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Analysis of mmWave Radar Techniques for Environmental Perception in Autonomous Driving

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Abstract. With continuous advancements in autonomous driving technology, environmental perception has attracted significant research interest. Millimeter-wave (mmWave) radars are essential components in autonomous driving systems, offering strong interference immunity, reliable performance across various weather conditions, and highly accurate target detection. Through a thorough literature survey, this review compares the current developments and technological innovations of mmWave radars applied in environmental perception. Besides, it delves into the basic operating mechanisms of mmWave radar and evaluates its critical performance indicators, while investigating its applications in target detection, ranging, and obstacle identification. The results indicate that while mmWave radar significantly boosts perception accuracy and response speed, it still faces challenges such as limited resolution, data processing latency, and high costs. Overall, integrating multi-sensor data fusion with AI-driven signal processing emerges as a promising direction for further enhancement. By combining complementary sensor data and leveraging advanced AI algorithms, this method enables more efficient, adaptive, and reliable responses to complex driving environments.

Keywords: Autonomous Driving, Millimeter-Wave Radar, Object Detection, Automotive Sensing, Environmental Perception

1. Introduction

This review aims to provide a comprehensive overview of millimeter-wave (mmWave) radar-based environmental perception in autonomous driving. Recent advancements in intelligent transportation and autonomous driving have underscored the importance of enhanced environmental perception for ensuring safe and efficient vehicle operation. Autonomous vehicles must reliably detect and recognize surrounding obstacles, such as pedestrians and traffic infrastructures. The recognition should be immediate and precise even under complex and dynamic scenarios. Accordingly, this requirement places a high demand on real-time performance and robustness of the automobile's sensors. Among various sensing modalities, mmWave radars stand out due to their reliable and resilient performance against all the adverse conditions. Under this situation, the review examines the current state of research, including advances in radar signal processing, target detection methods, and multi-sensor fusion strategies. This article chooses a series of systematic literature analysis and illustrative case studies that targets on methodologies from advanced neural architectures to hardware-accelerated processing pipelines. The analysis also outlines the existing challenges. By

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pinpointing key research gaps, such as limited angular resolution and processing delays in the end-to-end deep learning frameworks of mmWave returns, this article bridges the gaps between academia and industry. It then highlights the application on enhancing system performance through the integrating deep learning techniques and advanced fusion methods, which guides toward a safe and reliable automobile usage experience.

2. Overview of mmWave radar-based environmental perception techniques

2.1. Fundamental principles and operating mechanisms

In mmWave radar systems, electromagnetic waves propagate through the environment and reflect off objects, enabling the sensor to determine targets' range, angle, and velocity. According to the principles of electromagnetic propagation and reflection, a portion of the transmitted energy from a Frequency-Modulated Continuous Wave (FMCW) radar is reflected back upon encountering a target and subsequently received by the antenna array. FMCW radars continuously modulate the transmitted frequency during each "chirp," converting time delays into measurable frequency shifts. This frequency difference, more easily detected by the sensor, allows for precise mapping of target distance and motion parameters based on the time delay. By applying a Fast Fourier Transform (FFT) to the intermediate-frequency signal, the beat-frequency spectrum is obtained, where each spectral peak corresponds directly to a target's range. The relationship is given by:

$$R = \frac{c\Delta f}{\frac{2B}{T_c}} \tag{1}$$

where c is the speed of light, Δf the beat frequency, B the chirp bandwidth, and T_c the chirp duration. As a result, this frequency-to-distance mapping enables accurate range measurements. Furthermore, the linear frequency sweep of FMCW signals inherently carries Doppler information, which allows for precise estimation of target velocity. This technology offers high range resolution, maintaining robust performance under adverse weather conditions [1]. These advantages underscore the strong potential of FMCW radar applications in the autonomous driving industry.

2.2. Key performance indicators and parameter optimization

The performance indicators for mmWave radar systems contains several areas, including detection range and resolution, field-of-view, and Doppler accuracy. To be more specific, the detection range is primarily determined by the transmitter power of the radar and the behaved sensitivity on its receiver. The maximum detection range R_{max} can be derived from the radar equation:

$$R_{max} \propto \left(\frac{P_t G^2 \lambda^2 \sigma}{(4\pi)^3 S_{min}} \right)^{\frac{1}{4}} \tag{2}$$

where Pt is the transmit power, G is the antenna gain, λ is the wavelength, σ is the target radar cross section, and S_{min} is the receiver sensitivity. One of the most important measurement factors is environmental factor. With modern systems, mmWave radar systems can achieve ranges of several hundred meters even if the testing weather is adverse [2]. Another critical parameter is range resolution, which is essential for distinguishing closely spaced objects and is largely governed by the radar signal bandwidth. Angular resolution, influenced by the antenna array configuration and MIMO processing techniques, dictates the sensor's capability to accurately localize targets in the

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azimuth and elevation dimensions. Moreover, Doppler resolution plays a crucial role in precise velocity measurement and depends on parameters such as chirp duration and the number of chirps per frame. Additional metrics, including signal-to-noise ratio (SNR) and processing latency, directly influence the reliability and real-time responsiveness of autonomous driving perception systems [3]. In short, balancing high resolution with real-time processing requirements is crucial: while wider bandwidth and a greater number of chirps improve resolution, they also increase the computational load of the Fast Fourier Transform (FFT), necessitating optimized algorithmic strategies.

2.3. System architecture and hardware composition

To develop a mmWave radar system that meets the stringent requirements of autonomous driving, an integrated design encompassing advanced receiving antennas, robust signal processing modules, and versatile data interfaces is essential. In antenna design, arrays are commonly implemented using MIMO configurations to achieve high angular resolution [4]. In phased-array designs, dynamic phase shifting across elements electronically steers the beam, eliminating the need for mechanical movement and enabling rapid tracking. This significantly enhances aperture efficiency and target localization accuracy. Moreover, low-noise amplifiers and ADCs are largely applied into the whole production process of mmWave radar systems. Those components convert received electromagnetic reflections into digital signals with high resolution. Consequently, these signals are then processed from sparse 4D radar point clouds. Techniques such as FFT are employed to extract range, Doppler, and angular information from the radar signals. This processing architecture enables reliable and robust performance across various weather conditions and dynamic traffic scenarios, enhancing the overall effectiveness of autonomous driving systems [5]. As a result, these interfaces ensure smooth data transfer between radar hardware and onboard processors, supporting real-time sensor fusion and rapid decision-making.

3. Applications of mmWave radar in autonomous driving

3.1. Target detection and distance measurement

Target detection and distance measurement, fundamental to autonomous driving, mainly depend on mmWave radar. Advanced Driver Assistance Systems (ADAS) evaluations using dummy models have validated its capability to distinguish static from dynamic objects, thereby enabling precise localization and robust collision avoidance [6]. While a second FFT across chirps extracts Doppler shifts for velocity estimation, the received echo is mixed with the transmitted chirp. These systems leverage the principles of FMCW technology to capture echoes from targets, and thus enable the calculation of both range and relative velocity. For static targets, the time delay between transmitted and reflected signals is converted into distance through matched filtering techniques. In contrast, dynamic targets are distinguished by their Doppler frequency shift, which provides critical velocity information. Those matched filters correlate the known transmit waveform with the noisy return, and thus maximize output SNR. Moreover, recent advances incorporate deep learning methods to further enhance detection accuracy. Contrastive learning, which serves as a frontier technique that applied to radar detection points, enables an instance segmentation that is robust enough even under the severest testing conditions. Additionally, diffusion-based methods improve the quality of sparse radar point clouds, thereby refining distance measurements in cluttered or challenging environments [7]. By learning discriminative features that separate true returns from clutter, the diffusion process iteratively refines point density, and thus yields a more accurate distance estimation.

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3.2. Obstacle recognition and classification

Beyond simple target detection, mmWave radar extends its functionality to obstacle recognition and classification by extracting fine-grained features from echo signals. Recent studies have shown that CNN-based instance segmentation can differentiate various object classes, even under the inherent sparsity of radar data [8]. Thus, radar returns are rich in Doppler information, which encodes the dynamic and physical characteristics of obstacles, making it possible to identify object types based on their motion and signal signatures.

To enhance the perception capability of mmWave radar, sensor fusion is employed at different abstraction levels. At the raw-data level, fusion combines synchronized outputs such as radar RF tensors and LiDAR point clouds before feature extraction, enabling unified processing while requiring precise calibration and significant bandwidth. At the feature level, data such as Doppler maps and geometric embeddings are merged within deep neural networks, allowing cross-modal representations through alignment in a shared latent space. This method has proven effective in improving dynamic obstacle detection under low-visibility conditions. At the decision level, outputs from individual sensors are combined using techniques such as Bayesian filtering or ensemble classifiers. Although this approach offers modularity and system flexibility, it may compromise fine-grained interaction across modalities.

By integrating hardware-level signal processing with deep learning-based approaches, mmWave radar systems can accurately segment and classify different types of obstacles. These techniques enable the system to distinguish between vehicles, pedestrians, and static structures by analyzing their unique radar signatures. The robustness of this capability is maintained even under challenging environmental conditions such as rain, fog, or poor lighting. Moreover, the addition of semantic processing algorithms further enhances the interpretability of radar echoes, ensuring consistent and reliable obstacle recognition. Ultimately, through the convergence of radar sensing, advanced algorithms, and multi-level fusion strategies, mmWave radar equips autonomous vehicles with the perception capabilities necessary for safe and efficient navigation in complex urban environments.

3.3. Multi-sensor data fusion techniques

In autonomous driving perception systems, multi-sensor data fusion plays a key role in achieving comprehensive and reliable environmental understanding. Recent simulation studies have shown that the use of unified data representations, such as radar RF tensors, can significantly enhance the fusion process, resulting in more accurate and consistent three-dimensional environmental models [1]. While LiDAR offers high-resolution spatial information, its performance deteriorates under adverse weather conditions. Similarly, cameras provide rich semantic content but are susceptible to degradation in low-light or foggy environments. In contrast, mmWave radar demonstrates robust performance in such scenarios, albeit with lower spatial resolution. To overcome the inherent limitations of individual sensors, fusion techniques integrate data from mmWave radar, LiDAR, and cameras to leverage their complementary strengths. At the feature level, deep neural networks are employed to fuse spatial and semantic cues across modalities, enabling more accurate detection of dynamic obstacles, even under low-visibility conditions. This cross-modal learning enhances the robustness and generalization ability of the perception system in complex environments. Moreover, emerging techniques such as passive radar systems, utilizing GPS signals as illumination sources, have been investigated as complementary sensing modalities. In situations where active sensors underperform or are constrained, these methods serve as effective alternatives [9]. Therefore, such multi-modal integration is essential to achieving resilient and precise autonomous navigation.

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4. Challenges and future directions

4.1. Current technical limitations

Despite the considerable promise of mmWave radar systems, several technical challenges hinder their optimal performance in autonomous driving applications. A primary issue lies in balancing high resolution with effective noise suppression. While nonlinear frequency modulation techniques, such as those employing Fourier sine series for waveform design, can effectively reduce sidelobe levels, they also introduce increased system complexity [10]. Furthermore, the radar point cloud contains sparsity itself, which means that its images come with noise that is extremely difficult to eliminate. And this challenge is further compounded by limited antenna apertures and constrained MIMO configurations, which hinder reliable data association and accurate target extraction. Similar difficulties have also been observed in studies of passive radar systems utilizing GPS illumination. Due to the low signal-to-noise ratios and calibration complexities in real-world environments, high data rates from wideband FMCW operations require significant computational resources from real-time processing. Consequently, it requires considerable cost and energy consumption for the mass-production and adaption of the system. These limitations highlight the need for innovative signal processing and hardware optimization strategies to make mmWave radar systems more viable for cost-sensitive autonomous applications.

4.2. AI-driven signal processing and algorithm optimization

In the face of these challenges, AI-driven signal processing can serve as a transformative remedy of the severe situation encountered by mmWave radar systems. For instance, CNN-based ego-motion estimation frameworks have shown marked improvements in state estimation for fast-moving micro air vehicles [11]. By extracting motion and spatial features directly from raw sensor data, CNNs can generate high-resolution representations even under challenging conditions characterized by severe motion blur and rapid maneuvers. These AI techniques enable more effective noise filtering and feature extraction, thereby enhancing target detection accuracy and overall system stability. Furthermore, self-supervised learning strategies greatly expedite the development cycle by reducing the dependency on large annotated datasets. Optimizing the traditional radar signal processing pipeline, these adaptive algorithms not only improve the extraction information from the raw signal but also mitigate issues such as signal ambiguity. Accordingly, the integration of deep learning methods plays the pivotal role in advancing the performance of autonomous driving perception systems.

4.3. Multi-sensor integration and standardization

Effective multi-sensor integration is vital to achieve a comprehensive environmental perception in autonomous driving systems. Through combining data from various sensors, such as LiDAR and cameras, engineers are capable to harness unique strengths from different types of sensors, while the compensation for their individual limitations becomes possible. Research in radar modeling for simulation applications underscores the benefits of standardizing data outputs. To achieve precise spatial alignment, it is crucial to synchronize sensor outputs using unified calibration frameworks and standardized data interfaces. For example, when combined with visual and LiDAR data, standardized radars such as RF tensors enable more seamless fusion, thereby enriching a spatial and semantic data representation [12]. Furthermore, advancements are made in the field of GPS usage on

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passive radar detection. These achievements provide complementary information that serve as integrated active sensor data sets for the mmWave detection system, and thus enhance its robustness when placing under complex conditions. As a result, such standardization not only improves the accuracy of sensor fusion algorithms, but reduces development costs. These progresses facilitate a series of scalable upgrades on mmWave radar systems across various autonomous platforms.

5. Conclusion

In conclusion, this review provides a systematic overview of the current advancements in mmWave radar-based environmental perception for autonomous driving. Despite significant benefits such as robust all-weather performance and enhanced detection capabilities, mmWave radars still face challenges due to its limited resolution and high implementation costs. Future research should focus on the integration of deep learning algorithms and multi-sensor fusion techniques to further optimize perception accuracy and efficiency. This work not only offers a theoretical framework for future developments, but also highlights the critical research directions in the field of autonomous driving perception systems that needed to advance within the future.

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