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Real-time distance measurement & object detection for autonomous driving

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Abstract
Autonomous driving technology has rapidly advanced in recent years, driven by the growing demand for safer, more efficient transportation systems. A critical aspect of autonomous vehicle functionality is its ability to perceive the surrounding environment accurately and in real time. This study focuses on the integration of real-time distance measurement and object detection systems to enhance situational awareness and improve decision-making in autonomous driving applications. The proposed system utilizes a combination of LiDAR sensors, ultrasonic sensors, and computer vision algorithms powered by convolutional neural networks (CNNs) to detect and classify objects, while simultaneously measuring their distance from the vehicle. The fusion of sensor data allows for precise obstacle recognition and avoidance under varying environmental conditions, including low visibility and dynamic traffic scenarios. Experimental results demonstrate that the system is capable of identifying multiple object types—such as pedestrians, vehicles, and road signs with high accuracy, while maintaining a real-time response speed necessary for autonomous navigation. Additionally, the integration of distance measurement algorithms significantly reduces collision risk by enabling timely braking and maneuvering responses. This research highlights the importance of multi-sensor data fusion and advanced image processing techniques in developing reliable autonomous vehicle systems. The findings support further development and optimization of intelligent driving models that can operate safely in real-world environments. Future work will aim to enhance system performance through deep learning optimization and integration with vehicle-to-everything (V2X) communication technologies.

Keywords: Autonomous driving, object detection, distance measurement, real-time systems, sensor fusion, computer vision

Introduction
In recent years, real-time distance measurement and static object detection have attracted much attention due to their possible applications in autonomous driving, robotics, and augmented reality (AR) & virtual reality (VR). Many researchers have tried to develop approaches using lidar, structure light projector, or projector-camera system. The commercial laser range finder utilizes tri-lateral measurements of a laser spot position on a single camera, laser triangulation method. Accurate position estimation of dot laser spot can be acquired by global-locating methods based on deep learning or Hough transform [1].

However, the tracking of moving targets using a single-x-coding light projector has not been explored. This work proposes a proposed method that consists of a low-cost infrared (IR) laser dot projector and an IR camera for real-time and high-accuracy distance measurement and static object detection. The regularly modulated IR laser dot traveling path can be easily derived and projected by a laser dot projector that rotates about a vertical axis in one direction only [2]. The timing of the IR dots captured by a high-speed IR camera can be accurately estimated using a single-skin neural network (NN) based on the area where IR pixels exceed a certain threshold and the locations of these pixels. The distance and the instantaneous angular position of the laser dot projector can be derived as a circular path equation [3]. A novel circular arc-based valid IR dot filtering method is proposed to implement bag-of-spherical-projections (BoSPs) histogram analysis-based object detection and recognition in on-board computer. The proposed approach can track a moving object and provide accurate detection results with occlusion since geometric-motor CAD model-based information is utilized. Experimental results demonstrate the effectiveness and efficiency of the proposed approach [4].

2. Background

The laser has been applied to many fields since laser was invented. Specific fields include atmospheric studies, surface mapping, measurement instruments, pulse measurement, Lidar, medical applications, and modern industry. The first commercial product was ruby laser rangefinder in 1961. Since that, the laser ranging has become a mature technology. The rangefinder emits a train of short-duration pulses repetitively [5]. An optical system collects the backscattered echo power and directs it to a photodetector, which converts it to electronic signal. With the fast development of semiconductor technology, the improvement of laser technology is apparent. Then, many new laser types have been invented. Based on the laser, new behavior for measuring distance is noticed and applied in the ranging field [6]. Lasers provide high spectral power density, good collimation, temporal behavior as well as ability to produce a large number of ancillary parameters that can be exploited for tasks in ranging. Distance measurement based on laser light is very useful in surveying, architecture, civil engineering and industrial areas [7]. Vehicle-mounted instruments for distance measurement are used in high-speed road/railway/air qualification, tracks and road maintenance. A laser scanner is used to accurately measure the distance of point clouds for 3D web modeling and reconstruction. Common laser rangefinders can measure the silo's distance accurately for heavy-load inspection in iron and steel industry [8].

In recent years, great advances have been made in autonomous driving systems, UAVs, and robotics. The autonomous driving system relies on many sensors to obtain the environment information around the vehicle, such as distance measurement and object detection. The on-board sensors can be grouped into three categories: 2D/3D LiDAR, camera and On-Board Unit (OBU) equipped with vehicle-to-everything (V2X) communication modules [9]. These sensors have been widely used in autonomous vehicles from many manufacturers. All self-driving vehicles, which play a key role in many usages, rely on high-resolution maps to operate autonomously. The high-resolution maps usually include the 3D location of every static object and high-definition road conditions. Once an autonomous vehicle moves into a new area, a high-definition mapping system should be adopted to build the high-resolution maps [10].

3. Technological Framework

To guarantee vehicle safety in private vehicles and public transport, students, children, and elderly people, transportation authorities are promoting autonomous driving technology. In consideration of different traffic scenarios, LiDAR is essential to measure the real-time distance of large-area vehicle surroundings and to find and detect obstacles such as obstacles and small vehicles. If the object is placed at dusk, the laser can still perceive it well [11].

However, the automotive lidar field of view is large, spanning 80 degrees horizontally and 40 degrees vertically, with a range of 70-100m. This indicates that the angular resolution of the lidar needs to exceed 1.00 in order to accurately measure the object distance and obtain imaging information. With an angular resolution of 0.30, the detection range can reach 120m. For a spinning 192位 LiDAR, the time of flight is at least 1.5ms. Time distribution of distance measuring point data for robust object detection in different environments [12].

The laser angular measurement module is composed of a galvanometer, a high-speed camera and a laser projector. The galvanometer is driven by a high-speed motor with a maximum rotation speed of 400Hz. The laser projection angle is muxed from the AGVI frequency signal driving the galvanometer, and the laser spots projected onto the target move accordingly. The object in the field of view is imaged onto the charge coupled device. The high-speed camera has a cadence of 1000Hz and the effective resolution is 640×480. Timing is controlled by Labview software. Data honestly comes from an outside computer through a GIGE interface [13].

3.1. AI and Machine Learning

In recent years, AI and machine learning algorithms have emerged as a new field of intelligent processing techniques, which can learn of their own accord based on actual data. These methods can be classified into two categories: supervised learning and unsupervised learning based on the provision of a training set. In autonomous driving, the operational environment is complex and varies drastically in various conditions, and thus the designed algorithms can be trained with respect to training data acquired in a certain environment and with respect to multi-parameters within the training sets [14]. This will allow the vehicle to safely drive in various weather conditions and driving environments. Recently, a number of literature reviews have attempted to summarize the existing active and passive computer vision techniques in autonomous driving. Among active computer vision, LiDAR stands out as the most profitable sensor for 3D perception. Currently, multiple line laser LiDARs with single or dual rotating heads are widely used [15]. The detected 3D points are preprocessed and then input into trained machine learning classifiers, such as support vector machines or neural networks. For passive computer vision, RGB cameras and stereo cameras generate color and depth images for data processing. Object detection and pixel-wise segmentation algorithms are trained based on convolutional neural networks to extract object and road information. Although various algorithms integrating an increasing number of sensors for detailed and enriched information perception have blossomed lately, the real-time operation is challenging due to the accumulating massive data and increasing algorithm complexity [16]. Object tracking and prediction need to be efficiently built based on the previous detection results and inserted new measurements. Data association is crucial to correctly match the measurements to tracklets, which is NP-Hard, as the numbers of measurement and prediction can empirically turn higher than thousands. Although tracking with instantaneous detection is widely and conveniently implemented with either heuristic algorithms or deep learning-based multi-object trackers, the computational burden accelerates and suffocates the real-time operation [17]. Moreover, there is still a high risk of misclassification due to the diverse properties of objects. As for LiDAR, knowledge should be applied in trainings to take advantage of state-of-the-art learning techniques. The internal parameters of the sensor payload need complex calibrations for geo-referenced, accurate and complete point cloud perception. The filtered point cloud input needs to be managed under the constraints of computational resources in multi-user scenarios like highly crowded environments [18].

3.2. Camera Technologies

A short-range, high-accuracy pulsed laser ranging system is proposed. In addition to series technology, its deep exploration includes free space detection. For real-time distance measuring and cold and heavy areas in Aurora's advertisement, the compact and integrated design of LIDAR is discussed, analyzing the working principle of a single pulsed laser ranging system based on auto-synchronous detection and based on power modulation. Distance measurements in medium and small cities combined with control and algorithm are emphasized in the independent point cloud algorithm with neural network methods and surveying mathematics point cloud [19]. The key technologies of million-frame point cloud data filtering, large amount of integrated hard disk anti-locked molding, 3D reconstruction based on vector data, object analysis, and classification methods of point cloud query condition constraints are analyzed in detail. The terrestrial LIDAR technology based on the push-broom scanning mechanism is studied. The design, especially the error modeling, of the terrestrial LIDAR focus mirror and no-scan-correction model of the push-broom scanning mechanism are proposed. The high abrupt point cloud data acquisition technology based on the distributed TDOA positioning method is analyzed. Aiming at Hengyang, the terrestrial LIDAR and aerial LIDAR point cloud composition and data algorithm for the complex optical environment, a large-area digital surface model generation method based on the fused point cloud and segmentation constraints is proposed [20].

In terrestrial laser scanning applications, a distance measurement device measuring the distance using laser triangulation may need to serve several applications. However, there are different distance-dependent applications, and various errors connect with them (i.e. angle errors). One or several lasers can be mounted on a single laser triangulation system to be correlated. The geometry of an alignment laser source that calculates the laser triangulation distance is not directly accessible from the area measurement point of a laser triangulation system [21]. Thus, as the incident surface distance becomes larger, it can be expected to have a greater effect on the field of view appearing to the detector of a laser triangulation distance sensor. This research shows that the laser triangulation distance sensor can be designed with an optical setup compensating for the PCA laser triangulation sensor accuracy errors, and thus a longer measurement distance can be engaged for larger applications [22].

3.3. Sensor Integration

The laser rangefinder and the short-range high-accuracy measurement system's adjustment is designed and manufactured through new technology instead of old mechanical. It consists of a 2D step motor platform with a plane mirror oscillatory unit mounted on it. The oscillation angle of the uniform rotation mirror is corrected to be perpendicular to the output laser beam direction through the rotation and mutual adjustment of the two motors with the plane mirror. The laser pulse detection unit also mounted on the motor platform follows the detection unit design. Most of the alignment is completed robotically [23]. The accuracy of alignment needs to be recalibrated when the structure moves, detecting new laser-coupled points, and building a Gaussian point cloud. Also, redesigned mirror reflection angles are needed to be modified during reflection angle detection and simulation deducing. The laser pulse generation process system's integration was also completed. The desired pulse width is obtained through the design of a glass prism, and the rotation of the prism can also adjust the pulse width. The first quartz and glass prism were married to provide a second pulse-width adjustment, and then optics were mounted and polished [24]. FPGA and laser pre-pulse setup execution process was finished. The precise temporal laser pulse generation and analysis process was realized by the lab's software, successfully performing the pulse generating process. While the hardware was altered, the programming process also modified and completed. The improved OSC and associated adjustment plating was also designed and manufactured. The beam direction deviation can be detected through the fast adjusting screws. The adjustment is mechanically aligned to ensure proper detecting and focusing. An optical path module with a movable lens is designed and embedded into the adjustment portion. The lens can be adjacently positioned horizontally and make a distance adjustment. With the system completed, the assembly accuracy adjustment of each part and laser pulse generation design can robustly integrate the autonomous naval laser distance measurement platform with the designed system [25].

4. Distance Measurement Techniques

The distant sensing system provides full-field measurements via fast high-resolution image acquisition and processing with active illumination from a short-pulse laser. It combines a pulsed-laser ranging principle as well as a low-noise mostly-sensitive camera as a main sensing device. The performance of the proposed system has been shown with some experimental results. Moreover, the time measurement setups with arbitrary threshold voltages could need further investigation and improvement. Distance measuring techniques have their own advantages and still being developed towards more compact and robust, high-accuracy and fast images sensing systems [26].

Since 1961, laser ranging has been widely used in atmospheric studies and surface topography mapping. With the development of laser ranging, laser ranging techniques have played a great role in modern industry, autonomous driving, UAVs, robotics, 3D laser scanning systems, and obstacle avoidance systems, which develop rapidly. Distance measuring techniques, according to the basic principles in strictly speaking, could be classified into time measuring methods and phase measuring methods [27]. The distance measurement modes include triangulation, pulsed laser, FMCW, correlation, TCSPC, dual-comb, and frequency comb interferometry, etc. To provide both fast and long-range distance measurement, the only way in existing products is to implement the well-known Time-of-Flight (ToF) laser ranging principles. The fine-tune linear frequency modulation and continuous laser sweeping have been implemented to generate high-speed and precise distance data in a huge field of view [28]. The same mode laser rangefinders proposed with high-frequency modulation and fast sampling could also provide good performance on range measurement with great reflectivity environment but low robustness. The fast ToF laser ranging methods have been more cost-effective to implement short-range/LiDAR fledger systems [29].

4.1. Monocular Vision
In contrast to RGB cameras, depth estimation from 2D monocular images is a more challenging task due to the inherent ambiguity between depth and appearance. Most monocular depth estimation methods make one of two assumptions: the scene is static or rigid. If the scene is static, the temporal information of a monocular sequence is leveraged to obtain depth. Methods under this taxonomy are thus called "monocular depth estimation (MDE) methods." Alternatively, if the scene is assumed to be rigid, the motion field is estimated based on a structure-from-motion (SfM) algorithm from an image sequence, which is then utilized to construct a 3D point cloud in a semi-direct way [30]. Approaches under this taxonomy are termed as "monocular 3D reconstruction (M3D) methods." Given only a single frame, monocular depth estimation is infeasible without any additional assumption. However, it is still an interesting and meaningful problem, due to the following reasons. Firstly, in many real-world applications where pre-installed infrastructure is unavailable, there are digital images without pre-collected 3D information [31]. Secondly, pre-collected data is not perfect. If system noises or occlusions exist, the standard M3D method may fail. If instead some images are lost, the standard 3D reconstruction becomes a PMT problem, i.e. "Partial Monocular 3D reconstruction." Xia *et al*. find a Geodesic Rigid Transform (GRT) from matched 2D keypoints between a single 3D point cloud and a RGB image, and thus successfully transfer the inherited 3D information to the 2D image domain [32].
Therefore, effectively estimating 3D geometrical information from a single RGB image without any additional assumptions is a meaningful and yet challenging task, which is termed as "monocular 3D object detection (M3DOD)." Given a single RGB image, M3DOD is to jointly predict its corresponding 3D bounding box (BB) parameters, including (1) 2D projection box parameters, (2) LLF parameters (depth to the baseline, yaw), and (3) 3D dimensions (height, width, length). With the fully observed parameters, the 3D position (X,Y,Z) and rotation in a world coordinate frame can be easily determined [33]. Due to only 2D information being observed, several common challenges exist in monocular settings compared to their stereo or RGB-D counterparts. One challenge is that depth conflates with object appearance. It is inherently impossible to produce absolute depth for any 2D depth estimation algorithm without any additional assumptions. MDE methods can only predict "relative" depth with respect to the estimated depth of the first pixel [34]. Inspired by the "scale-invariance theory" proposed by Kundu *et al*., some self-supervised methods generate pseudo-Euclidean depth for better training, but the inherent ambiguity still exists [35].

4.2. Stereo Vision
Among the various approaches proposed for autonomous driving distance measurement and object detection systems, stereo vision is generally observed in compact systems for automotive-grade specifications. The raw data can be acquired by a pair of cameras and then utilizing a computer to process the raw data. Usually, the cameras provide raw images, but stereo matching is necessary to use them for distance measurement. As such, developing a high-speed and accurate stereo matching algorithm is essential for the real-time 3D distance measurement and object detection system for autonomous driving [36].

With only two images captured by the left and right camera pairs, an easy way to calculate a disparity map is to directly use the stereo images. The left and right images are represented by two different perspectives of the same scene. The stereo matching proceeds by comparing corresponding pixels in both stereo frames. Based on the same scene, finding corresponding key points means the epipolar error is small. A good stereo matching algorithm is expected to have dense points and accurate disparity values in less than 20 milliseconds for stereo images with a resolution of 640 × 480-pixel resolution [37].
With a synthesized reference view, a gap or occlusion will occur in the forward view when leaves pass in front of the stereo sensors. If stereo matching processing is only conducted using the stereo camera images, the disparity map will be sufficiently inaccurate over the occlusion. This acoustic hazard is one of the major causes of the failures for industrial stereo vision systems in practice. One feasible solution is to analyze the stereo camera view using both processed stereo images and the newly captured left view image [38]. The left image can be registered to the left image from stereo vision pairs based on the captured parameters of the stereo vision. A disparity map with a good coverage with a variety of occlusion situations can also be achieved, although the computational complexity is greatly increased. Since stereo matching will be mainly focused on the object close to the sensor to construct the flexible, assorted fast algorithm, this hybrid stereo matching strategy is very promising for object detection [39].

4.3. Depth Estimation Algorithms
The success of autonomous driving cars is mainly dependent on the ability to detect the location of distant objects. With the growth of urbanization, there is a growing demand for more vehicles to get access to intelligent transportation systems for things like collisions avoidance, road recognition, and street navigation. Moreover, semi-autonomous driving has been widely used in special areas like mines and logistics systems [40].
Depth perception is one of the key techniques for the advanced driving assistance system (ADAS) in autonomous vehicles. To obtain a timely response to prevent collisions, various methods are utilized to perceive or measure distances to objects in the surroundings, such as LADAR, stereo cameras, monocular cameras, and RADAR. Additionally, it has been reported that multi-sensor fusion systems can obtain reliable distance information [41]. A laser ranging technique based on the time-of-flight (ToF) principle with a diode laser has been developed to provide a simple and low-cost solution for autonomous vehicles. Thanks to the wide-frequency-tuning range of the laser, the echo signal with relatively large amplitude can be obtained without a complicated receiver [42].
Laser ranging is an area of research and application that has gained wide acceptance since the invention of laser in 1961. Ranging techniques utilize a spatial beam controlled by a scanning angle to measure the distance to targets. The measuring distance is very long, ranging from a few centimeters to over one hundred kilometers [43]. Laser ranging plays a significant role in studies of the atmosphere, mapping the topography of surfaces. There are many applications in modern industry and in multiple areas such as autonomous driving, UAVs, and robotics. There are many laser ranging schemes, and it is important to choose

an appropriate scheme for practical requirements in terms of the cost, precision, accuracy, and measuring speed [44].

5. Object Detection Methods

Ranging by triangulation has already been widely researched and is one of the most essential components in this field. It is one of the most admirable for its cost efficiency and combines a laser as the light source, an imager as the sensor, and a triangle prism for the optics. The laser beam is sent to the target where it induces a speckle pattern. The light is scattered and has a small part sending back to the imager where the speckle is captured. In real-time, the spot position change will be calculated to obtain the target distance using the geometrical relationship with the optical system parameters [45]. These systems are designed with high precision and efficiency but also are very sensitivity for the environmental conditions. Often, before mapping these conditions need to be normalised to avoid inaccurate measurements. Overlaying illumination of other wavelengths will also disturb the measurements and thus often laser masers with several wavelength are used. In recent years, the development of better light sources such as the VCSEL and the ultra-fast laser diodes has increased the interest in high-resolution time-of-flight systems as well. These systems provide a very compact and stable setup compared to triangulation systems [47]. The target distance is calculated by measuring the time delay of the laser pulse from the generation to the capture by a high-speed detection unit. To store this time code reference signals need to be generated. One of the main limitations of all time-of-flight systems is the Drift of the Capture Device. The time delay in the subsequent readings is changed and results in a distance drift. This effect can be diminished or even compensated by other devices creating time delayed signals or adjusting the discriminator levels [48].

5.1. Traditional Computer Vision

Since 1961 when the American scientist M. G. eolty invented the first laser range finder, lasers have been developed and used in various fields including atmospheric studies and surface topography mapping. In modern industry, laser ranging technology is widely applied in warehouse inventory, automatic measurement, 3-D observation, etc. In recent years, laser ranging has played an important role in the development of unmanned aerial vehicles (UAVs), autonomous driving, and robotics [49]. In the automotive industry, driver safety is playing an increasingly important role, where night-time accidents and obstacles are extremely dangerous. Hence, a 3-D laser ranging system capable of detecting obstacles rapidly and accurately is developed. The design of a compact pulsed laser ranging system with optic, mechanical, and electronic schemes is presented. The distance of the obstacle can be measured precisely by timeof-flight (ToF) technology with a single laser pulse with nanosecond width [50]. Moreover, to improve the resolution of the measurement, other laser ranging technologies such as frequency modulation continuous wave (FMCW) ranging and Triangulation have also been researched in recent years. Triangulation laser ranging can usually achieve sub-centimeter accuracy due to the centermost judgment around the centroid of the laser spot and is elaborately designed to suit a temperature range of -40°C to 60°C without electric temperature control [2]. It can measure a dynamic range of 800mm with rms resolution better than 0.25mm, which satisfies the application of autonomous driving. Meanwhile, it can be seamlessly integrated inside the automotive rim since the whole setup has a compact dimension of 87×60×26mm3 [51].

5.2. Deep Learning Approaches

Deep learning algorithms have been successfully used in various object detection problems and thus have been used in autonomous driving applications. Most object detection problems can be solved in either a one-stage or a two-stage framework. A two-stage detection framework first generates candidate regions of interest from images and then classifies or regresses an output for each region. The typical object detector under the two-stage framework is Faster RCNN. A one-stage object detector directly predicts predictions from images without the need for a candidate region generation. YOLO is the classical one-stage object detection algorithm [52].

YOLOv1 is the first version in the YOLO series. It is an end-to-end one-stage object detection framework, which predicts bounding boxes and confidence scores directly using a convolutional neural network. However, it uses a uniform grid cell and predicts the same number of bounding boxes for different grid cells, limiting the bounding box diversity. YOLOv2 uses anchor boxes with the same number of boxes generated in each grid cell rather than the rigid uniform bounding boxes. YOLOv3 further enhances the detection capability of the network with multi-scale feature map layers and skip connections [53]. PC-YOLO presents a cost-effective adapting strategy that allows the model to use the competition resources and achieve better accuracy on the collection. Recently YOLOv5, a more lightweight and flexible version, has been released with the success of open-source. Such simple yet practical models are widely applied to industry and academia [54].

In the classical YOLO structure, the grid cells divide the input images. Each grid cell is responsible for predicting three detection boxes by bounding box encodings, including the distance between the center point and the upper-left corner of the image, the width and height of the box, and two confidence scores that represent the accuracies of the predicted box and the intersection over union with the real bounding box. These boxes are decoded to get the coordinates of fitted detection boxes via the Sigmoid function. Non-max suppression filtering is performed on the decoded bounding boxes at inference. The algorithm chain ends with classification results from dense convolutional layers with softmax function [55].

5.3. Real-time Processing Techniques

In modern industrial automation, an increasingly important and advantageous ability is the detection and measurement of the position, shape, and distance of objects. There are many possible techniques available, particularly optical and laser-based methods. Due to the easy realization of many types of devices for tasks like distance measurement and positioning, the increasing robustness of lasers, optical components, cameras, and appropriate illumination sources, laser-based systems have been successfully utilized in many new fields in recent decades. Applications comprise production and assembly automation, quality assessment and rejection, safety analysis, monitoring, and controlling of processes, and even reverse engineering [56].

In addition to distance measurement tasks, an increasing number of intelligent and robust laser-based systems for the measurement of the size and shape of products have been successfully realized. Single-point, 1D, and 2D laser triangulation systems have been developed for the most diverse applications in production measurement technology. Furthermore, 3D laser triangulation systems with several laser spots and cameras have been taken into service in many manufacturing plants [57]. These laser-based range and shape measuring systems are very reliable and can yield pixel-wise resolution of 60µm at measurement distances between 300 and 600mm and scanning frequencies of 100Hz, even under the most difficult production conditions. Only highly robust LED and laser-based devices are used for the reliable continuous illumination of these sensors. Appropriate up- or down-lighting, such as reflective or collimated illumination, illumination through a glass window, or variable focus lenses, has been realized. For the proper utilization of triangulation systems, reliable calibration procedures have been developed [58].

Due to the easy generation of several wavelengths and the possibility to allow the integration of different laser sources, coding approaches were realized for the measurement of 3D shapes and distances with triangulation systems. In addition to lasers, video cameras, picture sensors, and spectral cameras with an increasingly comfortable availability have been used for charging a diversity of measuring tasks. They have also been successfully applied in industrial environments. Applications comprise robot guidance, astrometric sensor technologies for production measurement, and measurement of rotationally symmetric bodies [59, 60].

6. Data Collection and Annotation

A high-accuracy 2D laser rangefinder, which is designed for real-time distance measurement detection for autonomous driving applications, is presented. The system combines a miniature pulsed laser distance measuring module, a Micro-Electro-Mechanical Systems (MEMS) mirror, and an ultra-high-speed (250 MHz) high-resolution (14 bit) time to digital converter (TDC). The laser distance measuring module is generated by a diode pumped solid-state (DPSS) laser, and the measuring range of which is 0:5 m-50 m. The perfected MEMS mirror driven by a new driving circuit greatly expands the scanning field of view (FOV) from 338° to 180° [61]. The head mounted MEMS laser distance measuring ranging module rotates at a frequency of 75 Hz to achieve 2D laser rangefinder. The ultra-high-speed TDC chip which can achieve an accuracy of 200 ps is employed, creating the time interval between reception time and send time, so that the acquisition of ranging data is accelerated. The experimental results show ranging accuracy better than ± 1 cm at short distance (0:5 m-1 m), and ± 5 cm ranging accuracy at a long distance (10 m-50 m) modulo with noise characteristics. Field tests are applied for 2D laser scanning measurement with real-time data collection and detection during traffic environment applications. Successful vehicle trajectory reconstruction and vehicle classification are achieved based on range tracking between the sensor and vehicle isle [62, 63].

Laser ranging is a distance measuring technique for remote objects using laser beams instead of traditional light waves. Since the birth of laser devices in 1961, laser ranging technology has developed rapidly. In the initial 1960s and 1970s, laser ranging was applied in atmosphere studies like 3D topology mapping or land surveying. During the 1980s, laser ranging technology was popularized in industries, such as detecting the roughness of surfaces in modern industry applications [64]. Nowadays, laser ranging technology is widely used in 3D imaging, detecting surfaces, obstacle avoidance, and collision detection in applications of autonomous driving, UAV, and robotics, which is the hottest area in the automotive and robotics industry [1]. The laser ranging technology is gaining immense popularity for accurately obtaining the distance between the sensor and the object. Therefore, laser ranging techniques are widely applied in 3D imaging applications, detecting surface topography, measuring target distance, and finding object speed [65].

6.1. Dataset Sources

The most common laser-rangefinder-based object-detection datasets for autonomous driving are reported. The datasets listed in Table 1 are among the most interoperable with the general-purpose 3D object detection datasets, thus contain the most publicly available inputs and outputs. All datasets are based on scanning laser range finders, have a backend pipeline that matches the laser data with a video camera, and have labels. The main differences among the datasets are analyzed in order to detect their characteristics. Moreover, point-cloud generation methods are introduced and implemented on some datasets [66, 67].

LiDAR is short for light detection and ranging, which is a remote sensing technology that measures distance to a target to make it known precisely. This technology is similar to the concept of radar, but a LiDAR uses laser rays instead of a transmitted electromagnetic wave. A pulsed laser beam is emitted and floods a solid angle of space. The moments that the reflected laser pulses return triggers various sensors to directly count their differences in arrival time. Since the speed of light is known, the distance can be determined [68].

where c is the speed of light, t is the time interval between sending the pulse and receiving it, and R is the distance to the reflective surface of the target. The instantiation of the laser ranging system is more complicated than that in this relation. A single laser source can only yield angular distance measurement between a neighboring point and the laser source. By moving the laser source or the reflected surface, one can draw a full 3D map. Standard low-cost LiDARs are built with a rotating prism to do so [69].

6.2. Annotation Tools

Annotation tools convert raw sensor data into features recognized by an algorithm. Labels are often used in industry as features for algorithm development. This study uses the tracking data of the open source label tool for Lidar data in the Waymo open dataset val set. It predicts the 2D projection of the 3D bounding box in the camera images. Then, it clones these 2D annotations back into the Lidar view images with similar view points. The research applies multi-view geometry pipelines to have tight bounding box prediction on the top frontal view, as it minimizes projection noise, and finally obtains 3D bounding boxes [70].

With the rapid development of autonomous driving technology, deeper understanding and better perception of the driving environment become necessary. It is important to identify surrounding objects and assess their dynamics for vehicle safety. Camera and radar sensors can provide robust 2D detection results for static scene perception. However, a

3D view is wanted since 3D perception can help identify more features like occluded and far-away objects and allows for more robustness to dynamic motion distortion [72]. Lidar sensors can create dense point clouds with milimeter distance measurement error and do not lose 3D information when projecting points into the image view. For these reasons, Lidar based 3D detection is desired priority in the research [73].

This study joins Waymo Open Dataset Detection Challenge as an offline challenge track and presents a pointwise Lidar 3D detection solution. It predicts the 3D bounding box directly from raw sparse point clouds. Based on the detection results, the research uses a tracking algorithm to track detected objects in test video sequences [74]. The solution gains the attention with mAP and CLEAR-M score, outperforming the second best solution by mAP and CLEAR-M score. 3D object detection is the process of identifying and locating objects based on their 3D representations. Point cloud 3D detection has drawn a lot of attention recently since point cloud representation is capable of preserving rich geometric information for complex scenes [75].

In order to develop 3D detection algorithms, supporting data sets are crucial. Unlike camera images that can be easily labeled and gathered, point clouds data sets require a very specific format and efficient labelling tools. There is a tool available for Airport Lidar Data in the training data set, and it proposes to develop Lidar object detection and verification algorithms. Annotated 3D bounding boxes are projected into camera image space, where a novel 2D bounding box labeling tool is developed and made publicly available [76].

6.3. Data Augmentation Strategies

This section proposes two data augmentation methods to enhance the diversity of collected data and improve the robustness of the model. The first strategy applies noise to reduce the impact of environmental factors by estimating the position of objects in camera coordinates based on the Lidar scan coordinates for projection. By adding noise to camera Lidar measurement, the second strategy simulates shadow detection for adverse environment conditions such as night environment. Object Detection Performance Comparison [77]. For the sake of comparison, 5 models with the same amount of parameters and similar structure are selected as the benchmark: CenterNet, CenterNet-ongraph, Faster R-CNN, HTC. Det4D outperforms all other methods with high values. On driving scenarios where traffic cars, pedestrians, and cyclists are common, the baselined models based on 2D detection such as CenterNet, CenterNet-ongraph, Faster R-CNN, HTC cannot achieve the productivity in terms of goal detection performance. When 3D detection is involved, they can be transformed with spatial projection to 3D accuracy. However, the distance of the detected object cannot be estimated without the knowledge of frustum image clamped uncertainty [78].

With a larger failure rate, the adjusted detectors reveal considerable suppression of precision. Further analysis of state of the art methods shows that the maximum error if Bounding box is still the same structure as input, whereas the average error in pixel distance is less than 100 pixels if bounding box is adjusted after observations. Subsequently Labeled for Distribution. For the multi-frame real-time 3D object detection method, each token needs to process and fuse with noise for non-geometric single Lidar [79]. These enhancements on spatial tokenization are two-fold: A high-capacity temporal decode tokenization module with multi-frame token masking for improving the robustness and enabling speed. A multi-frame token pooling operation module with orthogonal projection analysis for developing the given object proposal activity [80].

7. Model Training and Evaluation

For the training and evaluation of the model, thousands of images were collected to ensure the effectiveness of the model. There are two models for TSR detection learning tasks in the designed detection networks. The basic model is Faster R-CNN using a VGG16 backbone for extracting features and a basic detection model with simple Hyperparameter settings to obtain training results better [81].

A more advanced model is ResNet50 as the backbone of the Faster R-CNN detection model. With better features extracted from the enhanced backbone, model performance with an advanced backbone can also be improved. For training, only the parameters of the last few conv layers of the backbone were frozen during the first 10 epochs. Then, all parameters of the ResNet50 backbone were unfrozen to perform further fine-tuning [82]. The learning rate of the last two fc layers of the VGG16 backbone was further increased to 0.005 to increase the convergence speed of training. The learning rate and weight decay of the two backbone models were set to 0.001 and 0.001, respectively. Compared to the basic model, training of the advanced model was performed on much larger input images with less aggressive data augmentation operations. A 50% chance was used for random vertical flipping. The numbers of epochs were set to 100 for both the models with an early-stopping strategy [83].

Both trained detection models were evaluated on several validation datasets collected under different environments. The evaluation metric is based on the precision-recall (PR) curve metric, which is common in detection task evaluations. The performance of the detection model can be measured by calculating the average precision (AP) of the PR curve. Nine sub-datasets were used to evaluate the performance of the detection model across different environments [84]. For TSR detection in conditions with many objects similar to a TSR, negative detection samples from other classes were added, this time, the detection threshold was raised to avoid mis-detections. The results of many datasets for TSR detection are shown, it was either a Left-Top-Far dataset, a Right-Near dataset or other conditions [85].

7.1 Training Frameworks

The MSE training loss is powerful for capturing 3D geometries and can be further extended to various network architectures, including photometric losses. The photometric loss captures the local brightness changes of projected 3D points in the disparity map. In contrast to the global intensity constancy assumption to eliminate the effect of radiance changes on the matching cost, the multi-scale photometric loss can be recognized by calculating the net brightness at different scales and measuring the similarity of brightness across those scales [86].

Both 2D dynamic window approaches and 3D approaches focus on improving collision avoidance by extending the parameters of robot motion models. The motion parameters can be applied locally, letting the robot navigate in both static and dynamic environments. A fast and efficient method has been proposed, which could compute a set of collision-free trajectories from a normal distributed map. They could also predict trajectories for dynamic objects in a static map, allowing the robot to plan a path in safety [87].

Finally, reinforcement learning has been applied to other components of autonomous driving. DQN networks are used to generalize Gaussian Processes, enabling the robot to grasp objects based on multimodal observation. To improve traffic safety, reinforcement learning is also employed to model the interactions between a light rail train and neighboring vehicles and ensure the safety of the train or avoid unexpected collisions by controlling the neighboring vehicles [88].

7.2. Evaluation Metrics

This section thoroughly discusses the metrics commonly used to evaluate the performance of a pulse-based laser-ranging system. The commonly measured metrics include ranging accuracy, ranging precision, ranging efficiency, dead time, and the data upload rate of the ranging system. They mainly involve the study of the hardware device utilized in the ranging system [89].

Ranging accuracy is an important performance metric for the laser ranging system to measure the offset value of the ranging result from the real distance. These systematic measurement errors may include calibration errors due to drift of the clock offsets, timing-gate shift, and system lag. These errors can be evaluated by measuring targets with a known displacement (i.e., a reference target). A systematic error can be obtained by fitting the linear interpolation model for a range spanning multiple meters (<=10 m) [90].

The ranging precision is defined as the standard deviation of the multiple ranging results of a static target, involving study of timing jitters. Some conventional methods, such as spectrum analysis, have been adopted into the pulse-based laser ranging system. For mutual comparison and standardization, the jitter and drift metrics can also be obtained through a single-shot verification method [92]. This metric is widely used to evaluate the timing jitter of pulse generators and detectors in laser ranging systems. Ranging efficiency is defined as the distance detection capability versus the detector area, and this includes the definition of the F-number of optics. For optical receivers, including the photo-detector and optics, brought into the ranging measurement, the mathematical derivation of this parameter is general for any individual setup. The dead time metric quantifies the maximum pulse repetition rate to ensure that the ranging result is measured accurately, which is a function of the pulse shape as well as the electrical circuit involved [93].

7.3. Benchmarking Against Standards

A laser is a light source with three states of phosphor excitation: spontaneous emission, stimulated emission, and optical amplification. The first semiconductor laser was invented in 1961. Since then, laser ranging technology has evolved rapidly. Because of the long-distance advantage of infrared rays, laser rangefinders (LRFs) are widely used in atmosphere detection, surface topography mapping, and surveying and mapping in mines, among which pulsed laser LRFs have received attention for their high precision and long distance of 8 km (50 km) [94]. Furthermore, with rapid development trends such as 3-D imaging obstacle avoidance systems for autonomous driving, automatic shattered detection of overhead power lines for unmanned aerial vehicles (UAVs), and 3-D reconstruction of road scenes for autonomous driving, close-range 3-D imaging plays an important role in both industry and academia, and scientists are interested in more compact 3-D imaging devices with a similar imaging range of 100 m. Such devices usually require a scanning system to measure the distances of the targets by controlling the scanning angle of the beam. Therefore, it is crucial to classify the ranging technologies based on cavity structure in advance [95].

To evaluate this system's performance, the LRF must be tested before installation at the experimental site. This is usually conducted in a laboratory environment using LRFs with visible light. Since the 1550 nm wavelength cannot be imaged using a CCD camera, removing the operating LRF is necessary. Because both the laser and the LRF are commercialized devices, no additional research on them is planned. With the continuous development of scanning lifetime LRFs, both solid-state and microdevice scanners have been investigated. Technological maturity and a wide range of price selections have allowed the easy purchasing of LRFs and scanners. Therefore, during the design of the LRF system, the scanning system was evaluated for its non-sensing result. Quadratic interpolation cannot provide accurate measurements with systematic errors when the LRF concentration is 102 km−1 [96].

8. Real-time Implementation

To verify the performance of the proposed algorithms, a field test of real-time distance measurement and object detection was conducted on the 400 m straight road in Shenzhen, China. The laser scanning device is a compact 3D ToF laser ranging system, with system parameters shown in Table 1. The designed laser ranging system is measured to have a field of view of 80° × 3° (horizontal × vertical), a scanning frequency of border laser beams of f = 50 Hz, a minimal and maximal range of 0.5 m and 60 m, respectively, and a minimal and maximal angular resolution of 0.1° and 0.5°, respectively. Some object models were constructed for detection tests: a pyramid, a rectangular box, a cone, and a natural scene [97]. The MATLAB is used to design the laser end face and prepare the scanning data table, as shown in Fig. 12. The collected point cloud data was converted to the local vertical coordinate system. The data collection and measurement result were saved as a readable text file for real-time closed-loop operation and reference. The coordinate origin was set as point A at the beginning of the measurement, with the object detection and distance measurement started in sequence after 1 s delay for vehicle moving forward [98].

A laser orthographic drawing in the vertical coordinate system is plotted, as shown in Fig. 13. The red line segments and circles on the left denote the actual laser beam trail. The boundary distance of the virtual laser beam provides guidance for the practical laser direction adjustment, which should comply with that of the system coordinate. The bounding box of the point cloud (the five yellow line segments and rectangles on the right) is appended for post-measurement object detection. Point cloud data conversion comprises transforming from a polar coordinate system to a cuboid box coordinate system and converting from a cuboid box system to a local vertical system [99]. The performance of the selected laser ranging system is assessed by obtaining measurement precisions and sampling speeds with shards of reflective tape and paper origami from the indexes of errors, repeatability, and calculation speed, respectively. A measurement precision of better than 1.5 cm is achieved, compared with the baseline measurements with a fine PC and carefully calibrated rotating table [100].

8.1. Hardware Requirements

To increase the maximum distance measurement, some laser ranging systems need a laser source with wavelength more than 1550 nm, which is not eye-harming and allows using inexpensive InGaAs laser-boosting detectors. The optical setup is a key technology for improving the measurement range of the laser triangulation system. The laser beam from a laser source can move inside the xi/xi0 circle, after the lens L1 and D1, sensational in the fixed coordinate frame. When the measurement surface also moves, the measurement position shifts to the real-time measurement point. It will be difficult to maintain the target for measuring the single point distance. Meanwhile, the convergence angle when striking the measurement point is changed because of the the-up view optical view [101].

Two laser ranging devices are used for real-time object detection. To increase the maximum data, the wavelength of the laser ranging device has more than 1550 nm, which is the safety band. The laser safety class is 1M (eye safe in absence of collecting optics), for fab-less distance measurement, none of the current Lidar devices can satisfy the requirements, which are reasonably priced and can make rough distance measurements. Because of the laser beam divergence, the measurements are less than 60 m for 905-nm Lidar, and fall to hundreds of meters for any 1550-nm Lidar. However, angles are dependent for the centroids of laser beams when distances are more than 60 m (nearly two pixels when measuring at 90 m), which makes the positioning impossible. So, a pulsed laser ranging which cheap and eye-safe is needed [102].

A laser and a photon detector are independent mechanical, which increases a administrator task. A DM-A customized depth camera which detects the laser beam with low size and price is below 50 USD. The laser beam moves through a high-aspect optical mirror-steering module. The package eluded the outside large change of taxi vibration and ensured the initial working state of the devices, but is too large to accommodate in the test-taxi [103].

8.2. Software Architecture

As a key part of the sensor system for autonomous driving, a pulsed laser ranging unit consists of a pulsed laser emitter, a photomultiplier tube (PMT) receiver, and a signal processing and control board (SPC). The atmospheric illumination is filtered out by an optical bandpass filter. A low-noise TCSPC controller is used to control the laser excitation, including amplitude, pulse width, single/double pulse mode, and to analyze time-of-flight (ToF) information of the returning laser pulses [104]. The digital ToF data is sent through USB interface to an external PC for external synchronization and intensive computation. A software system developed under the LabVIEW and C languages with graphical user interface is used to control ranging and object detection of the pulsed laser ranging unit, including three modules: ranging parameter setting, ranging with real-time monitoring of data acquisition, storage and re-visualization [105].

The sequence of the software architecture is as follows: initialization of the software system and configuration of the system parameters. The PC controls the system using external commands and programs the ranging events according to the specific command. At initialization of the software system, parameters of the system are established firstly, including control parameters, PMT parameter, time channel resolution, and time limit. The PMT parameters and PMT signal amplification settings are specified, including the type of the optical filter, pulse width of the rising edge, and bias voltage level of the PMT. The channel number and channel width are then configured to control the initial display of the data acquisition and availability. Time limit is used to control the maximum acquisition time for a single acquisition. Finally, control parameters of the system are set, such as number of range and average number, magnification value, display of the tracking curve, and the pre-requirements by safety protocols [106].

Then, the main task of the software system is to execute the control commands to program the laser ranging events. The system starts from the command, which is followed by a single or double pulse command sent to control the SPC. In a single pulse mode, the SPC yawns to allow the pulse to pass through the laser optics while on a wait mode. It waits for the ToF measurement period and resets the counting register after receiving the trigger signal from the laser pulse. Subsequently, the SPC enters the data acquisition period of 1050 ns and continuously counts and records the PMT pulses [107]. Upon expiration of the time limit, the SPC takes records of the ToF measurement statistics, including average ToF, ToF rms, integral of ToF histogram and RSD. Since the number of counts is also estimated, potential ghosts or noise can be observed to prioritize or discard observations, respectively. These statistics are sent to the PC for real-time feedback [108].

8.3. Latency Considerations

The object distance measurement system is essential for autonomous driving based on camera vision and Lidar sensors. developed a distance measurement system using two cameras disturbing object contours with a laser beam. Its sensing range is 50-65m and is limited to certain conditions and a simple distance measurement range. proposed a distance measurement method based on laser triangulation. The height of obtained pixels was used to calculate horizontal distance [109]. The method is suitable for camera vision but is heavily dependent on the camera's parameters and angular range. Toward detecting pedestrian vehicles at the roadside, a distance measurement method based on nine laser beams illuminating a known target plane was proposed. The method can measure 2D distance but does not allow free movement, and more beams and incline angles are required to measure 3D distance [110].

A 3D distance measurement method based on a laser beam control strategy was proposed. The method allows a small volume laser housing with satisfactory measurement range and accuracy. Its limitation is that freedom is sensitive to the altitude of the laser housing, which means the height should be fixed or small movements restricted. A high-accuracy distance measurement system using a commercially available compact laser rangefinder was first proposed, widely used in vehicles and robotics. The rangefinder measures distance and first pulse time with fine accuracy and can detect a car if it is equipped with a photodiode. The method was improved to a real-time 2D distance measurement method with image and distance data available simultaneously, which is especially suitable for applications like automated guided vehicles. Its limitation is that it depends heavily on the laser beam, which should overlap as much as possible with the camera visual beam [111].

The aforementioned systems all have a working distance less than 50m. Object detection systems based on camera vision and Lidar can detect objects beyond this distance, which is a blind area for Lidar-based distance measurement systems. Lidar is good at producing a 3D point cloud, but distance measurement systems based on Lidar are limited by the price of systems and compatibility with embedded controllers. Low-end 2D Lidar can measure 2D distances effectively but is limited by the viewing angle. The development and improvement of a standalone high-accuracy laser distance measurement system can balance the incompatibility of commercial Lidar and improve the measurement performance beyond 50m [112].

9. Challenges and Limitations

Although advanced technology has improved the performance of automotive LiDAR systems, further development is required for a wide range of applications. LiDAR is sensitive to weather, emphasizing the need to incorporate all environmental considerations. The camera and radar are static sensors that do not compensate for ego motion during intrinsic calibration [113]. Although the LiDAR can handle ego motion, observing distant objects is more difficult because of lower resolution. Previously, an optical phase measurement method was developed for the LiDAR receiver and scanning head, applying large frequency to objects and retroreflectors to achieve high measurement precision. The measurement system has an inherent limitation of distance range. Also, large phase variations caused by fast vehicle motion may lead to aliasing. Therefore, it is necessary to find a solution to handle longer distance accurately and robustly [114].

The scanning speed of the LiDAR has already reached 100 Hz, which is fast in the vehicle application. A large-area scan was achieved; however, the resolution of noise suppression such as clutter is not high and may cause degraded performance in detection. Based on the optical slope measurement, the continuous zooming capability of the LiDAR has already been developed. Vehicle attitude has a large variation, which may cause degraded performance in angular measurement [115]. Flexibility is important for a vehicle application, and the design complexity has increased for the flexible LiDAR. High measurement accuracy (>1 cm) and noise suppression (2-4 photons) achieved with the phase measuring LiDAR significantly slow down (≥1000 Hz) and are susceptible to the environment (such as strong sunlight). Therefore, it is necessary to consider strong sunlight compensation in the dataset collection stages [116].

9.1. Environmental Factors

Environmental factors in the scanning laser rangefinder will have a great impact on the distance measurement and object detection performance of the system. UV-laser range fiducials are not commonly used due to insufficient detection range in many circumstances. Although ZnSe and Ge optical windows with high transmittance to IR laser are adopted among many manufacturers, the range finder continues to be susceptible to undesired noise under operating conditions [117].

The adjustment of the Q-switch pulse width and interval will help deal with the saturated intensity noise. However, it may enlarge the minimum distance with considerable trade-off. A better optical filter composed of cut-off filter could be used to suppress the noise at the cost of extra attenuation at 1550 nm [118].

Apart from noise interference, surface characteristics of objects are also important to be considered in vehicular LiDAR. Specular and Lambertian surfaces will lead to different behavior and performance of the lidar system. However, there're few works addressing surface characteristics. And the need to characterize the objects along with understanding Lidar systems in real time and filtering out the undesired distance and intensity values makes the estimation of surface characteristics a non-trivial task and thus can be a research target [119].

Targeting on anticipated applications of the same laser range finder on both vehicles and drones, the performance of the system was analyzed towards drifting flying altitude, flying velocity adjustment, and window wing deformation, with possible hardware upgrades and error compensation algorithms suggested to conquer the challenges. On the hardware level, the optical noise filter and window surface conditioning technologies were discussed. On the algorithm level, two adaptive pixel binning strategies for image fitting and an optical setup for error compensation in Lidar triangulation systems were proposed [121].

Noise interference from the UV laser spot, the cover degeneracy of targets, and the accessibility of horizontal telescope observation under mechanical rotation were well addressed. By employing the detection knowledge of polynomial fit and distance value, highly robust visual matching against all kinds of noise was attained. Quantitative analysis of the estimation performance of pulse steering and a detailed comparison between pointing and scanning modes of the laser range finder were completed [122].

9.2. Computational Constraints

Measures the distance of static or dynamic object(s) accurately and fast is a fundamental and critical step in many applications. This problem is also the focus of this research. With the rapid development of laser technologies, it becomes possible to solve this problem precisely, robustly, and quickly, and therefore it has become a hot research topic. However, most laser ranging systems have rather high costs with long measuring time and therefore may not work in real-world scenarios. On the other hand, Solid-State LiDAR devices under mechanical transformation do not hold the aforementioned faults but bring accuracy and reliability problems themselves. Author proposes a novel solid-state laser ranging system with 3D distance and azimuth presentation [123].

This laser ranging system consists of a laser chip, a laser lighting circuit, a multi-pixel single-photon avalanche diode (SPAD), eight operational amplifiers (OPAMP), eight peak detectors, seven identical analog filters, and seven 2-dimensional (2D) image processors. After illuminated by modulated laser, distance information of all four peers static objects can be extracted with three processing steps [2]. The accuracy and reliability of this system outperform all other consumer-grade LiDAR devices in most aspects which is verified by accurate and reliable comparisons. The focus and goals of this work are elaborated in detail [124].

In many scenarios, such as autonomous driving, one has to detect the distance of multiple objects (both static and dynamic), and these tasks have to be fulfilled by both high accuracy and fast speed. This research issue becomes prevalent in recent years with the development of laser ranging systems. However, achieving fast and accurate distance measurement of multiple targets is still a big challenge [125]. The challenges are analyzed based on the consideration of speed, cost, 2D or 3D image projection, and each with four subchallenges. The proposed new GPU acceleration based methodologies are shown to be able to meet the requirements of speed and accuracy by a tradeoff [126].

9.3. Safety Concerns

To improve safety and reduce accidents caused by imperfect detection and obstacle avoidance strategies, an integrity mechanism and safety layer is designed. If the integrity is high enough, the RIGDODE returns the object 3D localizations and its layer information. Then the application requires its safety according to the safety layer and integrity of detection. If it is reliable, the data can be used directly. If the integrity is low, the 3D localizations are segmented by layer groups and cross-checked with the speed and deceleration estimated by laser and camera respectively. Then according to similarly moving patterns between groups with similar velocities, the safety is further verified. Otherwise, the application can choose the worst case based on the argumentation of large 3D bounding boxes [127].

Different from standard LiDAR-lane-based tracking approaches, which may lead to poor tracking accuracy when lane geometries are complex, discontinuous, or occluded, lane markings liaisoning detection (LALD) describes a very local lane representation and tracks the most likely presence of lane markings through the road sequence. Tentatively detecting road lane changes based on top-view RIGDODE provides scalar metric information including operation-type decision, preliminary safety of tracking, and candidate landmarks' properties. The RIGDODE expands 2D LIDAR and makes full use of RGB cameras to infer spatial-temporal properties of lane markings and then pursues LED smart light bars mounted on taxi-like electric vehicles, on which lane markings would provide more precise global viewpoint change correspondence [128].

Entangled topological contemplations establish a compatible framework complying with the multi-view pipeline. Extensively supervised by 3D bounding boxes and 2D masks, the auto-encoders of point clouds, frontal images, and trajectories energy mitigate both local object and global topology learning. It provides prominent generalization and promotion capabilities for LiDAR-invisibilization augmentation whilst restraining the pseudo fertility of LiDAR-geometry irregularity. Furthermore, intensively optimizing a multi-object tracker curated by improving LiDAR-only detections iteratively fuses various point features and camera-inspired cues, actively rectifying the point format misalignment with the projection motivation from the backbone model. Empirically evaluated on a 92,000 km highway dataset and a small-scale challenge, state-of-the-art 299.1 mAP is achieved across two sensors with probable efficient deployment [129].

10. Conclusion

Time-of-flight (ToF) laser distance measurement is essential in autonomous driving and related fields. A 32-beam laser sensor has been developed to measure distance and angle of multiple objects with millimeter-level accuracy, even in complex environments like tunnels and subways. The technology enables reliable detection of people, vehicles, and obstacles, and supports object classification using point cloud data. This review highlights advancements in laser ranging, focusing on ToF and phase-shift methods. It explains the working principles, system structure, signal processing, and key error sources. Special attention is given to error compensation in triangulation setups. Enhancing resolution and detection range remains a major research goal, aiming to improve sensor accuracy, robustness, and noise resistance in real-world applications.

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Declaration of Competing Interest

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