi b \tau_m t} e^{j2\pi T f_{\mathrm{d}m} k} e^{j2\pi f_c \Delta\tau_{m,n}} + \tilde{v}_{n,k}(t), \quad (3)$$

where $\tilde{A}_m = A_m e^{j\pi b \tau_m^2}$. It can be seen that the model consists of a product of sinusoids in slow-time k and fast-time t data. For uniform planar arrays, $\tau_{m,n}$ is linear in indices of horizontal and vertical elements. Thus, the model includes a product of sinusoids in these axes as well. This implies that, to extract range–Doppler–azimuth–elevation information, one needs to implement a 4D FFT. Prior to the digital FFT, the signal is sampled with a sampling time of T_s, yielding $x[l,k,n] = \tilde{x}_{n,k}(lT_s)$. The 4D FFT is performed by

$$X[p,q,\theta,\varphi] = \sum_{n_v=1}^{N} \sum_{n_h=1}^{N} \sum_{k=1}^{K} \sum_{l=1}^{L} x[l,k,n] e^{-j2\pi p \frac{l}{L}} e^{-2j\pi q \frac{k}{K}} e^{2j\pi \frac{d}{\lambda} n_h \sin\theta \cos\varphi} e^{j2\pi \frac{d}{\lambda} n_v \sin\varphi}, \quad (4)$$

where n_h and n_v are the horizontal and vertical antenna indices, respectively, $n = n_h + H(n_v - 1)$ for H horizontal antennas, and d is the antenna spacing. The resulting data cube is depicted in Figure 5. Targets that are distinguishable at least in one of these parameters can be resolved.

Leveraging the separation of the received radar echoes from multiple objects in the four domains, the receiver reports the target presence at a particular point in this space by the comparison of the received signal energy to the threshold (detection). Conventionally, automotive radars use CFAR detection, in which a detection is declared for cells that satisfy the following condition:

$$|X[p,q,\theta,\varphi]|^2 > T + \hat{\sigma}_v^2[p,q,\theta,\varphi], \quad \forall p,q,\theta,\varphi, \quad (5)$$

where T is the CFAR threshold and $\hat{\sigma}_v^2[p,q,\theta,\varphi]$ is the noise variance, estimated around the cell defined by its arguments. As radar operation in an automotive environment pushes the radar design toward higher sensitivity (longer detection ranges of weaker targets), lowered CFAR thresholds raise the false-alarm rate beyond the desired point. Therefore, additional detection-level spatiotemporal filtering, denoted as *clustering and tracking*, is conventionally implemented in vehicular radars. The conventional density-based spatial clustering of applications with noise (DBSCAN) [21], [22] takes advantage of the high spatial resolution, groups together closely located detections, and represents them as a single cluster. Groups that contain few detections are marked as noise and removed, leaving the point cloud with an improved detection-to-false-alarm rate. Temporal filtering, which is usually implemented using Kalman, particle, or multimodal filters [23], further increases the fidelity of the output data by associating temporally close clusters into tracks.

Finally, additional information on the detected and tracked target is extracted from the received echoes via classification, which may be performed with extracted micro-Doppler features [24], spatial spread, movement along the space, or other information. These features can be used to characterize the detection or even improve upon the estimation of its parameters. The processing flow is depicted in Figure 6.

Antenna design

The automotive radar antenna must provide high angular resolution and accuracy while being mass-produced at low cost. To satisfy these criteria, microstrip patch technology is often used for vehicular radars operated at the carrier frequency of 77 GHz (a wavelength of $\lambda = c/f_c = 39$ mm) with a wide bandwidth of 4 GHz. For this wavelength scale, the required fabrication accuracy is on the order of micrometers, which is higher than currently available fabrication technologies, resulting in suboptimal antenna performance. The majority of modern automotive radars prioritize angular resolution in azimuth over that in elevation. However, the practical implementation of the radar-based active safety features and autonomous driving requires high angular resolution in both azimuth and elevation. Therefore, a planar antenna layout is needed to provide such resolution. The microstrip antennas on the printed circuit board have an inherently poor isolation between the antennas and therefore provide degraded performance.

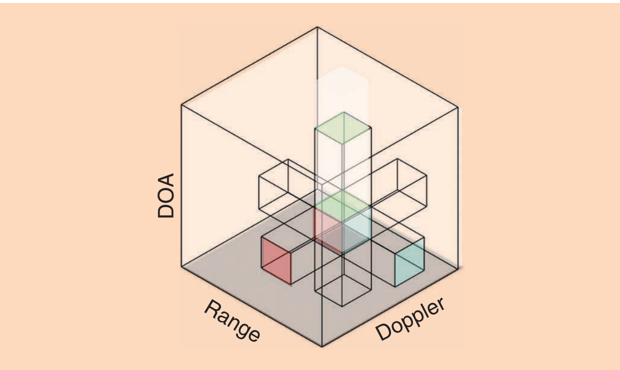

FIGURE 5. A range–Doppler–DOA data cube, an output of the 4D FFT.

Future solutions

This section describes the performance gaps in state-of-the-art automotive radars and discusses some of the required signal processing improvements. Parts of these topics have been developed and intensively investigated in recent years. These areas have the potential to move vehicular radar technology forward, but adaptation to the special needs of automotive radars is necessary.

Cognitive radar

Highly dynamic and varying roadway scenarios motivate the adaptive allocation of automotive radar resources. Moreover, the cost reduction requirement drives the consolidation of sensing capabilities to support multiple automated features within a single sensor. Cognitive sensing that introduces feedback between the receiver and the transmitter to improve scene perception can address these challenges. Specifically, the radar waveform needs to be adapted to the scene and mission: different ranges, FOVs, target types, RCSs, and velocities. The array configuration can also be changed according to the tradeoff between angular resolution, FOV, and maximal range.

The basic idea of cognitive radar is presented next (see Figure 7). MIMO radar allows flexibility in the design of the transmit waveform, which may be different for each transmitting element. After the introduction of colocated MIMO radar in [13], the problem of optimal waveform design for various scenarios and under different criteria has been intensively investigated. In automotive radar applications, the radar task and scenario continuously change, and thus the transmit waveform needs to be adaptively modified based on history observations, using a cognitive approach.

The idea of cognitive radar was proposed in [25] and has been investigated in several works. A cognitive radar system adaptively interrogates the environment using the available information from previous observations, external databases, and task priorities. The transmit waveform can be sequentially adapted in the space, time, and frequency domains, based on previous observations, which provide relevant information on the scenario. Adaptive beamforming for cognitive MIMO radar was investigated in [26]. However, in that paper, the focus was on only spatial waveform design, ignoring the range and Doppler dependency.

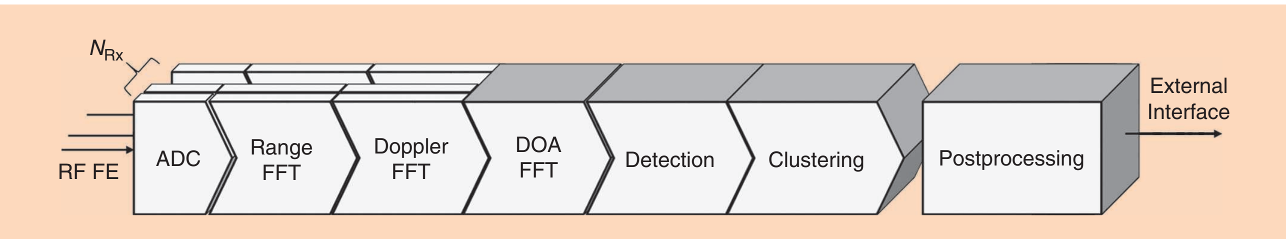

FIGURE 6. A conventional automotive radar processing flow. FE: front end.

Consider a monostatic MIMO radar with colocated transmit and receive arrays of N_T and N_R elements, respectively. In the presence of M targets, the received signal model at the kth pulse/chirp can be expressed as

$$\mathbf{x}_k(t) = \sum_{m=1}^{M} \alpha_m e^{-j\omega_{Dm}k} \mathbf{a}_R(\varphi_m)\mathbf{a}_T^T(\varphi_m)\mathbf{s}_k(t-\tau_m) + \mathbf{v}_k(t),$$
$$k = 1, 2, \ldots, \quad t \in [0, T], \tag{6}$$

where $\mathbf{x}_k(t)$, $\mathbf{s}_k(t)$, and $\mathbf{v}_k(t)$ denote the vectors of the received data, the transmit signal, and the noise vector, respectively. The parameters α_m, φ_m, τ_m, and ω_{Dm} are the complex attenuation, direction, propagation delay, and Doppler frequency shift of the kth target, respectively, and $\mathbf{a}_T(\cdot)$ and $\mathbf{a}_R(\cdot)$ are the steering vectors for the transmit and receive arrays, respectively. The Fourier coefficients of the data model in (6) are given by

$$\mathbf{x}_{kl} = \mathbf{H}_{kl}(\theta)\mathbf{s}_{kl} + \mathbf{v}_{kl}, \quad k = 1, 2, \ldots, \quad l = 1, \ldots, L, \tag{7}$$

where $\mathbf{x}_{kl}$, $\mathbf{s}_{kl}$, and $\mathbf{v}_{kl}$, are the lth Fourier coefficients of the received data, transmit signal, and noise vectors, respectively, and

$$\mathbf{H}_{kl}(\theta) = \sum_{m=1}^{M} \alpha_m e^{-j\omega_{Dm}k} e^{-j\frac{2\pi l}{T}\tau_m} \mathbf{a}_R(\varphi_m)\mathbf{a}_T^T(\varphi_m) \tag{8}$$

is the MIMO transfer function. Let $\mathbf{X}_k = [\mathbf{x}_{k1}, \ldots, \mathbf{x}_{kL}]$ and $\mathbf{S}_k = [\mathbf{s}_{k1}, \ldots, \mathbf{s}_{kL}]$. A cognitive radar adaptively modifies the transmit signal sequence at the kth step $\mathbf{S}_k$, given observations in previous steps denoted by $\mathbf{X}^{(k-1)} = [\mathbf{X}_1, \ldots, \mathbf{X}_{k-1}]$.

The transmit signal is usually constrained according to one of the following approaches:

- *Limited total energy*: $\sum_{l=1}^{L} \|\mathbf{s}_{kl}\|^2 = \text{const}$
- *Limited energy at each transmitter element*: $\sum_{l=1}^{L} |[\mathbf{s}_{kl}]_n|^2 = \text{const}, \ n = 1, \ldots, N_\text{T}$
- *Limited total energy at each frequency bin*: $\|\mathbf{s}_{kl}\|^2 = \text{const}, \ l = 1, \ldots, L$.

The cognitive scheme can be formulated as follows:

$$\begin{array}{ll} \underset{\mathbf{S}_k}{\text{optimize}} & C(\mathbf{S}_k, \mathbf{X}^{(k-1)}) \\ \text{subject to} & \text{signal energy constraint,} \end{array}$$

where $C(\cdot,\cdot)$ denotes the optimization criterion, which reflects a measure of performance. Performance bounds can serve as possible optimization criteria. For cases where one is interested in optimizing the parameter estimation accuracy, lower bounds, such as the Cramér–Rao bound or other large-error bounds, are usually adopted as optimization criteria. The non-Bayesian framework is not applicable because non-Bayesian bounds are usually parameter dependent. Although the unknown parameter may be substituted by its estimates, this solution usually results in poor performance. To obtain a performance measure independent of the parameters to be estimated, the Bayesian framework is usually preferred. This approach has been proposed for target localization [26].

For detection or classification problems, one may use the sequential hypothesis testing framework. In this approach, one is interested in minimizing the average sample number (ASN) where the decision error probabilities are fixed. Lower ASN bounds are inversely proportional to the Kullback–Leibler divergence (KLD) between the probability density functions under the given hypotheses. This implies that, for detection or classification tasks, one is required to maximize the KLD to optimize the performance.

Extended target detection

In typical urban scenarios, high-resolution automotive radars with a range resolution of several centimeters are required to detect range-extended targets that occupy multiple range–Doppler cells. At such fine resolution, every single extended target appears as a set of point targets, as shown in Figure 1(a). Single-cell-based detectors do not aggregate the entire spread target energy and, therefore, provide shorter detection ranges. Conventional radar detectors, such as CFAR, offer degraded performance in such scenarios because of contamination of the noise estimation by the interfering cells. Therefore, the development of alternative detectors that are robust to interference from other cells is required. In military applications, detectors for distributed targets were first introduced in [27] and further developed in [28]. These approaches cannot be directly applied to automotive radars, since prior information on the targets in the vehicular domain is typically unavailable because of the vast variety of their types and sizes. Alternatively, what is needed is the development of a detection approach utilizing rigid-body information on the automotive targets to integrate energy spread over multiple cells.

Doppler ambiguity

TDMA implementation of the state-of-the-art automotive MIMO radars results in a contradiction between the Doppler and the DOA requirements. This occurs because the DOA estimation is performed per range–Doppler cell, and, as a result, the DOA estimation performance directly depends on the Doppler estimation [29]. In TDMA–MIMO radar, as the number

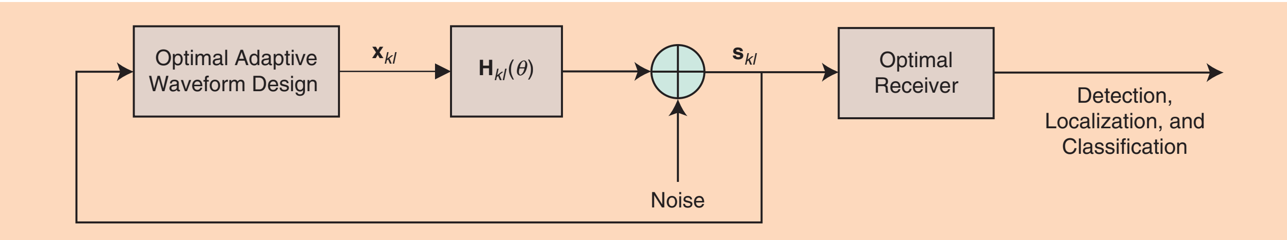

FIGURE 7. A cognitive radar configuration.

of transmit antennas increases, the maximal unambiguous Doppler frequency decreases. Therefore, novel methods to resolve the Doppler ambiguity of automotive MIMO radars are required. For this purpose, several approaches may be adopted. One interesting technique is the chirp sequence waveform design presented in [30]. Moreover, at longer operational ranges (e.g., in freeway scenarios), a longer chirp duration is required, which challenges the Doppler ambiguity mitigation methods.

Multipath mitigation

Flat surfaces on roads, guardrails, buildings, signs, and bridges characterize automotive scenes. The radar transmitted signal reflects from these surfaces and interferes with the direct signal that echoes from targets. Figure 8 shows typical traffic situations, with vertical, road-induced and horizontal, guardrail-induced multipath scenarios.

Indirect signal parameters, such as range, Doppler, azimuth, and elevation, differ from those of the direct signal. If they are similar to those of the direct signal and are beneath resolution, they may interfere with it, potentially disrupting target detection and parameter estimation. Angular information has the highest sensitivity to multipath, and its estimation performance can be greatly degraded. If the indirect signal parameters differ beyond the ability of the radar to resolve, a false target may appear. This phenomenon is difficult to mitigate, and current radars suffer from it.

The indirect signals are determined by radar–target–environment geometry and correlated with the direct path signal. Current mitigation methods utilize the difference between the direct and indirect signals in the time-delay, Doppler, and DOA domains: [15] utilizes the angular difference to filter multipath with MIMO space–time adaptive processing, [31] employs correlation, [32] proposes to track both the direct and indirect signals simultaneously, and [33] takes advantage of the different indirect signal responses for up and down LFM signals to distinguish and mitigate them. All of these methods cannot be directly applied to automotive radars and need to be modified since the use of different waveforms is limited because of several reasons. These include the requirement of low cost, the difference of automotive clutter from that encountered with airborne radars, the occurrence of vehicular multipath in both azimuth and elevation, and the multiple moving objects that induce the large number of multipath returns in dense urban environments.

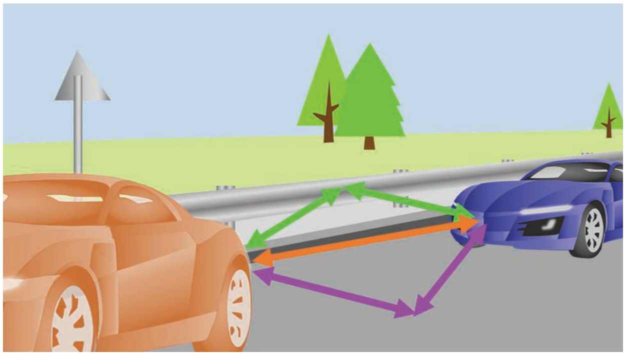

FIGURE 8. An illustration of multipath, with the target echo traveling in additional indirect paths, reflected by the road surface and guardrail.

Angular superresolution

State-of-the-art automotive radars have a low angular resolution determined by the antenna aperture. The resolution attained through conventional beamforming cannot break this physical limitation. Therefore, vehicular radars adopt a MIMO radar approach to achieve higher angular resolution at a smaller aperture and a feasible number of channels [7]. Superresolution methods that are successfully used in military applications, such as MVDR and MUSIC, are expected to be implemented in automotive radars. This task requires the development of low-computational processing algorithms and their adaptation to automotive scenarios with angularly spread targets (short-range and large objects, such as vehicles) that may occupy multiple angular cells.

Clustering

Because of high range resolution in automotive radars, targets (such as vehicles and pedestrians) appear as a cloud of point targets, and thus the association of these point targets to a single object target, denoted as *clustering*, is required. The clustering process consists of point target association to centroids representing actual objects. Thus, the DBSCAN was shown to be able to generate arbitrarily shaped clusters and to disregard noise-generated detections without a need for a priori knowledge of the number of clusters [21]. The DBSCAN was adapted to a variety of applications and input data characteristics [22]. However, its major shortcoming is its inability to provide centroids that are related to real-life objects. Moreover, in dense automotive environments with multiple adjacent objects, the association task is computationally demanding. Therefore, novel clustering methods are necessitated that take into account point detection densities in the entire range–Doppler–DOA domain and provide an indication of object shapes.

Waveform optimization

State-of-the-art automotive radars that adopt the MIMO approach achieve the required waveform orthogonality via TDMA operation at the expense of shortened maximal detection range and lower maximal unambiguous Doppler. Therefore, the practical implementation of vehicular MIMO radars requires the development of a more efficient method to achieve waveform orthogonality through code-division multiple access (CDMA) via phase or frequency coding. The CDMA approach was intensively studied in the communications literature, and many efficient codes, such as Gold and Hadamard, were shown to achieve high orthogonality among transmitted sequences [34], [35]. However, the orthogonality provided by these codes degrades with the delay or Doppler shifts that characterize automotive applications. Therefore, new code families need to be developed for efficient implementation of the Doppler- and delay-shift codes that in turn could enable efficient CDMA–MIMO implementation of vehicular radars.

Synthetic aperture radar

Synthetic aperture radar (SAR) mounted on the moving vehicle platform has a potential to improve automotive radar angular resolution and enhance imaging capabilities [36], [37]. Vehicular SAR is especially efficient for a variety of side-looking applications, such as parking spot detection [38] and road boundary localization

[39]. However, the forward direction is of the greatest interest for automotive radar for autonomous driving, and some preliminary results on forward-looking automotive SAR were shown in [40]. Major challenges in the application of airborne-based SAR methods to vehicular radars are motion compensation, nonlinear host vehicle motion, and low-grazing angles. Therefore, efficient methods for automotive SAR are a subject for future research.

Multiradar coexistence

The last decade showed an exponential growth in the number of automotive radars deployed in retail vehicles, and a similar tendency is expected in the future. Thus, the density of automotive radars on the road per area is growing. As all vehicular radars share the same spectrum, mutual interference between them is expected to become a major concern. The probability of interference is determined by the radar waveform, transmitted power, beamforming properties, and distance between the radars. The power of the direct interference at the receiver is

$$P_{rH} = \frac{P_{tI} G_{tI} G_{rH} \lambda_I^2}{(4\pi)^2 R^2 L_H}, \tag{9}$$

where P_{rH} and G_{rH} are the received power at the host radar and its gain toward the interfering radar, P_{tI} and G_{tI} are the transmit power of the interfering radar and its gain toward the host radar, λ_I is the signal wavelength, R is the distance between the radars, and L_H is the propagation loss between the radars. Notice that, in (9), the interference source experiences one-way propagation loss and thus increases the detection threshold of the host radar, which results in significant detection performance degradation.

State-of-the-art automotive radars rely on frequency, spatial, and directional diversity and thus assume a low probability of interference. However, in the near future, this assumption will not hold, and, therefore, new interference mitigation methods are needed. Interference can be direct or indirect and can be categorized according to the modulation scheme. There are three approaches for interference mitigation:

1) resource allocation, e.g., via spectrum allocation, which results in degraded system performance when no interference is present
2) synchronization, which requires online coordination between adjacent radars via an additional communication channel
3) waveform parameters randomization.

The first approach is the most attractive and easiest to implement (and is currently adopted in the automotive industry), but it might fail as the probability of interference increases. Moreover, fully autonomous vehicles will demand extremely high reliability for the automotive radars, which could be compromised by interference in heavy-traffic scenarios where multiple radars operate closely adjacent. Therefore, implementation of additional interference mitigation approaches will be required.

Synchronization of multiple-platform radars is another approach that is expected to be adopted in the future to address the mutual interference problem in automotive radars. Synchronization and interference mitigation approaches that are widely used in cellular networks, such as orthogonal frequency-division multiplexing (OFDM), which divides the time–frequency resources [41], are expected to be adopted in the dynamic network of vehicular radars. However, these additional countermeasures seem to be insufficient, and additional CDMA-like approaches to achieve higher interference suppression will be needed. Thus, different code families could be used at different time–frequency slots of the OFDM. Communication-based CDMA methods cannot be directly used in automotive radars where higher orthogonality and interference suppression are required for operation in practical roadway scenarios characterized by multipath, delay-Doppler spread, high DR, and range–Doppler–DOA ambiguity. Thus, development of interference-resistant codes and radar network management via ad hoc base stations will be needed. Finally, extensive regulations for vehicular radar operation and resource management will be required.

Multiple target tracking

Trackers play a significant role in radar signal processing. They improve localization estimation, reduce false alarms, deduce absolute velocity and trajectory, and generate a perception of the host vehicle's surroundings. A typical tracker comprises three main blocks: prediction, association, and update. Since conventional trackers have been developed for sparse, nonmaneuverable aerial and naval environments, they cannot be directly used in highly dynamic and dense urban environments with multiple, closely located, and rapidly maneuvering targets, such as vehicles, motorbikes, bicycles, and pedestrians. Moreover, detection-to-track association methods developed for the military sparse environment, such as nearest neighbors, fail in dense urban scenes. For example, Figure 9 shows one

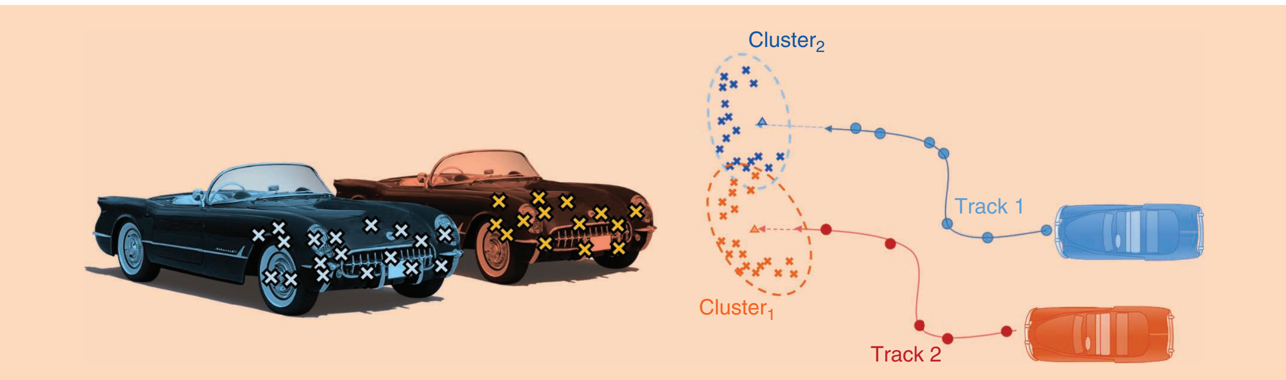

FIGURE 9. An interchanging vehicles association challenge.

of the typical traffic scenarios that challenge the conventional detection-to-track association techniques.

Therefore, the application of conventional tracking procedures for automotive radars requires multiple adaptations. Thus, alternative association criteria [42] need to be developed where multiple radars are used in a joint association fashion [43]. In addition, the multihypothesis tracking approach can be more efficient in vehicular radars compared with conventional Kalman tracking [44]. Association can also be improved by expanding the target's feature space. State-of-the-art automotive radars use target position and velocity for detection-to-track association. Features such as class, micro-Doppler signature, and size can be used to improve the solution to the detection-to-track association problem.

Classification via micro-Doppler

Autonomous driving requires reliable knowledge of the vehicle's surroundings. Therefore, scene perception is an important component of vehicle sensing. In particular, classification of the detected targets is needed for threat assessment, sensing resource allocation, and automated control. Currently, target classification is performed mainly using computer vision methods applied to camera images. Typical automotive radar targets, such as pedestrians, cyclists, and vehicles, consist of multiple moving and rotating parts inducing micro-Doppler modulation to the radar echoes [45]. Micro-Doppler was extensively studied in military radar target classification and was suggested for automotive applications [46], [47].

Trends to increase the angular and Doppler resolution of automotive radars motivated recent attempts to use micro-Doppler features for vehicular radar target classification [24], [48]. High angularity and range resolution allows the receipt of the micro-Doppler of multiple moving targets' parts individually and thus the construction of distinctive spatiotemporal signatures of the moving targets, enabling high-fidelity radar-based target classification. Advances in deep-learning methods further enhance the significance of micro-Doppler features for radar target classification [49].

Deep learning

Deep learning is a revolutionary data-driven processing approach first introduced for image processing and lately adopted in other disciplines, such as speech and language recognition [50]. Recently, deep learning was used for radar signal processing, mainly for target classification [51]. Deep learning has a potential for automotive radar processing tasks beyond target classification, such as interference mitigation, extended target detection and localization, design (waveform and antenna), and more specific tasks, such as road estimation [52].

Conclusions

This work reviewed state-of-the-art conventional automotive radar processing and discussed its limitations when used in practical, highly complex automotive scenarios. Requirements for future vehicular radars as a main enabler of autonomous driving were discussed. This overview proposed directions to improve automotive radar performance by the development of alternative processing approaches that are currently missing or being implemented in conventional military radars and cannot be directly applied to automotive radar without significant adaptations. SAR, micro-Doppler-based classification, extended target detection, super-resolution beamforming, adaptive waveforms, CDMA, and other discussed methods were successfully developed for other applications and thus have the potential to significantly improve the performance of vehicular radars. Novel interference and multipath mitigation methods, Doppler ambiguity elimination, multitarget tracking, cognitive processing, and clustering methods need to be further developed for the unique automotive applications.

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