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SURVEY OF TARGET PARKING POSITION DESIGNATION FOR AUTOMATIC PARKING SYSTEMS

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ABSTRACT–This paper summarizes the results of research on target parking position designation for automatic parking systems and proposes development directions. First, as parking-related systems become increasingly common in the intelligent vehicle field, many terms are used confusingly, so automatic parking systems are defined in comparison with other systems. After that, various methods of the target parking position designation in automatic parking systems are classified into user interfaced-based, free space-based, parking slot marking-based, and intelligent parking management system (IPMS)-based, and the various approaches are summarized. In this paper, the fusion of image sensor-based parking slot marking recognition and range sensor-based free space recognition, which have complementary characteristics, is expected to be the most important approach in the near future. In particular, this paper proposes that in order to effectively apply the deep learning-based method with high recognition performance, open competition through datasets for various challenging situations is necessary. If vehicle to infrastructure (V2I) communication is standardized in the distant future, the importance of IPMS-based is expected to increase. In order to cope with this, this paper proposes that the commercialization and standardization of high-precision indoor positioning along with the standardization of vehicle to everything (V2X) communication are necessary.

KEY WORDS : Automatic parking, Parking position designation, Free space detection, Parking slot detection

1. INTRODUCTION

Parking is a subject that has been studied for a long time in the field of intelligent transportation system (ITS) as it is an action that must be performed whenever a car is running. Since ITS research and development related to parking has been conducted simultaneously in various fields, the concept and terminology are confused. To understand this systematically, it is convenient to divide the parking process into three steps. Step 1 is the process of proceeding to a parking lot having available parking space, step 2 is the process of approaching the available parking space in the parking lot, and step 3 is the process of parking in the target parking space. Although autonomous driving may or may not be applied to each step, this paper analyzed related studies from the perspective of the parking process. The research on steps 1 and 2 are mainly about how to shorten the driving distance and the time it takes for the driver to park. Drivers can save time and money, parking lots can improve the utilization rate of parking lots, and the city can reduce traffic congestion and environmental pollution (Khalid *et al*., 2021). The study of Step 3 is about the methods to improve driver convenience and prevent accidents by automating the parking maneuver, which is difficult for many drivers (Lin *et al*., 2017a). Figure 1 shows the steps involved in typical parking-related systems.

Smart parking or parking guidance and information (PGI) includes all services that support the process of accessing available parking spaces in steps 1 and 2. It can guide a vehicle only to the entrance of the parking lot, or can continue to provide guidance to the parking space. Intelligent parking management systems (IPMS) identify the number and locations of available parking slots in parking lots and delivers them to the service provider, and the service provider provides the information to the driver through a web

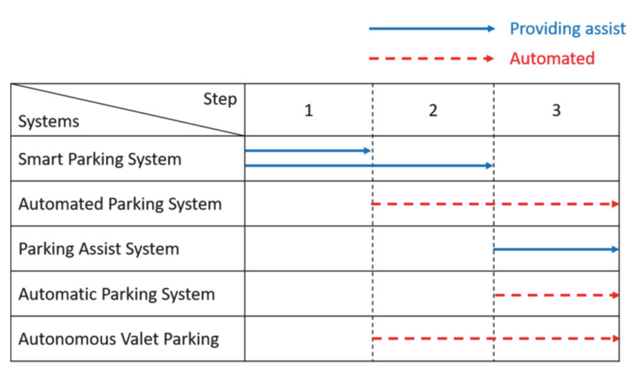

Figure 1. Parking steps involved in typical parking-related systems.

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page or a smartphone app (Kotb *et al*., 2017). Various methods of determining whether a parking slot is occupied or not, and which parking slot should be allocated to maximize the driver's convenience and utilization rate of the parking lot, are mainly studied. They are mainly studied in the field of information and communication technology (ICT). For further details, please refer to the related surveys (Khalid *et al*., 2021; Diaz Ogás *et al*., 2020).

Automated parking systems or robotic parking systems implement steps 2 and 3 as automated facilities. The driver exits the vehicle at the entrance of the parking lot, then the automated parking system keeps the vehicle in a suitable location and returns it later when the driver needs it. This approach is easily understood when considering the Paternoster type, i.e. an automatic circular elevator, that can be easily encountered in everyday life. Multi-story parking garages, where the parking lot is stacked vertically, requires space for vehicles and drivers to move in the parking lot, but automated parking systems can save space because this space can be eliminated (Automated Parking System, 2021). Products in a variety of sizes and shapes are already used in everyday life, ranging from a small scale that can accommodate several vehicles to up to 2,314 vehicles (Largest Automated Parking Facility, 2021). There are various ways to implement this, but since they are the same from the perspective of a driver or a car, they will not be classified in detail in this paper. It is mainly researched in the field of construction and factory automation. For more information, refer to (Robotic Parking Systems, 2021; Parkmatic, 2021; Mechanical Parking Systems, 2021).

Step 3 is applied not only to structured parking lots, but also to daily parking operations, and refers to the process of the driver designating the target parking position and actually parking. A product that helps parking, such as collision warning with an ultrasonic sensor or notifying the distance to an object, is called a parking assist system or a parking aid system, and if autonomous driving technology is applied to this process is called an automatic parking system. Automatic parking systems can simply be thought of as a part of autonomous driving, but there are two reasons to treat it separately: 1) It is possible to implement and sell products automating only the parking process before fully autonomous driving becomes widely used; 2) Automatic parking systems require different sensors and requirements from autonomous driving. For autonomous driving on general roads, environmental awareness of the front side is mainly required, whereas automatic parking system requires recognition of the rear environment. In addition, in the case of perpendicular parking, since it is necessary to enter a narrow space between parked cars without a collision, the requirements for positioning and control precision are higher. This is the field where the automotive industries mainly have an interest. Therefore, this paper focuses on this field.

The application of autonomous driving in both steps 2 and 3 is called autonomous valet parking, and can be thought of as a combination of autonomous driving in a parking lot and an automatic parking system. In this case, autonomous driving in a parking lot is distinguished from autonomous driving on general roads because it requires an IPMS that provides an infrastructure for target parking position designation and indoor positioning (Song, 2013). In other words, autonomous driving in step 2 proceeds to the target parking position on the map provided by IPMS, and positioning must be performed with the help of infrastructures instead of GPS, which is not generally available indoors. Remember that autonomous valet parking also includes an automatic parking system. Khalid *et al.* (2021) distinguished that leaving the vehicle at the entrance of a parking lot is called short term autonomous valet parking, and exiting the vehicle at an arbitrary place in the city is called long-term valet parking. However, this paper thought that long-term valet parking systems driving to parking lot should be classified as autonomous driving. The fact that the driver does not ride is different from the current concept of autonomous driving, but there is no difference in terms of car system configuration and control. And, at the time when long-term valet parking systems are used in daily life, it is expected that the driver's boarding is not important for autonomous driving.

Automatic parking systems consist of target parking position designation, path planning, path tracking, and user interface (Wang *et al*., 2014a; You *et al*., 2012; Jeong *et al*., 2010). Target parking position designation sets the parking position based on the current vehicle position, and path planning creates a path from the current vehicle position to the target parking position (You *et al*., 2012; Panomruttanarug 2017; Du *et al*., 2020). Path tracking controls deceleration and steering to follow the given path, while updating current position using various positioning or localization methods. Deceleration is generally implemented by an electronically controlled braking system including active braking, and steering is implemented by an electronically controlled steering system including active steering. Path planning and path tracking are issues in the control field, and in the field of recognition, the target parking position designation is the main issue, and this paper focuses on this. As a result, this paper aims to provide a survey of target parking position designation of automatic parking systems.

There are four methods of target parking position designation: user interface-based, free space-based, parking slot marking-based, and IPMS-based. User interface-based is a method for the driver to set the target parking position using a touch screen, etc. Although it is not automatic, it is important because of its practicality and provides a backup means for automatic alternatives. Free space-based assumes that a vehicle or pillar exists both on the left and right side of a free parking space, and recognizes the free space using various sensors such as ultrasonic and LIDAR. Parking slot marking-based is a method recognizing parking slot markings in a camera image, and can be used regardless of

Figure 2. Dependency problem on surrounding vehicles of free space-based.

the presence or absence of surrounding vehicles. IPMS-based is a method receiving a target parking position from an IPMS. Since the target parking position is given by coordinates in the parking lot, it can be used only if precise maps and precise positioning in the parking lot are available. In the case of indoor parking lots, since satellite navigation cannot be used, it is essential to provide infrastructures that support precise positioning. If the IPMS guides the free parking space in step 2, the free parking space can be naturally set as the target parking position. Since the automatic parking system is mainly used in parking lots in the city center and is not influenced by the existence or alignment of surrounding vehicles, parking slot marking-based is widely used. For the time being, parking slot marking-based is expected to be mainly used, but in future when autonomous valet parking is mainly used, the method of receiving parking slot coordinates from an IPMS is expected to become common.

This paper summarizes the results of research conducted to date on target parking position designation, and presents challenges and overall prospects for each of the various approaches. Section 2 categorizes the target parking position designation into four major categories, and explains the advantages and disadvantages of each. The two methods that had the most variety in previous studies because they were expected to be applicable in the near future will be reviewed in detail in Sections 3 and 4, respectively. Section 3 describes different approaches to free space-based and Section 4 describes the recognition of parking slot markings with and without deep learning techniques. Particularly, in Section 4, public datasets for parking slot marking recognition are described and the performances of the main methods are compared. Section 5 summarizes the research trends up to now and suggests future research directions.

2. TARGET PARKING POSITION DESIGNATION

Since the disadvantages of each method can be supplemented by fusion of various sensors and methods, there is a high possibility of adopting a sensor fusion-based method rather than a method using only one method in the field. However, as these configurations are so diverse that it is difficult to organize them enough to understand the overall flow and performance largely depends on the centrally used method, this paper divides previous works into four categories based on the central method.

2.1. User Interface-based

This category includes methods in which the driver recognizes the target parking position and inputs it into the system using the user interface. Alternatively, it is used to correct the automatically recognized target parking position (Griffin, 2021). Manual input like this was applied to the first mass production because it is lighter and easier to implement than automatic methods, and will continue to be used as a backup or correction means considering that automatic methods cannot be perfect. The method applied to the Toyota Prius (Griffin, 2021) shows a number of buttons along with the potential target parking position recognized by the ultrasonic sensor on the rear view monitoring screen. The user can translate or rotate the target parking position by clicking a button. Jung *et al*. (2006a) proposed a drag-and-drop operation to reduce the number of user operations. Dragging the inside of the target parking position can translate it, and dragging the outside can rotate it.

2.2. Free Space-based

Free space-based includes methods designating the target parking position by recognizing vehicles or pillars on both sides of a free parking space. Among the automatic target parking position designation methods, the ultrasonic sensor-based method first applied to mass production also belongs to this. Most of the automatic parking systems mass-produced by automakers are based on ultrasonic sensors (Satonaka *et al*., 2006; Degerman *et al*., 2006; Park *et al*., 2008; Jeong *et al*., 2010). Various methods of detecting parked vehicles and estimating their pose have been tried. They can be again divided into active sensor-based method emitting signals and passive sensor-based method only receiving signals. Active sensors include ultrasonic sensor, LIDAR (Jung *et al*., 2008; Zhou *et al*., 2012), radar (Görner and Rohling, 2006; Schmid *et al*., 2011; Dubé *et al*., 2014), photonic mixer device (Scheunert *et al*., 2007), and structured lighting (Jung *et al*., 2007; Jung *et al*., 2010a). Passive sensor-based is mainly based on cameras such as monocular image understanding-based (Hashizume *et al*., 2005), binocular stereo-based (Kaempchen *et al*., 2002; Jung *et al*., 2006b), and motion stereo-based (Vestri *et al*., 2005a; Suhr *et al*., 2010; Unger *et al*., 2014). LIDAR-based methods are simple to implement and exhibit remarkably high performance (Jung *et al*., 2008; Zhou *et al*., 2012). However, its disadvantage is that sensors are expensive and the durability of the current mechanical steering is weak. Each of these methods of using various sensors has its own strengths and weaknesses, which are described in detail in Section 3.

The free space-based method has a limitation in that it strongly depends on the pose of the surrounding vehicles. If

Table 1. Comparison of advantages and disadvantages between various approaches.

	Advantages	Disadvantages	Representative references
User interface-based	Light, easy to implement	Requiring manual operation	Griffin, 2021; Jung, 2006a
Free space-based	Collision warning with surrounding vehicles can be integrated	Dependency on the presence and pose of surrounding vehicles	Jeong *et al*., 2010; Unger *et al*., 2014; Zhou *et al*., 2012
Parking slot marking-based	No dependence on surrounding vehicles. Relatively light and easy to implement with a monocular camera.	Requiring additional collision warning methods.	Suhr and Jung, 2013; Suhr and Jung, 2018; Do and Choi, 2020; Suhr and Jung, 2021
IPMS-based	Minimum requirement of environment recognition sensor. Native integration with parking space reservation.	The standardization of indoor positioning is a prerequisite.	An *et al*., 2011; Sung *et al*., 2011; Schwesinger *et al*., 2016

the surrounding vehicles are parked at an angle as shown in Figure 2 (a) the target parking position cannot be properly aligned with the parking slot. Also, if there are no obstacles on one side of the target parking slot as shown in Figure 2 (b), the target parking position cannot be properly positioned in the parking slot because the free parking space and the target parking position do not match. When recognizing the position and pose of surrounding vehicles for the automatic parking system, higher precision than the forward recognition for autonomous driving is required. Since these higher requirements increase the difficulty and the price of the system, the methods recognizing the parking slot markings, which is a relatively limited in the shape and installation variation, is receiving more attention.

2.3. Parking Slot Marking-based

Various methods have been developed to designate the target parking position by recognizing the parking slot markings in the rear camera image or AVM image. Since automatic parking systems are mainly used in urban areas, it is very unlikely that they will be used in parking lots without parking slot markings. Therefore, this approach insists that the recognition of the parking slot markings is sufficient for designating the target parking position. The parking slot marking is installed so that it can be seen relatively clearly in consideration of the driver's visibility, and its shape is also limited according to the standard, so its detection is easy. In addition, when a target parking position is designated based on parking slot markings, it can be accurately set even if there are no vehicles or pillars around it. It is also easy to implement in an embedded system because it can be implemented lightly compared to free space-based such as methods detecting parked vehicles in a monocular image. The methods detecting the free space between surrounding vehicles in a monocular image and the parking slot marking-based have a common point that a monocular image is used, but the targets of recognition are different, so they are classified into separate categories.

The methods recognizing parking slot markings can be divided into traditional methods using prior knowledge about the shapes of parking slots and emerging methods using deep learning, which has been developed recently. Although methods using deep learning show superior performance compared to traditional methods, there is a limitation in mass production application because they require dedicated hardware such as a GPU. This paper predicts that parking slot marking-based is more important than free space-based because automatic parking system is mainly used in urban areas. The fact that recent papers focus on parking slot marking-based rather than free space-based adds weight to this prediction. In particular, since traditional methods are required for application in the near future and deep learning-based methods are required assuming an embedded implementation of deep learning, this paper will examine each of them in detail in Section 4.

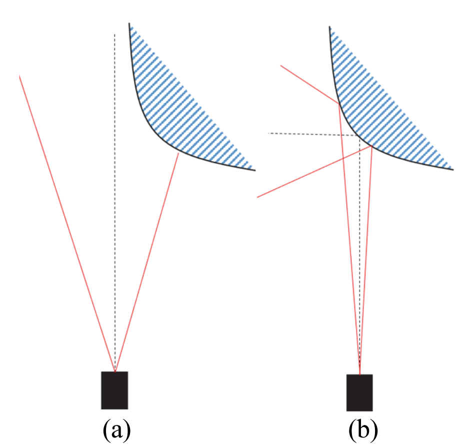


Figure 3. Limitation of ultrasonic sensor.

2.4. IPMS-based

IPMS-based is mainly used in PGI or autonomous valet parking in parking lots. IPMS allocates a specific parking space to a user, and this action is corresponding to the designating a target parking position in an automatic parking system (Wada *et al*., 2003; Wada *et al*., 2004). Suzuki *et al*. (2005) proposed a system that offers a bird's-eye view image of a parking situation including parking slot markings and adjacent vehicles using surveillance cameras. Wada *et al*. (2003, 2004) presented a system that assigns a target parking position to a vehicle entering a parking lot and provides rough guidance to the vicinity of the target parking position and fine guidance to the target parking position. An *et al*. (2011) and Sung *et al*. (2011) suggested an automatic valet parking system that conducts fully automatic parking after drivers exit their vehicle at the entrance of a building by utilizing both infrastructure and in-vehicle sensors. An automatic valet parking system has also been researched as an EU project entitled V-Charge (Schwesinger *et al*., 2016).

Since the target parking position can be interpreted on the map of the parking lot, it is expressed in the relative coordinate system within the parking lot rather than the global coordinate system. The automatic parking system can utilize a precision global navigation satellite system (GNSS) for outdoor parking and separate positioning facilities for indoor parking. However, since precision GNSS equipment is expensive, it is possible to use a separate positioning facility even in an outdoor parking lot. At this time, it should be noted that the specifications required for positioning precision are different when approaching the parking slot and during the actual parking process. In other words, in order to implement the automatic parking system, the positioning system used in PGI that only provides guidance is insufficient. If IPMS-based becomes popular, indoor positioning devices will be standardized (as Wi-Fi did), eliminating the need to install additional devices every time all vehicles enter the parking lot.

Various methods have been developed for indoor positioning (Hameed and Ahmed, 2018; Pérez-Navarro *et al*., 2019), and each approach has its advantages and disadvantages. The accuracy of the method using WLAN (Wi-Fi), infrared, Bluetooth, Zigbee, and RFID, etc., is several meters. Considering that the accuracy of ultrasonic wave and ultra-wide band (UWB) is several tens of cm, it can be said that for automatic parking systems ultrasonic wave and UWB are the most likely as of now. Marvelmind robotics (Indoor GPS, 2021) based on ultrasonic wave and VIPS (VBOX Indoor Positioning System, 2021) based on UWB provide 2cm precision. UWB is better in terms of operating range and robustness to the environment (Pozyx, 2021; Anderson, 2021), and ultrasonic wave is superior in terms of cost and manageability. Each method seems to be still competing to achieve low cost and standardization while making up for their weaknesses. The IPMS-based method has the advantage of integrating the reservation of free parking spaces and excluding the effects of recognition sensor errors, but standardization of indoor positioning is a prerequisite.

3. FREE SPACE-BASED

Free space-based has been steadily studied since the beginning of automatic parking system development. Depending on the sensor used, it can be classified into active sensor-based and passive sensor-based. Active sensor detects the environment by emitting a signal, and includes ultrasound, LIDAR, radar, and structured lighting. The passive sensor detects the environment by simply receiving

Table 2. Comparison between free space-based methods.

		Main challenges	Representative references
Active sensor-based	Ultrasonic	Low positioning precision and resolution	Jeong *et al*., 2010
	LIDAR	Expensive sensor	Zhou *et al*., 2012; Lee and Wei, 2017
	Radar	Low angular precision and resolution	Daimler, 2021; Görner and Rohling, 2006
	Light stripe projection	Inapplicable during daytime outdoors	Jung *et al*., 2007; Ma *et al*., 2020
Passive sensor-based	Monocular vision	Vulnerable in dark lighting conditions, a lot of computation	Hashizume *et al*., 2005
	Binocular stereo	Vulnerable in dark lighting conditions, a lot of computation	Kaempchen *et al*., 2002; Jung *et al*., 2006b
	Motion stereo	Vulnerable in dark lighting conditions, a lot of computation	Vestri *et al*., 2005a; Suhr *et al*., 2010; Unger *et al*., 2014

the signal from the target, and the camera-based method belongs to this. Depending on the number and temporal use of cameras, it can be classified into monocular camera-based, binocular stereo-based, and motion stereo-based. The structured lighting method uses a monocular image, but it is classified as an active sensor because it uses a laser projector. At this time, even if an image is used, the recognition of the parking slot marking does not directly detect the free space, so it is classified as a separate category. Overall, all environmental sensors used in the automotive field were reviewed, and more precise requirements were added in addition to the problems encountered in the front environmental recognition problem. However, the driving speed of the vehicle is not high compared to that of the front environment perception, so the requirement for the reaction speed is slightly low.

3.1. Active Sensor-based

3.1.1. Ultrasonic sensor-based method

It is the most common target parking position designation method for parallel parking. The system collects range data as the vehicle passes by a free parking space and then registers the range data using odometry to construct a depth map of side region of the subjective vehicle. To precisely measure the edges of the free parking space, Siemens developed a new sensor with a modified sensing area, that is, horizontally narrow and vertically wide (Heilenkötter *et al*., 2007). Linköping University and Toyota both utilized the correlation between multiple range data sets, using multilateration (Pohl *et al*., 2006; Degerman *et al*., 2006) and rotational correction (Satonaka *et al*., 2006), respectively. Suhr and Jung (2018a) proposed a method to reduce false detection using AVM images.

However, fundamentally, there is a limit to the resolution of the ultrasonic sensor. If the field of view (FOV) is large as shown in Figure 3 (a), the surrounding obstacles are erroneously detected as located in the front. If the FOV is small as shown in Figure 3 (b), the curved part is not detected. Since the ultrasonic sensors applied in mass production use a somewhat wide FOV to avoid missing, false detections occur frequently. It is reported that the ultrasonic sensor in parallel parking situations acquires practically useful range data because the incident angle between the sensor and the side-facet of the objective vehicle is approximately perpendicular. However, in garage parking situations, as the incident angle between the ultrasonic sensor and the side-facets of adjacent vehicles is far from perpendicular, range recognition usually fails (Degerman *et al*., 2007). Consequently, garage parking requirements are tighter (Heimberger *et al*., 2017).

3.1.2. LIDAR-based method

Schanz *et al*. (2003) installed the scanning LIDAR vertically on the side of the subjective vehicle, and the radar then collected range data while passing by free parking spaces. They proposed a system that constructed a depth map by registering range data with odometry and then recognized a free parking space. In this case, the scanning LIDAR was used as a precise ultrasonic sensor with narrow FOV (Schanz *et al*., 2003; Schanz, 2005; Regensburger *et al*., 2007). The CyCab project installed the scanning LIDAR horizontally on the front-end of the subjective vehicle, and the LIDAR recognized the positions of parked vehicles. They utilized the vehicle positions for path planning and simultaneous localization and mapping (SLAM) (Keat *et al*., 2005). Jung *et al*. (2010b) proposed a novel driver assist system called an integrated side/rear safety system (ISRSS), which installed one scanning LIDAR horizontally on the left side of the subjective vehicle's rear-end to incorporate four system functions: blind spot detection (BSD), rear collision warning system (RCWS), target position designation for parallel parking, and target position designation for perpendicular parking. When using the latest multi-layer scanning LIDAR, free parking spaces can be easily recognized. Lee and Wei (2017) left only points within a predetermined height range from the point cloud acquired by HDL-32E (HDL-32E, 2021), and detected vehicles by clustering. Then, it recognized the position of the parked vehicle with the minimum bounding box.

With the introduction of deep learning to point cloud processing in addition to multi-layer LIDAR, the performance of vehicle detection and pose estimation is dramatically improved (Arnold *et al*., 2019). Complex-YOLO applied YOLO to detect objects in a 3D point cloud by projecting it into 2D space (Simon *et al*., 2019). Li (2017) and Engelcke *et al*. (2017) proposed a method of detecting objects by applying 3D convolution to the 3D space including a point cloud. PointNet paper series (Charles *et al*., 2017; Qi *et al*., 2017; Zhou and Tuzel, 2018) proposed methods that can directly process point clouds without mapping them into a 3D space. Various methods using both point cloud and camera images are also being developed (Feng *et al*., 2021). Although these approaches show excellent performance, we have never seen any examples used for automatic parking systems. This seems to be due to the fact that deep learning-based methods require a large amount of computation and are still limited in embedded implementation, and expensive multi-layer LIDARs are not installed in the rear of mass-production vehicles.

3.1.3. Radar-based method

As short range radar (SRR) is widely used for BSD (Valeo, 2021), there have been studies trying to use it for parking collision warning (Ford, 2021) or target parking position designation. For parallel parking, the SRR sensor was tested instead of the ultrasonic sensor (Daimler, 2021). A method improving angular accuracy with synthetic aperture radar (SAR) algorithm was proposed (Görner and Rohling, 2006). Although SRR is expected to robustly detect the existence of vehicles, it is not applicable for detecting vehicle boundaries on the near side of the subjective vehicle. In general, SRR has low angular accuracy and outputs only a limited number of range data. Furthermore, the outputs are not deterministic because response strengths are considerably sensitive to the object's shape, orientation, and reflectance (Görner and Rohling, 2006). Recently, 4D radar or imaging radar is also being developed (Marenko, 2021; Radar, 2021; Benjamin, 2021), but it seems that the vehicle pose estimation performance is insufficient for designating the target parking position (Roos *et al*., 2016). Therefore, it is judged that the possibility that radar will be used to designate the target parking position is not high.

3.1.4. Light stripe projection-based method

Jung *et al.* (2007, 2010a) projects the light plane to the rear using a 1D laser projector installed on the rear bumper. The boundary information of the parked vehicle is acquired by capturing the light stripe created by this light plane encountering an obstacle such as a parked vehicle with a rear camera. It was proposed as a solution for dark underground parking lots where passive vision-based methods usually failed. Ma *et al.* (2020) projects the grid pattern laterally using a checkboard grid laser installed on the side, and captures the light stripe created by meeting objects with a side camera. The boundary of the obstacle is recognized by using the fact that the pattern on the obstacle, such as a parked vehicle, is discontinuous from the pattern on the flat ground surface.

In order to compensate for the inability to properly recognize obstacles in dark underground locations when using a passive camera, this method, paradoxically, has the disadvantage that it cannot be used outdoors in daytime (Jung *et al*., 2007; Jung *et al*., 2010a). Five methods are usually used to overcome this problem: 1) increase of projector power, 2) using wavelength where the ambient light is low, 3) narrow band filter, 4) pulsed light source and fast shutter, 5) background subtraction (Mertz *et al*., 2012; Gupta *et al*., 2013). However, there is the problem that a visible light image cannot be obtained with a rear camera, and additional hardware is required.

3.2. Passive Sensor-based

3.2.1. Single-image understanding-based method

Hashizume *et al.* (2005) implemented horizontal edge-based vehicle position detection after pattern recognition-based free space detection. With the recent development of deep learning-based vehicle detection and pose estimation, it is expected that a free parking space can be recognized by accurately detecting the poses of vehicles on both sides of the free parking space. Deep MANTA (Chabot *et al*., 2017), after detecting vehicles, estimates the positions of vehicle parts by regression using the fact that the vehicle is a rigid object. After that, 3D information is restored through visibility characterization and optimal 3D template matching. The 3D voxel pattern (3DVP) (Xiang *et al*., 2015) restores the 3D information of a vehicle by selecting the most suitable one of 3D voxel exemplars, which are obtained by projecting the 3D CAD model of a vehicle onto its image and manually inputting segmentation in the projected image domain. Xiang *et al.* (2017) proposed a method for detecting vehicles with Fast R-CNN and estimating their poses with 3DVP. However, as the existing vehicle pose estimators are applied to vehicles ahead or parked vehicles met while driving forward, it is not known whether they can satisfy the precision requirement for target parking position designation. Therefore, it is necessary to improve precision to satisfy that of the target parking position designation and to increase the execution speed for the embedded implementation. Additionally, since free parking spaces do not exist only between vehicles but also between a vehicle and pillar, additional development is required to restore 3D information of various interior structures such as pillars and walls.

3.2.2. Binocular stereo vision-based method

This method acquires 3D information by installing two cameras to the rear of the vehicle and estimating disparity from the captured image pair. The system of Kaempchen *et al*. (2002) reconstructs 3D information by using feature-based stereo matching and iterative closest point (ICP) algorithm with respect to vehicle model. It then designates the target parking position between the recognized vehicles. The system of Jung *et al*. (2006b) separates the feature-based stereo matching results into ground points and obstacle points according to the pre-calibrated homography of the ground surface, and searches for the optimal target position closest to the parking slot markings and farthest from obstacles. This method relies heavily on stereo matching

Table 3. Taxonomy of non-deep learning-based parking slot detection methods.

	Line-based	Corner-based
Semi-automatic	Jung *et al*., 2006c; Jung *et al*., 2014	Jung *et al*., 2006c; Jung *et al*., 2014
Full-automatic	Xu *et al*, 2000; Jung *et al*., 2006d; Tanaka *et al*., 2006; Houben *et al*., 2013; Wang *et al*., 2014b; Du and Tan, 2014; Hamada *et al*., 2015; Suhr *et al*., 2016; Lee and Seo, 2016; Lee *et al*., 2016; Chen and Hsu, 2017; Zong and Chen, 2018; Suhr and Jung, 2018b; Kim *et al*., 2020	Xu *et al*, 2000; Jung *et al*., 2006d; Tanaka *et al*., 2006; Houben *et al*., 2013; Wang *et al*., 2014b; Du and Tan, 2014; Hamada *et al*., 2015; Suhr *et al*., 2016; Lee and Seo, 2016; Lee *et al*., 2016; Chen and Hsu, 2017; Zong and Chen, 2018; Suhr and Jung, 2018b; Kim *et al*., 2020

performance and requires a lot of computation for precise results. In particular, there are no mass-produced cars equipped with stereo cameras in the rear for parking. It is not yet known whether a binocular stereo camera, which is relatively expensive compared to a monocular camera, can be mounted at the rear.

With the recent introduction of deep learning, stereo matching performance has improved dramatically (Laga *et al*., 2021; Hamid *et al*., 2020), and monocular depth estimation (MDE), which restores depth information using only monocular images, has also greatly improved (Zhao *et al*., 2020; Khan *et al*., 2020). However, all of them were tested in relatively bright lighting conditions. Generally, the performance of passive vision remarkably degrades in poor lighting conditions such as at night. It is difficult to overcome because it is an inherent limitation of passive vision sensors. In addition, vehicle surfaces are often reflective and the color is often black, which is a difficult feature to apply stereo matching.

3.2.3. Motion stereo-based method

This method restores 3D information using consecutive images captured while the subjective vehicle is moving. It is similar to binocular stereo in that it uses images taken from two viewpoints, but different in that the viewpoints are temporally different. In binocular stereo, the baseline, which is the distance between two cameras, is known in advance. But in motion stereo, translation and rotation are estimated using corresponding points between two images, and the physical distance uses odometry sensors. IMRA Europe developed a system that provides a driver with a virtual image from the optimal viewpoint by intermediate view reconstruction (IVR). This system reconstructs 3D information via odometry and using features tracked through consecutive images captured while the subjective vehicle is moving (Fintzel *et al*., 2003; Fintzel *et al*., 2004; Vestri *et al*., 2005a; Vestri *et al*., 2005b). Suhr *et al*. proposed a system that could recognize 3D information from consecutive images even without the help of odometry and then designates the target parking position (Suhr *et al*., 2010).

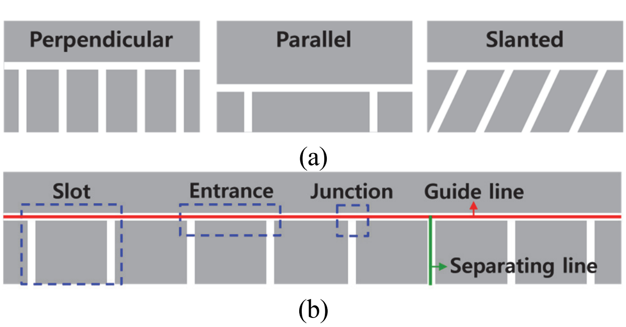


Figure 4. (a) Three representative parking slot types; (b) Terminologies used in parking slot detection.

Motion stereo has a wide baseline between two images, so it is difficult to reconstruct 3D information using only stereo matching between two images. To solve this problem, tracking feature points through consecutive images is applied. However, this approach requires a large amount of computation because feature points must be extracted and tracked for every input image. In addition, motion stereo, like other passive vision sensors, has a weakness that is very sensitive to lighting conditions.

As a result, free space-based is expensive compared to the parking slot marking-based method, which can be implemented relatively inexpensively with only a monocular camera. It requires expensive sensors such as scanning LIDAR, or requires an expensive GPU as in deep learning-based vehicle pose estimation. Of course, the method of fusing the ultrasonic or radar, already installed in mass-produced vehicles, and the recognition of the parking slot marking can improve the precision (Heimberger *et al*., 2017).

4. PARKING SLOT MARKING-BASED

The parking slot marking-based approach recognizes vacant parking spaces using markings on road surfaces. Its performance is independent of the positions and existence of parked vehicles. However, this approach can only work correctly when parking slot markings are presented. All methods in this approach utilize cameras to capture markings on the ground. Figures 4 (a) and (b) show three representative parking slot types and terminologies used for parking slot marking recognition, respectively. The parking slot marking-based methods can be categorized into non-deep learning-based and deep learning-based.

4.1. Non-deep Learning-based

In terms of automation, non-deep learning-based methods can be categorized into semi-automatic and full-automatic. Also, in terms of features, they can be categorized into line-based and corner-based. Table 3 shows the taxonomy of the non-deep learning-based methods in terms of automation and features. Jung *et al*. recognize parking slot markings in a semi-automatic manner (Jung *et al*., 2006c, 2009; Jung, 2014). Jung *et al*. (2006c) detect parking slot markings using a single location designated by a driver. This method analyzes lines around the manually designated location to detect parking slots. They proposed an efficient version of this method (Jung, 2014). Because this method has a limitation of detecting only one type of parking slot marking, Jung *et al*. (2009) suggested a method that can detect various types of parking slots by recognizing positions of junctions around two locations designated by a driver.

Methods that recognize parking slot markings in a full-automatic manner have also been proposed. Xu *et al*. (2000) find two perpendicular lines using a neural network-based color segmentation to recognize parking slot markings. Jung *et al*. (2006d) recognize parking slot markings by detecting parallel line pairs based on Hough transform with a specialized filter. Wang *et al*. (2014b) also suggested a similar method that uses parallel line pairs detected by Radon transform. Tanaka *et al*. (2006) use an improved random sample consensus (RANSAC) algorithm to detect straight lines and recognize parking slot markings by combining the detected lines. Houben *et al*. (2013) find parking slots by detecting vertically oriented lines and classify their occupancies based on a difference-of-Gaussians-based histogram. Du and Tan (2014) detect boundaries of parking slots using a sequential RANSAC line estimator and binarized ridge images. Hamada *et al*. (2015) use a probabilistic Hough transform to find parallel line pairs and lines perpendicular to them and combines those lines to detect parking slots. Chen and Hsu (2017) recognize parking slot markings by finding guide and separating lines using a FAST corner detection result. They classify occupancies of the detected parking slots based on a region growing algorithm and naïve Bayes classifier. Suhr and Jung (2016) utilize guide and separating lines found by RANSAC and distance transform in order to detect parking slots in indoor and underground parking lots reliably. Zhang *et al*. (2018) find parking slots by combining junctions, which are detected by adaptive boosting with integral channel features.

Since all the above methods can handle only one or two types of parking slot markings, methods that can deal with more types have been proposed. Suhr and Jung (2013) analyzed various parking slot makings using a hierarchical tree structure and detect parking slots from rearview camera images using the suggested structure. They extended this method to AVM images (Suhr and Jung, 2012) and fused them with ultrasonic and in-vehicle motion sensors for occupancy classification and parking slot tracking (Suhr and Jung, 2014). Lee and Seo (2016) recognize various types of parking slot markings in rearview camera images by clustering a con-hat filtering result and lines found by RANSAC. They also extended this method to AVM images (Lee *et al*., 2016). Zong and Chen (2018) find L-shapes using line segments and combine them to recognize various types of parking slot markings. They classify occupancies of the detected parking slots using ultrasonic sensors and track them by Kalman filter. Suhr and Jung (2018b) detect and track separating lines and pair them to reliably recognize various types of parking slot markings in daytime, nighttime, and indoor situations. They classify occupancies of parking slots using ultrasonic sensors and recognize entrances of parking slots by detecting lines and corners. Kim *et al*. (2020) detect parking slots in various types by generating and combining free junction type features. They classify occupancies of parking slots based on a color histogram and support vector machine (SVM).

4.2. Deep Learning-based

In recent years, deep learning-based object detection has been extensively researched because of their outstanding performance for various target objects (Liu *et al*., 2020). Deep learning-based object detection methods are mainly categorized into two-stage and one-stage approaches. The two-stage approach generates category-independent region proposals in the first stage, and predicts locations, sizes, and classes of objects in the second stage. Faster region-based convolutional neural network (faster R-CNN) (Ren *et al*., 2016), region-based fully convolutional network (R-FCN) (Dai *et al*., 2016), and mask R-CNN (He *et al*., 2017) are representative methods. This approach gives a high detection performance, but its detection speed is slow. The one-stage approach has been proposed to overcome the speed limitation of the two-stage approach. This approach directly predicts locations, sizes, and classes of objects without generating region proposals. Single slot multibox detector (SSD) (Liu *et al*., 2016), You only look once (YOLO) (Redmon *et al*., 2016), and RetinaNet (Lin *et al*., 2017b) are representative methods. This approach shows a fast detection speed, but its detection performance is relatively lower than that of the two-stage approach. Unfortunately, the aforementioned methods cannot be directly applied to the parking slot detection due to the following reasons: First, they detect objects only as upright rectangles, which is inappropriate because parking slots are captured in a variety of direction. Second, they roughly predict sizes and locations of objects rather than providing precise positions. Positions provided by the above detection methods are suitable for some applications but are not accurate enough to be used for parking slot detection because the predicted positions are used to control vehicles in automatic parking systems.

Table 4. Taxonomy of deep learning-based parking slot recognition methods.

	One-stage	Multi-stage
DNN with geometric rules (Not end-to-end trainable)	-	Zhang *et al*., 2018; Huang *et al*., 2019; Jang and Sunwoo, 2019; Yu *et al*., 2020; Li *et al*., 2020a; Jang *et al*., 2020; Jiang *et al*., 2020
Only DNN (End-to-end trainable)	Li *et al*., 2020b; Suhr and Jung, 2021	Zinelli *et al*., 2019; Jong *et al*., 2019; Do and Choi, 2020; Min *et al*., 2021

Parking slot detection methods that utilize deep learning have also been suggested. Those methods can be categorized into the following two approaches: One uses both deep learning and traditional rule-based techniques, and the other uses only the deep learning technique. Table 4 shows the taxonomy of the deep learning-based parking slot detection methods. The methods that utilize both deep learning and rule-based techniques consist of multiple stages because they first extract features using CNN, and then use geometric rules to combine or discard the extracted features. Since these methods utilize manually designed geometric rules, they cannot be trained end-to-end and require inconvenient process to design those rules and their associated parameters. Zhang *et al*. (2018) detects junctions using YOLOv2 and combines them using geometric rules to generate parking slot candidates. This method uses a CNN-based classifier to verify the generated candidates and estimates their orientations based on a template matching technique. Huang *et al*. (2019) suggests a similar method that detects junctions with orientations using a customized CNN and finds parking slots by combining the detected junctions using geometric rules. This method has a limitation of detecting only perpendicular and parallel parking slots. Yu *et al*. (2020) extracts corner and line features using a CNN. This method combines corner features using geometric rules and selects line features based on the combination result of the corner features. The combined corner features and selected line features are integrated to detect parking slots. This paper mainly focuses on the DNN acceleration and does not provide a detailed procedure for parking slot detection. Li *et al*. (2020a) detects entrances and junctions of parking slots using YOLOv3. This method determines final parking slots by considering relations of the detected entrances and junctions using geometric rules and handcrafted features. Occupancies of the parking slots are classified by applying a CNN to cropped areas of parking slots. This method cannot deal with cases where the ego-vehicle is placed inside a parking slot and its orientation estimation is inaccurate when handing slanted parking slots. Jang and Sunwoo (2019) and Jang *et al*. (2020) first classify each pixel of AVM image using CNN-based semantic segmentation into four types: marking, car, wall, and road. They use geometric rules to detect parking slots and classify their occupancies. Jiang *et al*. (2020) detects and segments junctions using mask R-CNN. This method finds lines based on the segmentation results of junctions and detects parking slots by combining junctions using geometric rules.

The methods that utilize only the deep learning technique can be trained end-to-end and categorized into two approaches: multi-stage and one-stage. Zinelli *et al*. (2019) applies an anchor free faster R-CNN (Zhong *et al*., 2019) to the parking slot detection. Its first stage roughly predicts locations of the parking slot's four corners as a region proposal, and the second stage refines those locations while classifying the parking slot's occupancy. Even though this method is the first proposed end-to-end trainable method, it has limitations of positioning accuracy and detection performance because the general object detection method is adapted without being specialized for the parking slot detection. Do and Choi (2020) uses a two-stage approach specialized for parking slot detection. This method predicts the parking slot's availability, type, and orientation using MobileNetV2 in the first stage and estimates the precise

Table 5. Comparison of two public datasets.

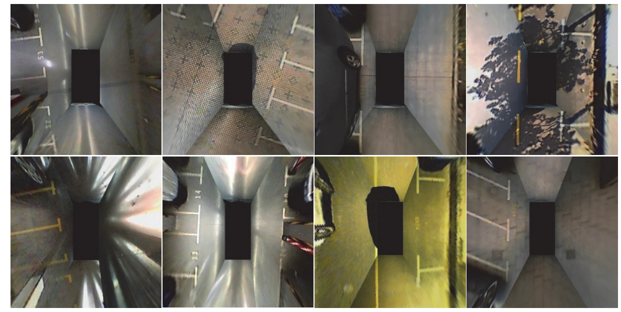
	Dataset in PS2.0 (Zhang *et al*., 2018)	Dataset in (Do and Choi, 2020)
Camera	AVM images with four cameras	Bird's-eye-view images with two cameras
Resolution	600×600 pixels (10×10 meters)	768×256 pixels (14.4×4.8 meters)
Environment	Indoor, outdoor, daytime, nighttime	Indoor, outdoor, daytime, nighttime
Slot type	Perpendicular, parallel, slanted	Perpendicular, parallel, slanted
Labels	Location and orientation	Location, orientation, type, and availability
# Of situations	166	571
# Of images	9827 (training) / 2338 (test)	18299 (training) / 4518 (test)
Pros	Full AVM images are provided. Many methods have been evaluated.	Relatively diverging and challenging cases are included.
Cons	Many methods already showed very high performances.	Only half AVM images are provided. Few methods have been evaluated.

position of the parking slot using Darknet53 in the second stage. It is end-to-end trainable, but requires a relatively high computational cost due to the use of two different backbone networks. Min *et al*. (2021) proposes a three-stage parking slot detector. The first stage detects junction locations and extracts junction features using a CNN. The second stage uses an attentional graph neural network to aggregate junctions based on the result of the first stage. The final stage determines if the aggregated junctions form an entrance of parking slots using a multilayer perceptron. This method is end-to-end trainable and needs no manually designed post-processing, but cannot handle slanted slots because angles of the parking slots are not estimated. The above three methods in the multi-stage approach are relatively slow in terms of the inference time compared with those in the one-stage approach. Li *et al*. (2020b) detects parking slots using a one-stage approach. This method applies convolutions to a feature map extracted by a customized CNN to find parking slots by predicting the entrance, orientation, and size of the parking slot. It requires relatively less computation cost, but has a limitation of positioning accuracy in terms of location and orientation. Suhr and Jung (2022) detects parking slots by combining global and local information based on the one-stage approach. This method extracts rough location, type, and occupancy of the parking slot as the global information along with precise location and orientation of two junctions as the local information. It applies convolutions to a feature map obtained by VGG16 to extract the global and local information simultaneously and combines them to detect parking slots. This method shows high performance in terms of both parking slot detection and position estimation.

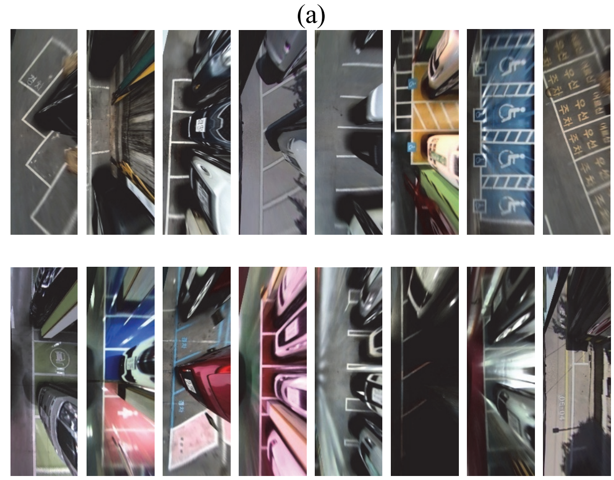
4.3. Public Datasets

Deep learning-based object detection methods usually require a vast amount of data to train the numerous weights included in networks. Accordingly, many datasets that include various objects have been publicly released (Lin *et al*., 2014). Since the public dataset reduces the effort of researchers to receive and label data on their own, it serves to promote research in the relevant field and provides a basis for fair and convenient comparison of various methods. The dataset for general object detection is relatively easy to build because it can be collected using the internet or conventional cameras. However, since the dataset for parking slot detection is relatively difficult to build, there are a small number of publicly available datasets. This dataset is generally acquired from the AVM system, which requires a process of removing radial and perspective distortions from multiple images acquired by two to four fisheye cameras mounted on an actual vehicle. Besides, this dataset must be acquired while driving a vehicle by visiting various places in a variety of weather and lighting conditions. To overcome this limitation, Chen *et al*. (2020) proposed a method of generating photo-realistic virtual AVM images for parking slot detection. They showed that parking slot detectors can effectively be trained by combining virtual and real AVM images.

Two public datasets for parking slot detection in AVM images have been released. The first dataset is Tongji Parking-slot Dataset 2.0 (PS2.0) (Zhang *et al*., 2018). This dataset was released in 2018 by Tongji University by augmenting PS1.0 released in 2017 (Li *et al*., 2017). It is composed of images acquired by the AVM system installed in a small electric vehicle. The AVM images were generated by stitching together four bird's-eye view images acquired from four fisheye cameras. The spatial resolution of each AVM image is 600 × 600 pixels that correspond to 10 × 10 meters. This dataset includes perpendicular, parallel, and slanted parking slots taken indoors and outdoors in daytime and nighttime. Its labels contain locations and orientations of parking slots but not their types and availabilities. 9827 training images and 2338 test images taken in 166 parking situations are included. This dataset is composed of full AVM images, which are most widely used for parking slot detection, and there are a number of previous methods already evaluated with it. However, it has a limitation of showing the difference in performance because most of the previous methods showed very high detection performances due to the similarity between the training and test images.



(a)



(b)

Figure 5. (a) Sample images of the dataset in PS2.0 (Zhang *et al*., 2018); (b) Sample images of the dataset in (Do and Choi, 2020).

The second dataset was released by Seoul National University and LG Electronics (Do and Choi, 2020). This dataset was acquired from two fisheye cameras mounted on both side-view mirrors of two sedans and one sports utility vehicle (SUV). It provides half AVM images produced by converting raw images into bird's-eye view images. The spatial resolution of each half AVM image is 256 × 768 pixels that correspond to 4.8 × 14.4 meters. This dataset includes perpendicular, parallel, and slanted parking slots taken indoors and outdoors in daytime and nighttime. Its labels contain locations, orientations, types, and availabilities. 18299 training images and 4518 test images taken in 571 parking situations are included. This dataset is useful for evaluating practical performance because the parking situations included in the test and training datasets do not overlap. However, it has limitations of providing only half AVM images and there are few previous methods evaluated with it. Table 5 and Figure 5 show the comparison of the two public datasets and sample images included in them, respectively. Table 6 shows the performances of eight deep learning-based parking slot detection methods in the PS2.0 dataset. This table also includes GPUs, frameworks, and criteria to determine true positives and false positives. In

Table 6. Performance comparison of previous deep learning-based methods using PS2.0.

Method	Criteria	Recall	Precision	Inference time (ms)	GPU	Framework
Suhr and Jung (2022)	12 pixels, 10 degrees	99.77 %	99.77 %	16.66	GTX 1080Ti	Tensorflow
	3 pixels, 1.5 degrees	96.22 %	96.22 %			
Li *et al*. (2020a)	12 pixels, 10 degrees	99.31 %	99.40 %	20.29	GTX 1080Ti	Pytorch
	3 pixels, 1.5 degrees	93.87 %	93.95 %			
Zhang *et al*. (2018)	12 pixels, 10 degrees	98.99 %	99.63 %	23.83	GTX 1080Ti	Darknet, Caffe
	3 pixels, 1.5 degrees	81.87 %	82.40 %			
Huang *et al*. (2019)	12 pixels, 10 degrees	93.13 %	96.51 %	10.97	GTX 1080Ti	Pytorch
	3 pixels, 1.5 degrees	71.68 %	74.28 %			
Yu *et al*. (2020)	12 pixels, 10 degrees	72.14 %	99.24 %	3.75	GTX 1080Ti	Pytorch
	3 pixels, 1.5 degrees	63.01 %	86.57 %			
Li *et al*. (2020b)	10 pixels, 15 degrees	99.68 %	99.41 %	13.00	Titan XP	Pytorch
Do and Choi (2020)	20 pixels, 2 degrees	98.70 %	97.88 %	42.79	GTX 1080	Tensorflow
Min *et al*. (2021)	10 pixels, no angle criterion	99.56 %	99.42 %	25.30	GTX 1080Ti	Pytorch

terms of the criteria, N pixels and M degrees mean that the detected parking slot is considered a true positive if distances between its two junctions and the ground truths are within N pixels and the angle between its orientation and the ground truth is within M degrees. Otherwise, it is considered a false positive.

5. CONCLUSION

The automatic parking system consists of target parking position designation, path planning, path tracking, and user interface, and the target parking position designation covered in this paper is largely divided into four categories: user interface-based, free space-based, parking slot marking-based, and IPMS-based. It is expected that the fusion of the image sensor-based parking slot marking recognition and the range sensor-based free space recognition, which have mutually complementary characteristics, will be mainly used in the near future. In the case of parking slot marking recognition, AVM, which have been mass-produced and widely used, are expected to be mainly used. In the case of free space recognition, an ultrasonic sensor is mainly used at the beginning, but it can be replaced later if a LIDAR is adopted on the side. However, since the automation method cannot be perfect, user interface-based is expected to continue to be used as a backup or modification means.

Various methods have been steadily developed for parking slot marking-based, and with the recent introduction of deep learning-based methods, remarkable performance improvement has been achieved. For the time being, deep learning-based methods are expected to become mainstream, but there are two expected challengers. First, efficient deep neural network architecture development and its simplification for embedded implementation. Second, a large dataset and performance comparison platform to secure performance in everyday situations. The new dataset is expected to include different types of parking slot markings in different countries and to cover bad weather conditions. In addition, it is necessary to encourage development acceleration through open competition by operating a KITTI dataset-like leader board.

In future, autonomous valet parking combining autonomous driving and automatic parking systems in parking lots is expected to be introduced, and for this, precise positioning in parking lots is expected to be an essential prerequisite. Once precise positioning in the parking lot is introduced, the target parking position designation can be completed simply by allocating a parking slot. It is important to keep in mind that commercialization and standardization of indoor precise positioning can have an effect on automatic parking systems, and it is necessary to continue to promote cooperation while paying close attention to the trends in this field.

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