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Comparative Analysis of LiDAR, Radar, and Camera Sensors for Autonomous Perception: Principles, Challenges, and Fusion Strategies

Yitian Wu

Hertfordshire College, Changzhou Institute of Technology, Changzhou, China
13605171601@163.com

Abstract. Due to the fast development of self-driving, robotics and AI technology in recent years, environmental perception technology is becoming one of the cutting-edge technologies with both research hotspots and wide industrial applications. The three most commonly used sensors for environmental perception are laser radar, millimetre-wave radar and camera. Every kind of sensor works differently and has different usage areas and limits. This paper compares the sensor's properties based on essential factors: the working principles, key performance indicators, robustness under severe conditions, adaptability in different applications, etc. Data come from manufacturers, laboratory tests and peer-reviewed articles. It found that LiDAR has high 3D spatial precision; millimetre-wave radar can work normally in bad weather and in cases of a low-reflective surface; and camera sensors can classify objects very well. In addition, fusion strategies such as radar-camera or radar-LiDAR integration can improve detection accuracy, semantic segmentation and SLAM robustness, respectively. And based on the research results, it's concluded that a single sensor cannot meet the requirement of complete autonomous perception. However, reliability and robustness in practice applications can be achieved through a complementary nature and by integrating multiple sensor inputs.

Keywords: LiDAR, Radar, Camera, Autonomous perception, Sensor fusion

1. Introduction

Environmental perception capabilities are fundamental to the automation of machine systems, as they enable them to detect, analyse and perform specific functions autonomously. Over the last decade, many related sectors, such as intelligent driving vehicles, have relied primarily on LiDAR sensors, millimetre-wave radars or cameras to achieve intelligent driving functionality. Each sensor modality furnishes distinct and valuable data: LiDAR systems produce dense, three-dimensional point clouds indicative of spatial relationships; millimeter-wave radar offers robust measurements of range and velocity, particularly under adverse conditions; and optical cameras acquire semantic information, discerning lane markings, traffic signage, and object characteristics [1,2].

Although sensor applications have been significantly successful in many sectors, numerous problems or limitations remain. LiDAR's efficacy is hampered by specular reflections, inclement

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weather, and economic considerations [3]; millimeter-wave radar data suffers from sparsity, high noise levels, and semantic interpretation difficulties [4]; and camera-based systems are challenged by depth estimation, illumination variations, and occlusions [5].

It is worth exploring how these sensors can be used individually or in combination to build a reliable perception system.

This article addresses the issue through a structured comparison of LiDAR, radar, and camera sensors in four dimensions: (1) technical principles, (2) performance parameters, (3) robustness in adverse conditions, and (4) adaptability to application scenarios. These research methods are based on empirical results from laboratory evaluations, reference datasets, and published experimental studies, and we analyse fusion strategies that achieve superior performance by combining complementary advantages.

By systematically examining each sensor's unique contributions and limitations, this article aims to provide helpful information to engineers and researchers engaged in developing scalable and reliable autonomous perception solutions, as a starting point for future research.

2. Technical principles and working mechanisms

2.1. LiDAR

(ToF) Detection and Ranging (LiDAR) determines distance via the time-of-flight (ToF) of laser pulse backscatter, and emits thousands of pulses per second to produce high-resolution 3D point clouds, which deliver centimetre-level spatial accuracy. For example, the Livox Mid-360 LiDAR uses a hybrid solid-state non-repetitive scanning (NRST) mechanism with different operating principles than traditional mechanical rotational LiDARs that depend on spinning motors. Conventional rotating radars employ motor-driven mirrors to rotate 360° to accomplish panoramic scanning, but inevitably suffer from structural complexity, poor reliability and limited lifespan. However, the Mid-360 realises complete scanning of the detection area at a much higher speed. It achieves full frame rate via a special optical structure and non-repeating scanning tactics for projected spot movement covering all scanning areas of interest. As a result, point clouds become much denser over time, delivering high-definition three-dimensional information of the environment. This way, no wear and energy dissipation due to mechanical rotations happens at all. Modern spinning and solid-state LiDARs are well-received and used in ADS for autonomous vehicle obstacle detections, HD-mapping, as well as SLAM; benefits are good resolution of space and depth, while LiDAR has limitations in poor performance in foggy, rainy or smoky environments, and expensive relative to radar or camera setup cost [6, 7].

2.2. Radar

Radar detectors depend on electromagnetic radio waves, mainly using FMCW technology based on the Doppler frequency shift effect to measure targets' range and relative velocity [8]. Radar systems operating in the millimeter wave spectrum (24GHz or 77GHz) function by emitting electromagnetic waves towards a designated target and subsequently capturing the reflected echo signals. By analyzing the amplitude, phase, and frequency characteristics of these received signals, parameters such as distance, velocity, and angle of the target can be determined. Radar performs detection even better than visible light imaging when working in extreme conditions, making it robust against occlusion, reflections, or ambient obstacles like dazzling and dust. Still, it will cause radar failure for some angular directions, and it needs more data compared with an RGB image, so the amount of

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data will be affected. However, millimetre-wave radars usually use Frequency-Modulated Continuous Wave (FMCW) to measure distance based on their functional mechanism. The radar emits a chirp signal, which is a signal of varying frequency over time, toward a target. A time delay is involved when it meets the target and gets back as an echo. Millimetre-wave radars are indispensable for collision avoidance, adaptive cruise control, and long-range detection [9,10].

2.3. Cameras

Based on optical imaging principles, camera-based vision sensors project light through lenses onto image sensors (CCD or CMOS). CCD sensors successively transfer charge line by line, giving better images at the expense of more power. CMOS sensors integrate amplification and readout circuits inside each pixel unit; hence, they offer higher resolution visual data with richer texture, colour, and shape information and facilitate semantic tasks like lane detection, traffic sign recognition, and pedestrian classification. Cameras are cheap and small, but do not provide depth perception capability and suffer from insufficient illumination or occlusions. Depth can be computed using stereovision, structure from motion, which brings a huge computation cost and lower robustness [11].

2.4. Sensor calibration

Direct linear transformation (DLT) to enhance performance, cross-sensor calibration is needed, most of the time it's needed for the combination of radar with cameras, which have entirely different sensing mechanisms for spatial resolution, coordinates representation and perceiving domains, such misalignments between these two kinds of sensors could cause many errors including severe localization errors, fused information fusion inaccuracy, and so on which would eventually make the system degrade or even fail in safety-critical tasks. Three commonly used calibration techniques are pseudo-inverse affine transformation, direct linear transformation (DLT), and nonlinear optimization [12].

Pseudo-inverse affine transformations have been the algorithm of choice in such applications because of their computational efficiency and suitability to low-resource, real-time systems. However, errors accumulate in them more easily than in other algorithms in certain situations. The combination of the DLT approach with pre-processing normalization is thus sought after to provide a better compromise in terms of trade-offs between both processing time and precision. The DLT-based approach, besides being insensitive to random noises (i.e., robust), is almost as accurate as NL/O and even more robust when the correspondence noise, depth noise and/or intrinsic/external parameters are uncertain, while also having less computational load than the pseudo-inverse approach. NL/O has the most excellent potential accuracy, but unfortunately, it involves tedious iterative refinement, making it unsuitable for embedded devices requiring fast response times and tight latencies.

Effectively calibrated sensors provide accurate sensor fusions that help perform higher-level perception tasks such as object tracking, trajectory prediction and semantic scene understanding. Stability over a more extended period is necessary, where factors like temperature changes, mechanical vibrations, and ageing of the sensors will degrade sensor alignment with time. Researchers have developed adaptive calibrations that either calibrate online or calibrate semi-automatically, which are currently being actively pursued. This indicates that robust calibrations are more than just a supporting function; they are at the core of creating a reliable and effective multi-sensor perception system.

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3. Core parameter indicators

3.1. Detection range

LiDAR provides a detection range of around 200 m with high spatial accuracy, making it an excellent solution for navigation in urban areas, object classification and precision 3D mapping. It is, however, essential to keep in mind that the range is generally not constant among all surfaces; dark and low reflectivity objects can be seen at a much shorter range than the advertised value. Automotive radars have an effective range of over 250m, which extends their reach during high-speed highway driving. Still, their resolution drops considerably when the target gets further away, meaning they can't discriminate between objects that are very close together. The camera range is controlled mainly by its optical properties: the focal length (angular resolution), the aperture of the lens (allowing more/less light through) and the sensor's sensitivity. Under ideal daylight conditions, a camera may detect objects over several hundred metres and resolve information such as road lines or traffic signs. However, this depends heavily on lighting and visibility. When exposed to adverse weather or poor lighting, these cameras are no longer helpful in a safety context.

3.2. Accuracy and resolution

LiDAR's accuracy is at the centimeter level and its angular resolution is as acceptable as 0.1°; enabling highly accurate space restoration and accurate object localization. This makes it essential for tasks like Simultaneous Localization and Mapping (SLAM) that require highly accurate distances. In comparison, radar accuracy is at the meter-level and has a coarser angular resolution. However, recently, high-definition radars have developed better regarding range resolution and angular discrimination than before (compared to traditional radar). However, the improvement is still far from LiDAR. The camera's spatial resolution is naturally very high, in most cases higher than millions of pixels per frame. Therefore, they can capture many semantic elements like color, texture, and shape in a rich scene. However, the metric accuracy from cameras is inferred rather than directly measured by stereovision or deep-learning-based depth estimation methods. Therefore, it is affected easily by illumination changes or poses (e., occlusions) or other environments (e., rain or snow) [10].

3.3. Refresh rate and latency

The refresh rate of the LiDAR sensor is different, from 5 to 20Hz according to its configuration, which is more than enough for a moderate speed to get mapping and navigation. However, this updating rate will become a bottleneck in its use in high-dynamic environments like autonomous driving on highways. Automotive radars can reach near real-time performance at 20 ~ 30 Hz, with very low latency suitable for fast responding applications, such as adaptive cruise control or emergency brake. Typically, a camera operates at more than 30 Hz - 60Hz or above for a smooth visual stream similar to what humans see. Still, the actual performance greatly depends on the speed of image processing. Advanced tasks such as object recognition, semantic segmentation, and depth estimation may induce the delay, eventually harming the system's real-time sensitivity to some degree [11].

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3.4. Resistance to environmental interference

One of the major distinguishing characteristics among these sensors is the mental robustness. The effective range of Lidar sensors can be drastically reduced due to poor weather conditions such as rain, fog, and smoke [3], with lower reflectivity surfaces decreasing the laser pulses to only about 33% [3], which originate from the scattering and absorption of the laser pulses by the suspended particles. Radar has almost no such issue because the atmospheric particles hardly hinder its longer wavelength and are still able to function effectively even in heavy rain or dense fog conditions [4]; therefore, it can not only significantly improve the safety for cars during nighttime driving but also replace LiDAR in all-weather perception systems. Compared with cameras, in low light, glare or back-light conditions, the perceived information of a camera could become very bad. Even though high dynamic range HDR sensors could solve this problem to some extent, they would be significantly affected when there was a fast change in lighting. The reason was that the lens of these high dynamic range sensors was sensitive to certain types of pollution, such as dirt and raindrops. These problems have shown that there must be sensor fusion so that cameras, radars, and lidars work together to guarantee the safety and effectiveness of the cars in all situations [10].

4. Application adaptability

4.1. LiDAR applications

LiDAR proves its advantage in high-precision SLAM, 3D mapping, and autonomous navigation [6], including real-time obstacle avoidance and inspection of infrastructures through mapping. The usage in the field of autonomous driving includes supporting HD maps with high accuracy in curvature estimation. However, there are still limitations because of the high cost of the weather and its harmful effects [7].

4.2. Radar applications

Radar is the best for adaptive cruise control, collision avoidance and object detection in poor conditions [8], and is necessary for long-range fast-moving objects (and thus particularly for FMO) in ADAS and autonomous driving applications. However, it is difficult for radar to classify complex objects because of its low data volume [9].

4.3. Camera applications

Cameras are applied for lane recognition, traffic sign recognition, pedestrian detection and object categorization [10]. As a result of their reasonable cost and accuracy in capturing semantic information, they remain a principal element for all computer vision task requirements. However, these cameras lose their efficiency when subject to illumination problems or occlusions, so they can only be partially or nearly completely ignored [11].

4.4. Sensor fusion strategies

(mAP) Several solutions work around the drawbacks of single-sensor data. Using radar and camera fusion methods, object detection and semantic segmentation will perform better even in adverse weather and lighting conditions [12]. Radar–LiDAR fusion increases mAP by up to 2.6% in poor weather. Advanced frameworks, such as CR3DT, give extra improvement, with detection gain at

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5.3% and tracking gain at 14.9%. These gains demonstrate that multi-modal data fusion greatly benefits real applications [13, 14].

5. Conclusion

This paper provided a systematic and thorough comparison of different sensing modalities – namely LiDAR, radar, and cameras – used for autonomous perception by analysing their working principles, evaluation criteria, robustness, and the fit-for-purpose situation. From the results, all sensors alone cannot guarantee a whole, reliable, and safe autonomous perception, no matter the needed circumstances, for every sensor has unique capabilities yet limitations too. Although LiDAR could provide millimetre-level accuracy measurement together with vast collections of extremely detailed points, its performance would be influenced by bad weather conditions and the reflectivity of the surfaces, besides its expense. Radars have obviously more remarkable robustness against rain and fog, providing excellent accuracy of distance and velocity, which play a significant role in achieving Collision Avoidance and long-distance view in the overall scene, but lack semantic description ability because of the large, sparse point clouds being gathered, having poor angular resolution. Since cameras ' information features extrinsic properties, in terms of environment illuminated relative intensity and temporal dynamic changes, their determination based only on object or characters ' outline becomes inevitably unstable due to the requirement for the surrounding environment to have good visibility.

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