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Pandharipande, Ashish; Wang, Pu; Hakobyan, Gor

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Ashish Pandharipande, Pu (Perry) Wang, and Gor Hakobyan

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Index Terms—Radars, Edge Sensing, Industrial Robotics, Mobile Robotics.

I. INTRODUCTION

The growing adoption of robotics in industrial and mobility domains requires robust environment sensing and perception [1]–[4]. This information is used for decision-making and robot control. Sensing modalities like LiDAR, cameras, and ultrasonic sensors have been used conventionally in robotics. However, each of these sensor modalities comes with its specific limitations: cameras are sensitive to varying lighting conditions and raise privacy concerns, LiDARs remain expensive and relatively bulky, and ultrasonic sensors have limited range and resolution. In this context, radars can serve as a complementary modality with added redundancy, or as an alternative modality due to their higher robustness in adverse environmental conditions, including full independence of light [5]. Radars provide detection capabilities over short to long ranges with a wide field-of-view, instantaneous velocity estimation, and support azimuth and elevation angle estimation via the use of antenna arrays and advanced signal processing. Further, 4D radar measurements in the form of 3D position and velocity are especially useful in dynamic environments

to distinguish between close, moving objects. Millimeter-wave radars can see through many materials and visual obstructions, such as dust, smoke, cardboard boxes, plastic containers, or cloth [6], [7]. Beyond the above sensing functionalities (e.g., range, Doppler, and angle estimation), radar-based perception is increasingly being used in higher-level tasks such as 3D bounding box (BBox) detection, skeletal pose estimation, semantic and instance segmentation, trajectory estimation and prediction. These advanced capabilities are essential for robot navigation and manipulation in complex environments, and also to enable safer and more intuitive human-robot interaction by providing robust situational awareness under a wide range of environmental conditions.

Alongside developments in radar sensor technologies, deep learning approaches have reached a high level of maturity for a number of tasks. Such machine learning (ML) approaches can capture abstract and complex details and recognize data patterns far beyond handcrafted features. Newer ML approaches, such as foundation models, promise performance improvements across a wide range of tasks. However, these ML models are too large for edge implementation that requires local data processing on the robot and real-time decision making. The convergence of radar sensing with lightweight edge learning architectures can thus enable responsive robotic systems capable of operating reliably and adaptively in complex, dynamic environments.

This paper explores the synergy between radar sensing and edge learning in robotics, focusing on industrial automation and mobile robots. We analyze particular use cases to identify requirements for environment sensing and perception. We highlight how the requirements for mobile robotics are different from those for automotive, where radars are an established modality in the sensor suite of autonomous vehicles. Subsequently, we analyze the advantages and limitations of radars to deduce their fit to the sensing requirements in different robotics use cases. We then discuss technological advances made in radar edge sensing for robotics, as well as identify challenges and new directions for future research.

II. APPLICATIONS AND SENSING NEEDS

Robotic systems are integral to warehouse automation, assembly lines, and goods delivery. Figure 2 depicts representative robotic use cases in diverse industrial and mobility scenarios.

Automated Guided Vehicles and Autonomous Mobile Robots: A well-established application for robots is warehouse automation with Automated Guided Vehicles (AGVs)

Ashish Pandharipande is with NXP Semiconductors, Netherlands (e-mail: ashish.pandharipande@nxp.com).

Pu (Perry) Wang is with Mitsubishi Electric Research Laboratories, Cambridge, MA, USA (e-mail: pwang@merl.com).

Gor Hakobyan is with Waveye (e-mail: gor@waveye.com).

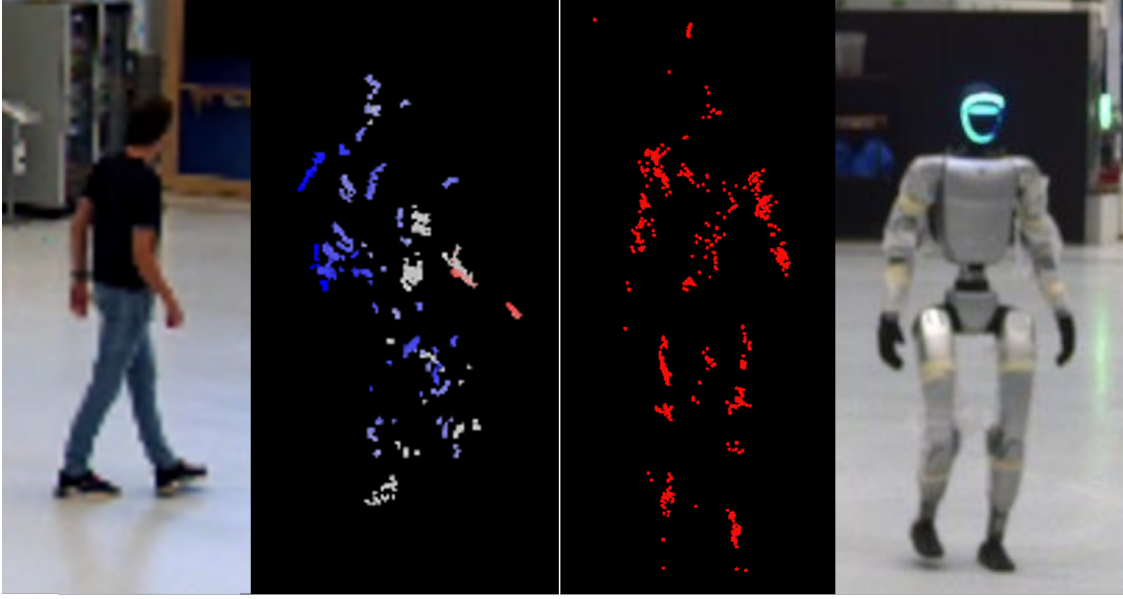


Fig. 1. Imaging-radar sensing examples for a human and a humanoid robot; point color encodes velocity.



(a) Automated guided vehicles, e.g., delivery robots, in automated warehouses.



(b) A robot arm operating in human collaboration in manufacturing.



(c) Outside-in-safety collaborative robotic system in manufacturing.



(d) Scene perception for automotive driving.

Fig. 2. Robotic systems in diverse industrial and mobility scenarios.

and Autonomous Mobile Robots (AMRs), as illustrated in Fig. 2(a). Typically, wheeled robots are used for automated transport of goods in a warehouse or a factory shop floor. The perception system of an AGV ranges from simple line-following functionality to 2D safety laser scanners capable of perceiving the environment in a single horizontal layer of a laser scan and avoiding collisions. AMRs may have a more complex sensor suite including cameras for visual perception and in some cases 3D LiDARs. While most of these applications are currently indoors, there are increasingly more industrial and outdoor AMRs, e.g., outdoor delivery AMRs. Another major shift is that current AMRs mostly assume that

the 3D world is represented in a 2D plane of the safety laser scan, which is increasingly not a given in complex industrial environments, especially for large AGVs and AMRs.

Robotic arms: Assembly plant robots are widely used to perform repetitive, high-precision, or hazardous tasks, e.g., a robotic arm operating with human collaboration as depicted in Fig. 2(b). Examples of such tasks are material handling, component assembly, inspection, and quality control. While robots in these assembly applications traditionally operate in highly structured environments, they are increasingly being used in more complex, unstructured manufacturing applications. This calls for new sensing features such as 3D localization, object recognition, and proximity sensing.

Robotic manipulation using cameras and depth sensors faces well-known limitations when dealing with transparent, reflective, or occluded objects, i.e. conditions where light-based sensing often fails due to distorted or missing depth signals. These challenges often arise in industrial tasks such as bin picking, sorting, and handling of items in cluttered or visually ambiguous settings [8], [9]. Some of the sensing needs to improve safety of such robotic operations are detection of people and objects in the vicinity, as well as robust perception and path planning and navigation.

Collaborative Robots: In recent years, collaborative applications of robot arms alongside humans have become part of advanced manufacturing plants, as illustrated in Fig. 2(c). Since these robotic systems operate in the vicinity and in interaction with humans, they need to guarantee the safety for humans at all times. The main challenge is thus to provide safety while not overly limiting the capabilities and speed of the robot [10]. This is achieved either with force sensors capable of detecting contact with the human body and stopping the robot or by wireless sensing systems that detect human presence near the robot.

The above two use cases are often referred to as inside-

TABLE I
SENSOR REQUIREMENTS FOR DIFFERENT ROBOTIC USE CASES.

Use Case	Detection Range	Resolution	Velocity Estimation	Velocity Resolution	Angular Resolution
AMRs	0.1-20 m	cm	Moderate (0-2 m/s)	0.1 m/s	1°
Robotic arms	0.1-2 m	sub-mm to mm	Low (pre-defined motion)	0.1 m/s	0.1°
Cobots	0.1-5 m	mm to cm	Moderate (0-2 m/s)	0.1 m/s	0.5°
Automotives	1-300 m	0.1 m	Very High (0- 50 m/s)	0.2 m/s	0.1°

out-safety, since the sensors are on the robots themselves. Another noteworthy use case is outside-in-safety, for which the sensors and the intelligence is part of the infrastructure, as opposed to each individual robot. This approach allows to cover safety functions for all participants on a shopfloor, including robots, humans, forklifts, etc. The same data can be used as a sensory input for the fleet management system. For this use case, sensors are required to have a long operation range to cost-effectively cover the shopfloor.

Automotive driving systems: An adjacent domain where robotics and autonomous system technologies have been adopted and matured is automated driving. Sensor modalities such as camera, radar and LiDAR are used in advanced driver assistance systems and automated driving for environmental perception, see Fig. 2(d). At the sensing level, accurate and robust detection of targets in the environment is needed to ensure that safety-critical driving decisions are error-free. This high level of sensing performance is required in diverse driving scenarios, including adverse weather and different lighting conditions. Given the dynamic and heterogeneous nature of driving, extraction of rich features such as object class, and higher-level information such as trajectory and occupancy grid maps becomes important. An accurate and robust understanding of the driving environment is the basis for achieving higher levels of driving autonomy.

A summary of requirements for the discussed use cases is shown in Table I. Examples of conventional sensing functions in these applications are ranging, shape estimation and object classification. Clearly, whereas all four application need sensors for autonomy, their needs for information density (accuracy, resolution), robustness, and cost-effectiveness varies significantly between domains.

III. RADAR AS A SENSING SOLUTION FOR ROBOTICS

Radar sensors operate by emitting radio signals and analyzing the echoes reflected from surrounding objects. Today's radars allow for accurate measurement of range, azimuth and elevation angles, as well as the Doppler speed of an object. For example, robotic arms equipped with a radar can detect and avoid collisions in collaborative manufacturing environments, improving safety and operational efficiency. Radar is much more robust than optical sensors in challenging operational environments with smoke, dust, or poor lighting, common in heavy industry. A comparison of radar with other sensors commonly used in various robotics use cases in terms of robustness, features, integration, and edge-processing suitability is shown in Table II. The key advantages of radars are:

- **Spatial perception:** Unlike cameras or 2D-LiDARs, radars directly measure the surroundings in 3D, thus natively providing a 3D environment perception.
- **Velocity estimation:** Based on the Doppler effect, radars provide direct (radial) velocity information of the surrounding objects, making them a suitable sensor modality in dynamic environments, e.g. with humans present near operating robots.
- **Robust environmental operation:** A radar is unaffected by lighting conditions and experiences little to no performance degradation in dust, dirt, and other challenging operational conditions.
- **Privacy:** Unlike cameras, radars do not capture personally identifiable image data, making them suitable in environments where human surveillance is a concern.
- **Cost and scalability:** Compared to LiDAR, radar sensors have significantly lower cost and are easier to miniaturize.

In addition to its robustness to lighting and weather, radar has the ability to penetrate materials such as cardboard, plastic, glass, and even walls, and supports non-line-of-sight (NLOS) perception, revealing objects invisible to conventional vision systems [11]. However, integrating radar is non-trivial: challenges include limited labeled data, sparse and low-semantic features, calibration complexity, and the need to co-optimize radar sensing with the robot's manipulation strategy.

The main limitation of radars is the angular resolution, resulting from orders of magnitude larger wavelength than optical sensors. This makes object classification and scene understanding more challenging. Furthermore, radar sensing often involves advanced signal processing to deal with artifacts like signal clutter and multipath reflections that occur in complex industrial and outdoor environments, making radar data less humanly interpretable.

To alleviate the resolution drawback, one recent development is the use of high-resolution imaging radars for robotics. Some imaging radars achieve an information density comparable to a 3D LiDAR on moving objects such as humans. Furthermore, the high information density allows for capturing the details on an object in 3D, while having the velocity of every point to represent a **spatio-dynamic signature**. This allows for robust object classification, since e.g. humans have a distinctly different signature than a robot, both spatially but also the way they move. For example, in Fig. 1, the color coding shows the velocity of every point. Approaching points are red, moving away is blue. Based on the radar point cloud, it can be readily inferred what the movement of the human is, whereas no camera or 2D/3D LiDAR would be able to instantaneously infer the motion based on the equivalent image.

TABLE II
COMPARISON OF SENSOR MODALITIES IN INDUSTRIAL AND MOBILITY ROBOTICS.

Use Case	Sensor Type	Environment Robustness	Privacy-Friendly	Range	Resolution	Velocity Estimation	Cost	Size / Integration	Edge Suitability
Warehouse Automation Robots	Radar	High	Yes	Med-Long	Medium	Yes	Low-Med	Compact	Med-High
	Camera	Low	No	Medium	High	No	Low	Compact	Medium
	LiDAR	Medium	Yes	Med-Long	Very High	No	High	Bulky	Medium
	Ultrasonic	Medium	Yes	Short	Low	No	Very Low	Very Compact	High
Assembly Plant Robots	Radar	High	Yes	Short-Med	Medium	Yes	Low-Med	Compact	Med-High
	Camera	Medium	No	Medium	High	No	Low	Compact	Medium
	LiDAR	High	Yes	Medium	Very High	No	Medium	Bulky	Medium
Cobots	Radar	High	Yes	Short-Med	Medium	Yes	Low	Compact	Med-High
	Depth Cam	Medium	No	Short	High	No	Low	Compact	Medium
	Ultrasonic	Medium	Yes	Very Short	Low	No	Very Low	Very Compact	High
Autonomous Vehicles (Outdoor)	Radar	Very High	Yes	Long	Medium	Yes	Low-Med	Compact	Med-High
	Camera	Low	No	Medium	Very High	Limited	Low-Med	Compact	Medium
	LiDAR	Medium	Yes	Medium	Very High	No	Very High	Bulky	Medium

A. Radar in automotive driving applications

Radar is an established sensor technology in automotive driving applications. Radars are used to provide environmental perception around the automotive to support different levels of driving autonomy. Automotive radars typically need to sense large ranges (up to 300 m on highways) and fast-moving objects (up to 50 m/s on highways). The radar itself can experience very high speeds given its automotive mounting. The radar field-of-view (FOV) is typically narrow in azimuth for front radars (less than 30°) and is medium for corner radars (up to 90°), with narrow FOV in elevation.

B. Radar in industrial and mobile robotic applications

A fundamental difference between radars used for automotive driving and those needed for industrial robots lies in the operating environment. Automotive radars often encounter open roads with some multipath occurring due to guard rails or other vehicles. In comparison, industrial robotic environments are metal-laden indoor spaces (e.g., racks, machinery) that create strong multipath reflections, occlusions, and are thus NLOS-constrained.

Automotive radars are optimized for long-range (100-300 m) driving scenarios with narrow FoV. In comparison, industrial robots move slowly and have short-to-medium ranges (typically 0.05-20 m), needing wider FoV and near-field coverage. The requirement for angular resolution is both in azimuth and elevation to detect obstructions along the floor, and resolve humans and rack uprights. This requires robotics-specific radar designs to accommodate for the sensing needs of the corresponding use cases.

IV. RADAR SENSING TECHNOLOGIES

In this section, we use the typical radar point cloud processing pipeline as depicted in Fig. 3 to discuss waveform and modulation designs and multi-input multi-output (MIMO) antenna configurations. We first review current state-of-the-art, and then lay out future opportunities in addressing open problems when designing radar systems for robotics.

A. Radar modulation and waveform designs

On the transmitter side, the design of MIMO waveforms determines how the environment is probed. For automotive driving applications, frequency modulated continuous wave (FMCW) is the de facto waveform. An FMCW radar offers a simple receiver implementation, and enables range and Doppler velocity estimation using computationally efficient fast Fourier transform (FFT) operations along the fast-time and slow-time chirps [12]. This receiver architecture offers a simple solution to dealing with self-interference that exists due to the transmitter and receiver antennas being co-located. However, it also adversely impacts the detection of objects in proximity. FMCW radars do not readily offer scalability to a large number of antennas needed in imaging applications. A time- or Doppler-division multiple access scheme used in MIMO FMCW radars leads to Doppler ambiguities.

To offer better MIMO scalability while supporting a large unambiguous Doppler velocity, digital waveforms like phase modulated continuous wave (PMCW) and orthogonal frequency division multiplexing (OFDM) have been considered [13], [14]. Works [15]–[18] have addressed different challenges in PMCW radar like sequence design, self-interference mitigation, and radar coexistence. Others [19]–[21], have presented OFDM radars as another flexible approach for automotive applications considering aspects like waveform design and radar interference avoidance. The flexibility offered by digital radars is particularly attractive given the diverse performance requirements across industrial and mobile robotics use cases.

New waveform designs can also be used to enable joint radar and communication capabilities. Unified radar-communication waveform design for automotive driving applications was considered in [22]–[24]. Communication information across vehicles can be used to coordinate radar interference or enhance the sensing range. Such joint communication and sensing systems can also be used for collaborative human-robot applications. However, the promise of such designs are yet to be realized in practical robotics applications and warrant further exploration.

TABLE III
RADAR FOR AUTOMOTIVE DRIVING VS INDUSTRIAL ROBOTICS.

Requirement	Automotive driving	Industrial robotics (warehouse, assembly, cobots, forklifts)
Operational environment	Diverse weather; mix of fast-moving vehicles and slower moving vulnerable road users; fewer strong signal reflections	Object clutter, metal-dense; NLOS-constrained; dust/smoke; humans in vicinity
Resolution	High range and Doppler resolution; angular resolution improving with imaging radar	Centimeter-level range resolution and fine 2D angular resolution to resolve humans and rack uprights
FoV & elevation	Multiple radars create 360° surround view, but individual radars have narrow FoV	Wide azimuth FoV and usable elevation to see floor-level hazards; side monitoring during turns mandated for AMRs
Interference resilience	Increased automotive radar density increases interference	Indoor robot fleets are small-sized result in limited interference

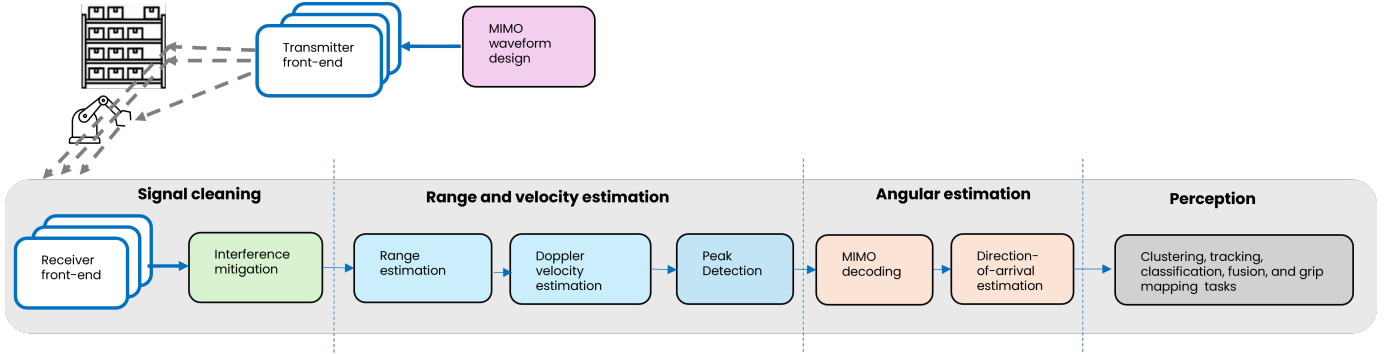


Fig. 3. Illustrative radar point cloud processing chain.

B. Radar processing for 4D target information

Fig. 3 illustrates a typical FMCW chirp sequence radar processing chain. The signal received at the receiver antennas is a superposition of the transmitted signal reflections from different surrounding objects. The first step in the radar processing chain is signal cleaning, wherein potential interference from radars operating in the vicinity is detected and suppressed [25]. The range of an object appears as a beat frequency in fast-time, and the radial velocity is reflected in the phase progression across chirps in slow-time. Range and Doppler estimation is done using FFTs across fast time and slow time [26]. Subsequently, peaks are detected in the range-Doppler map along with MIMO decoding to create multiple complex-signal channels for DoA processing. Azimuth and elevation angular information is estimated from the phase progression over the antenna array elements. The reader is referred to [27] for a state-of-the-art review on DoA estimation methods for automotive MIMO radars.

Whereas traditional signal processing methods have been developed for these sensing blocks, ML methods have recently been considered, showing significant performance improvements. For automotive interference mitigation, a two-stage autoencoder model for detection and reconstruction of interfered samples was developed in [28]. A review of state-of-the-art ML-based radar interference mitigation methods can be found in [29]. In [30], target detection was considered with multi-channel range-Doppler maps using a MIMO pre-encoder, a feature pyramidal network encoder, and range-angle decoder, followed by a detection head. This was one of the early works exploiting radar cube information for target detection. For DoA estimation, both data-driven deep learning [31], [32] and physics-informed hybrid ML approaches [33]

have been studied. The development of ML approaches for DoA estimation, while leveraging well-established signal array models is a promising avenue.

At the end of the sensing chain, a single-snapshot spatio-dynamic signature of a target is obtained. That is, based on a single radar frame, target location in three dimensions along with its radial velocity is obtained. This 4D point cloud of detection points is passed on the perception chain where tasks like clustering of detection points, target classification, fusion, tracking and occupancy grid mapping (OGM) are performed. Whereas Fig. 3 depicts processing for point cloud data generation, other radar data representations have received recent attention in conjunction with associated ML perception methods [30], [34].

C. Radar imaging

High-resolution radar imaging serves as alternative for LiDAR-based environment perception, e.g. for application such as collision avoidance on AMRs and AGVs, or for robust human detection for outside-in-safety. An imaging radar that resolves elevation angular information, in addition to range, azimuth angle and speed, is needed for 3D world perception, e.g. determining whether a robot can drive below an overhanging obstacles. There are three approaches to obtain high resolution imaging:

MIMO radar: High-resolution imaging is achieved in a MIMO radar by either using a high number of physical antenna elements, or by synthesizing a large aperture using a sparse array. In [35], a high-resolution 3D imaging radar design using only a compact 1D MIMO array in the elevation dimension was proposed. Sparse array designs for imaging radars have been proposed in [36]–[38], to support improved

angular resolution with fewer antenna array elements than for uniform linear arrays.

Distributed array radar: High angular resolution can also be achieved using multiple, physically separated sub-arrays to create a larger virtual aperture. In [39], DoA methods for distributed coherent millimeter-wave radars were presented. A wide aperture radar design with non-coherent sparse antenna arrays was proposed in [40] with near-field beamforming and evaluated for automotive driving applications.

Synthetic aperture radar (SAR): In SAR, motion of the radar antenna mounted on a moving robotic platform is used to provide finer spatial resolution. A forward-looking MIMO SAR that uses the AMRs motion for achieve low grating lobes despite large antenna array spacings was proposed in [41].

For robotics, imaging radars show excellent human detection performance. In Fig. 4, the radar is installed for outside-in-safety and is capable of detecting a group of humans (yellow bounding box) as well as an autonomous mobile robot (green bounding box) and a humanoid robot (blue bounding box). The information density is sufficient to interpret the image with a bare eye. One unique feature of 4D imaging radars is capturing spatio-dynamic signatures of moving objects. These signatures exhibit characteristic patterns and serve as excellent features for ML methods to detect and classify objects. Such information density (order of hundreds of points on a human/humanoid), combined with the privacy-preserving nature of radar, makes it a viable sensor modality for outside-in-safety, as well as other robotics applications that need robust human detection.

V. RADAR-BASED INTERACTION AND NAVIGATION

Below we discuss the radar processing approaches for human interaction, manipulation tasks, localization and navigation. We review state-of-the-art works, identify open challenges and lay out future opportunities.

A. Human and Robot Interaction

In different collaborative industrial applications, robot arms are required to perform complex tasks alongside humans [1], [42]–[46]. The need for human awareness in vision-limited environments for safe robot operation makes radar an attractive sensor modality to support flexible robot behaviors while staying safe. A K-band FMCW radar sensor with high-resolution in range (< 10 cm) and angle ($< 1^\circ$) for machine guarding and robot arms was presented in [47]. To form a protective cover around the robotic arms, a 160-GHz radar proximity sensor with distributed leaky-wave antennas on a dielectric waveguide was presented in [48]. Robot speed control for fenceless environments using proximity radar perception was proposed in [49]. Human-robot classification was considered in [50] using machine learning with range and velocity micro-motion radar data. In [51], the mmPrivPose3D system for human pose estimation and gesture command recognition using a 60 GHz FMCW radar was proposed for HRC tasks.

The use of radars to determine range and angle of an object, but also its coarse shape and relative velocity for safe HRC and efficient motion planning is a future opportunity that needs

further work. Cognitive radar sensing approaches that account for the state of the robot and the tasks being performed to improve operational safety is another exploration topic.

B. Robot manipulation and grasping

Radars, alongside vision and depth sensors, are increasingly being explored to address challenging robotic manipulation tasks, particularly in unstructured and NLOS environments. mmNorm [52] introduces 3D geometry reconstruction of fully occluded objects by estimating surface normals from multipath radar reflections. The approach achieves 96% 3D shape reconstruction accuracy through occlusions like walls or containers, demonstrating the capability of radars for precise NLOS manipulation and inspection tasks. Similarly, FuseGrasp [11] considers a radar-camera fusion system, and uses radar imaging in a robotic arm to capture shape information invisible to RGB-D cameras. Real-world trials demonstrate substantially improved depth completion and grasp success on transparent items compared to vision-only systems in challenging lighting and background conditions.

MITO [53] provides the first mmWave radar dataset tailored for robotic manipulation, featuring over 24 million frames collected using a UR5 robotic arm equipped with dual-frequency radars and an RGB-D camera. It includes 550 high-resolution SAR images of 76 everyday objects, captured in both line-of-sight and NLOS configurations. These objects are selected from 80 objects used in the YCB dataset, a widely adopted benchmark in robotic manipulation that contains standardized 3D models and physical objects commonly found in household and industrial settings.

C. Localization and mapping

Simultaneous localization and mapping (SLAM) in robotics, is the problem of constructing a representation of an unknown environment while simultaneously estimating the state of the robot within that environment. These two tasks are coupled: map estimation depends on uncertain robot states, while state estimation depends on the estimated map [54].

Radar SLAM is commonly organized into a front end and a back end [55]. The front end processes the raw radar data and converts them into a relative motion constraint. In radar-based systems, this stage typically includes radar point-cloud filtering, suppression of dynamic detections, and ego-motion estimation. Relative motion constraints can be obtained mainly in two ways. The first approach is point-cloud registration, using methods such as ICP, GICP, or NDT [56]–[58]. These methods can estimate the full three-dimensional motion of the robotic platform when sufficiently informative radar point clouds are available, but they depend on reliable geometric associations between consecutive measurements and can therefore be sensitive to sparse data, dynamic objects, and abrupt translations or rotations. The second approach is radar odometry or radar-inertial odometry, where Doppler velocity is used to estimate the platform ego-velocity [59]. Doppler-based methods do not require explicit geometric correspondences and are often more robust in degraded environments; however,

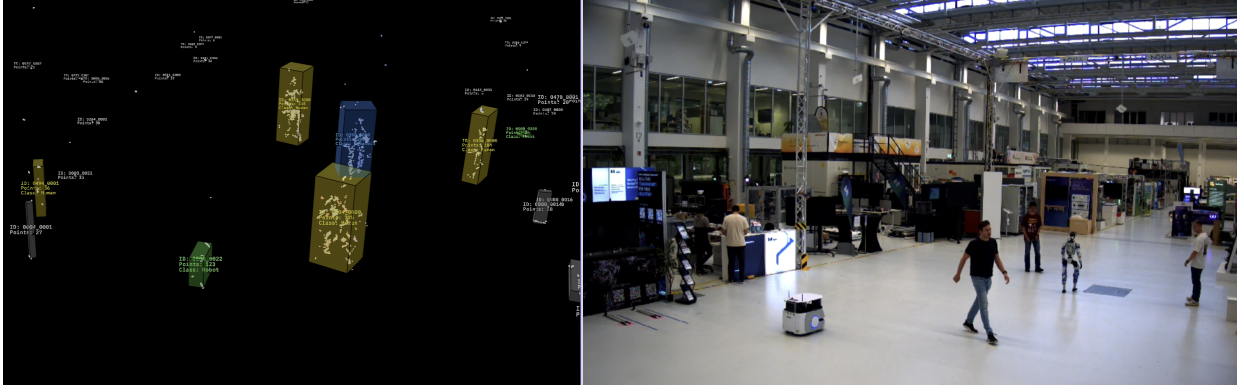


Fig. 4. Imaging radar detecting a group of people, a humanoid robot, and AMR. Color coding is the velocity of each point. Ground reflections have been filtered.

when using a single radar, yaw motion and lateral velocity, are coupled.

The front end is also responsible for detecting associations between non-consecutive measurements. When the system recognizes that the robot has revisited a previously observed place, a loop-closure constraint can be generated and passed to the back end. Radar place-recognition methods are therefore used to identify loop closures despite viewpoint changes, radar sparsity, and environmental ambiguity. Several algorithms implement radar-based place recognition, such as AutoPlace and RaPlace [60], [61].

The back end receives the constraints produced by the front end and formulates the SLAM problem as a pose graph. In this representation, robot poses are modeled as nodes, while relative-motion and loop-closure constraints are modeled as edges or factors. The objective of the back end is to reduce accumulated drift and obtain a globally consistent trajectory and map by solving a nonlinear least-squares optimization problem such as the g2o framework [62]. Figure 5 depicts a representative radar-based SLAM pipeline. The input 3-D radar point cloud is first preprocessed and, where available, fused with camera and IMU measurements. The SLAM front end exploits these data for ego-motion estimation and place recognition, yielding relative-pose and loop-closure constraints. The back end optimizes these constraints to estimate a globally consistent trajectory, which is subsequently used to register radar measurements and generate the final 3-D map.

Following the introduction of radar SLAM, we present the relevant methods for point cloud based SLAM approaches. In milliMap [63], LiDAR-supervised training was used together with geometric regularization to compensate for sparse, distorted radar observations and recover dense structure with semantics in degraded visibility conditions. PanoRadar [64] shares the idea of milliMap that uses cross-modal LiDAR supervision to learn SLAM-usable geometry from mmWave radar, but they differ in sensing setup and scope: milliMap targets robust 2D indoor mapping in low visibility by combining strong geometric priors and semantic features from radar reflections, whereas PanoRadar targets LiDAR-like panoramic 3D RF imaging with a rotating radar, where motion correction and rotation-induced nonlinearity compensation are key pre-

requisites for high-resolution reconstruction. CartoRadar [65] extends that imaging view into a 3D SLAM pipeline, treating learned RF images as uncertain measurements, so mapping can weight updates by predicted reliability. HoloRadar [66] leverages multipath by predicting high-resolution multi-return “RF range images” and then applying physics-guided reconstruction to un-mirror multi-bounce paths, seeking to map around corners and beyond LoS. Radarize [67] improves radar SLAM primarily from the motion-estimation side, leveraging Doppler signatures for its odometry component while actively suppressing multipath artifacts. In CRADMap [68], a 4D mmWave radar map is used to reveal metallic structures missed by vision. These works suggest that a combination of approaches is needed when dealing with radar signal multipath and sparse radar measurements so that dense and faithful maps are achievable in indoor environments where traditional vision pipelines suffer.

The use of learning priors in SLAM and OGMs via exploitation of spatial maps is an interesting future direction. Compressive recovery methods with learning priors have been shown high-accuracy OGM estimates in automotive applications [69], [70]. Extensions of these methods to indoor robotics use cases where multipath effects are dominant present new challenges. The development of collaborative SLAM and OGM methods for cobots is yet another exciting avenue.

VI. RADAR PERCEPTION AND EDGE LEARNING

This section provides an overview of different radar ML methods and datasets for robotics use cases.

A. Edge-native radar learning and hardware constraints

Edge learning using deep neural networks and signal processing algorithms optimized for radar data have attracted recent attention, especially for human activity recognition (HAR), gesture recognition, and automotive driving applications.

In [71], a lightweight CNN-based architecture, Mobile-RadarNet, was designed for activity recognition based on micro-Doppler signatures. An FMCW radar for harmful activity recognition was proposed in [72], with Range-Doppler maps fed into different CNN models and deployed on a

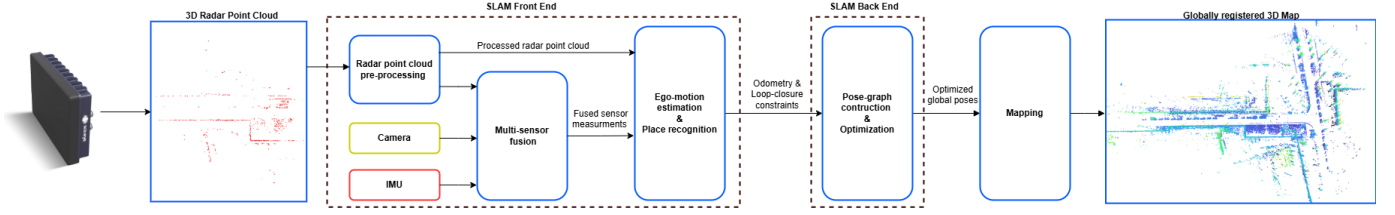


Fig. 5. Radar-driven SLAM architecture

Raspberry Pi4. A binary neural network using radar time-series point cloud data was proposed in [73] for HAR.

A radar gesture classification model with dedicated signal processing with cloud-based training, and pruning and optimization for the edge was presented in [74]. A 2D CNN combined with a temporal convolutional neural network using range-Doppler radar features was proposed for gesture recognition [75]. In [76], a 60 GHz FMCW radar was used with features derived from range, Doppler, azimuth and elevation over multiple measurement cycles input into a shallow CNN for gesture recognition.

A low-latency radar-based hand gesture recognition was proposed in [77] using an optimized hardware/software co-design. The neural network model employed symmetric weights, group 1-D-convolution, and power-of-two quantization for deployment on an FPGA platform and 65-nm CMOS. Greater co-design of hardware and radar edge algorithms for robotics applications in the future will pave the way to more energy-efficient ML solutions. Another topic of further exploration is efficient radar signal representations for ML models that allow good tradeoffs between computational cost and performance. Finally, the design of pruning and quantization strategies in ML models that consider radar-specific characteristics needs further exploration.

B. Low power radar ML approaches

Processing radar data at the edge using energy-efficient ML methods ensures low-latency inference, without the need for frequent operational interruptions, e.g., for recharging or battery replacement. Low power radar ML methods are thus crucial for robotics due to the inherent trade-offs between computational demands and operational constraints.

A lightweight, energy-efficient version of Mobile RadNet [71] with a hardware accelerator for radar-based HAR was proposed in [78], by noting that the high-frequency portion of radar signals contains sparse information. An energy-efficient FFT-CNN processor with reconfigurable dual-mode processing element that maximizes hardware resource sharing, while supporting both butterfly operations for FFT and multiply-accumulate computations for CNN acceleration, was proposed in [79].

Spiking neural networks (SNNs) with dedicated neuromorphic circuits have received considerable attention for achieving energy efficiency that surpasses traditional von Neumann computing based conventional deep learning approaches by orders of magnitude [80], [81]. Binary activated SNNs were used in [82] for hand gesture recognition using range-Doppler radar

data and shown to outperform models like [75]. A 4-b-weight SNN with preprocessing and encoding of radar intermediate frequency signals was shown to achieve 93% gesture recognition accuracy within four time steps in [83]. RadarSNN was proposed in [84] based on range, Doppler and angle data from an FMCW 60 GHz radar for gesture recognition showcasing small model size and low energy consumption. In [85], NEURORADAR, a radar based on a neuromorphic architecture was proposed with joint consideration of the analog sensor front-end and spiking signal processing designs. The proposed system was shown to achieve an order of magnitude lower power consumption on hand gesture recognition and target tracking tasks compared to deep learning approaches in [75], [76].

Joint designs of radar front-ends and neuromorphic processing to minimize power consumption and latency while achieving the desired detection and classification performance needed in diverse robotic applications presents exciting cross-disciplinary challenges. Design of neuromorphic methods that exploit the sparse nature of radar data for functions like SLAM and OGM in different industrial and mobility robotic use cases presents new opportunities.

C. Open datasets and benchmarking

There are limited public datasets with radar sensors that can be used across robotics applications. Open datasets have notably grown for automotive driving [87]–[90] and indoor human sensing [?], [91]–[95]. This has helped spur research activity in deep learning for radar sensing and perception in these applications.

In contrast, a smaller set of open radar datasets targets robot odometry and SLAM, often in controlled indoor environments. For radar odometry and mapping, ColoRadar+ [96] is an extended release of the ColoRadar mmWave dataset [97], providing improved ground-truth odometry and RGB-D alongside radar point clouds from both a single-chip and a cascaded radar (192 virtual channels). Complementary indoor benchmarks include OdomBeyondVision [98], which provides synchronized single-chip mmWave radar with additional navigation sensors across UGV, UAV, and handheld platforms. [99] released multiple radar-inertial (and radar-visual/thermal-inertial) sequences with pseudo- or motion-capture ground truth spanning office floors, labs, workshops, and basements. For industrial-like degraded-perception conditions, the LiDAR Degeneracy Datasets include synchronized FMCW radar with IMU/LiDAR collected in a fog-filled corridor and a long tunnel, enabling evaluation under obscurants and perceptual self-similarity [100].

Reference	Radar processing	Input features	ML method	Edge approach and HW	Results
[71]	Short-time Fourier transform	micro-Doppler signatures	1-D depthwise CNN	Depthwise convolutions/layer; ARM-based mobile device	Lightweight 11.5k parameter model; 97.31% HAR accuracy
[72]	2-D FFT	Temporal Range-Doppler maps	CNN/LSTM	Quantization floating-point 16	93.2% HAR accuracy
[73]	2-D FFT; Peak detector; DoA	Point cloud	Binary neural network with 3D dense blocks	Binary weights and activations	97.63% HAR accuracy on MMActivity dataset [86]
[74]	2-D FFT; Peak detector	Range-Doppler map	CNN	Model pruning; weight quantization for Intel Neural Compute Stick 2	Gesture classification accuracy of 97.57%
[75]	2-D FFT	Range-Doppler maps	Temporal CNN	Parallel RISC-V-based microcontroller with parallel ultralow power computing	46K parameter model; 92.4% single-user gesture recognition accuracy
[76]	2-D FFT; Peak detector; DoA	Point cloud features	Shallow CNN	Edge computing platform NVIDIA Jetson Nano	93.11% gesture accuracy on untaught subjects
[77]	2-D FFT	Range-Doppler maps	1-D CNN	Power-of-two quantization; Xilinx XC7S15 FPGA board and 65-nm IC technology	4.8K parameter model; 92.84% accuracy on radar gesture dataset [76]
[79]	FFT	Range-Doppler map	FFT-CNN	Reconfigurable dual-mode processing element	Energy efficiency in fall detection and HAR
[83]	2-D FFT/STFT	Range-Doppler maps and micro-Doppler	SNN with one convolutional layer and two fully connected layers	4-b-weight SNN	93% accuracy on custom single-antenna radar gesture dataset
[84]	2-D FFT	Range-Doppler maps; Range, Doppler and angle spectrograms	SNN with convolution layer and leaky integrate-and-fire neuron model	Prototype simulations on NengoDL	99.5% gesture recognition accuracy
[85]	Self-injection locking-based analog spike encoding	Spike sequences	SNN with convolution layers	Prototype simulations on NengoDL	94.58% gesture recognition accuracy

TABLE IV
SUMMARY OF EDGE-NATIVE RADAR LEARNING AND LOW-POWER APPROACHES.

For radar SLAM, CartoRadar [65] and PanoRadar [64] provide indoor mmWave datasets, especially in situations where optical sensing is challenged. CartoRadar provided an indoor-building SLAM evaluation set evaluated across 14 floors in 5 buildings, and it includes RF-predicted range images with per-frame uncertainty so mapping can account for measurement reliability. PanoRadar has synchronized raw I/Q and processed 3D RF heatmaps with LiDAR and IMU across 12 buildings, and it formalizes leave-one-building-out evaluation. This makes it a natural pretraining and transfer backbone for downstream RF-SLAM pipelines such as CartoRadar. Beyond imaging-centric benchmarks, Radarize [67] contributes a large radar-only SLAM dataset (146 trajectories across 4 buildings and 3 platforms) and evaluates both odometry and SLAM, highlighting the Doppler-odometry flavor of radar SLAM.

While the number of radar public datasets for diverse automotive and human sensing applications is growing, there is a clear dearth of radar datasets for other industrial and mobility robotics applications. An exception is the MITO [53] dataset discussed in Section V-B. Increased availability of public radar datasets for different use cases will accelerate innovation and enable better performance benchmarking.

D. Synthetic data generation

Collection of real-world data and subsequent annotation can be time-consuming, expensive, and difficult across diverse scenarios. For instance, for automotive driving applications, real-world data collection in complex driving conditions in extreme weather conditions such as snow is challenging. Deep learning approaches, however, require large and diverse datasets to train models. A solution to address this issue is to

generate synthetic data. One of the challenges in generating synthetic radar data is the ability to produce physical artifacts like multipath clutter.

In [101], a physical radar simulation technique, RadSim-Real, was proposed using the radar point spread function to generate reflection points, and shown to generate realistic radar images close to those produced by conventional ray-tracing radar simulation tools. In [102], a ResNet CNN backbone was used to estimate the parameters of a Gaussian mixture model for emulating radar point cloud data from RGB images. In [103], a radar range-azimuth angle (RA) map emulation model, RAIDS, was proposed that uses a monocular metric depth estimation UniDepth foundation model, a semantic segmentation Mask2Former foundation model, and a spatial and channel attention mechanism. In [104], radar RA data was fused with aligned camera images to generate depth maps, using pre-trained semantic segmentation and monocular depth estimation models with camera image inputs. In [105], low-resolution radar RA maps were used to generate high-resolution point clouds by employing a U-Net autoencoder emulating a scanning LiDAR. Synthetic radar point cloud generation using generative adversarial networks trained with LiDAR point clouds was presented in [106].

The availability of large public datasets of images revolutionized the computer vision. For robotics applications, an image synthetic dataset, Synthetica, has recently become available [107]. The use of synthetic radar data for human-robot interactions has been considered in [108], [109]. The field of synthetic radar data generation for diverse robotics use cases is expected to grow with new research opportunities in hybrid physics-modeling and ML methods, digital twin robotic

models, and simulation to real-world validation.

E. Radar-based fusion

Early works [110]–[113] used multiple sensor modalities and data fusion to develop intelligent robots. Since then, multi-modal sensor fusion has matured as a solution to overcome the limitations of a single sensor modality in a particular operating condition (e.g., camera in varying light conditions).

As discussed in Section III-B, a key difference between automotive driving applications and indoor robotics use cases lies in the strong multipath encountered in the latter. To deal with this, SAR imaging data was fused with inertial measurement unit (IMU) measurements using error-state Kalman filtering for robot tracking in [114]. In FuseGrasp [11], SAR radar images were fused with RGB-D images for enhanced depth completion for improved detection and robotic arm grasping accuracy of transparent objects. In [115], radar point cloud was fused with monocular camera data for metric depth estimation for mobile robotics in unknown environments.

It was recognized in [116] that a greater availability of multi-modal datasets, especially including radars with different signal feature representations, is needed to answer questions like: “which modalities to fuse”, “what stage (early, mid, or late) of fusion is most effective”, and “when to fuse”; all these questions remain largely unresolved. This is in line with the observations in [117], where a review of radar-centric multimodal fusion approaches for human sensing was conducted. The need to design and compile multimodal data that capture the complexity of real-world dynamic environments was identified as one of the future challenges. The need to develop fusion methods with consideration to complexity and latency is another challenge to tackle. Another facet of fusion is digital twins that involves virtualizing both human and robot behaviors [118].

While multimodal sensor fusion in a single robot (e.g., single automotive) has been well-studied, there is limited work on fusion across connected, collaborating robot systems. A future opportunity is the design of fusion schemes in cobots with communication constraints on bandwidth and latency.

VII. CONCLUSIONS AND FUTURE OPPORTUNITIES

We provided an overview of existing works on radar processing algorithms and edge ML methods. While radar is not yet an established sensing modality for robotics, it is an integral part of the sensor suite of autonomous vehicles, and is likely to establish itself as a valuable sensing modality for robotics. This process will be driven by better availability of robotics-designed radars on the market as well as broader deployment of robotics in various applications.

Several scientific and engineering challenges need to be addressed for wider adoption of radar sensing in robotics:

- **Information density:** conventional radars have much lower information density (especially angular resolution) than optical sensors. Given that cameras and LiDARs are currently used in prevalent robotics use cases, radar needs to achieve much higher information densities to



Fig. 6. Imaging radar prototype on a humanoid.

be adopted especially for use cases where traditionally LiDARs are used.

- **Imaging radars** achieve impressive information densities on moving objects and present themselves as a robust and cost-efficient alternative to robotic LiDARs. To obtain such high information densities, new MIMO array and waveform designs are needed. Moreover, unlike automotive radars mainly focused on long-range detection, robotics traditionally needs much shorter ranges, which requires robotics-specific radar designs.
- **Multipath** reflections are much more critical in indoor environments, where the majority of robots are used today. When not accounted for, they lead to ghost targets and ambiguities that adversely impact the localization and occupancy grid mapping performance. Radar methods to effectively suppress and exploit multipath is an open challenge.
- **Edge learning** methods with raw radar data tensor with inherent sparsity is another major research field. Optimization of radar ML models that preserve complex phase information needed for MIMO DoA processing needs further exploration. Most works on radar edge learning have focused on HAR, gesture recognition and localization; extensions to robotic arms and HRC are future opportunities.
- The field of ML/AI is rapidly evolving and new developments in **foundational models** and large language models (LLMs) present new opportunities in robotics [119]–[121]. Scene understanding using radar foundation models and LLMs can be used to optimize sensing tasks to the operational environment of the robot. Such radar reasoning (in combination with other modalities like acoustic and camera) can be translated in natural language interpretable formats to support explainability of the underlying ML-driven models [122]. Radar ML model explainability is another important future topic as ML-driven decision making is incorporated into robots to conform to new AI regulations.
- While **sensor fusion** is a well-studied topic, there is a need for new radar-centric fusion methods that are adaptive to the robot operating environment. Another open challenge is the need for simple, online calibration methods between multiple sensor modalities in the robot

system to support fusion between radar and other sensors.

- There is a lack of open **public radar datasets** for robotics use cases. While the number of radar datasets for automotive driving applications have grown recently, there are few datasets for indoor robotics. More attention is needed on real-world radar data collection and labeling, as well as developing synthetic radar datasets using digital twin and ML models with realism, for different robotic use cases.
- **Humanoids and legged robots** are an emerging form of mobile robotics. Early applications have been considered in the consumer domain for humanoids [?], [123], and in challenging terrains for legged robots [124], [125]. Radars can be used to detect humans and objects in unknown environments and provide an alternative to a safety fence. Cameras are dependent on outer conditions and hence have challenges in meeting safety standards. Imaging radars as shown in Fig. 6 can provide robust human detection capabilities in humanoids. Another challenge for humanoids is surround mapping while moving with a human like gait pattern. Given its complex movement pattern, both radars and depth cameras struggle with building accurate maps. Development of radar processing methods that leverage radar odometry and dynamics information from the scene to better reconstruct the ego trajectory and build a SLAM map are a future opportunity.

We hope this review will spur more scientific research on robotic radars and ultimately lead to a greater adoption of radar sensors in diverse robotics applications as has happened in automotive driving applications.

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