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SURVEY OF TECHNOLOGY IN AUTONOMOUS VALET PARKING SYSTEM

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ABSTRACT–This paper introduces the definition of an autonomous valet parking system, standardization trends, processes designed to implement the system. Autonomous valet parking is a system in which a vehicle can be parked in a parking space without a user, and can also be moved to a specific location when the user wants to. The autonomous valet parking system is being developed by dividing it into search driving process, autonomous parking process, and return driving process. Currently, the autonomous valet parking system can demonstrate the entire parking process in a specific scenario. However, there are limitations, i.e., the system requires high costs, and some technologies do not show stable results. In this paper, we have highlighted the problems that should be solved to complete the autonomous valet parking system and the technologies for solving these problems. From this paper, researchers will be able to learn about the technical aspects and the developmental direction of the autonomous valet parking system.

KEY WORDS : Autonomous valet parking system, Localization, Collision avoidance, Autonomous parking, Return driving

1. INTRODUCTION

Valet parking, a compound word of the French “valet”, which means surrogate parking and English “parking”, refers to a service in which a management agent parks instead of a vehicle owner. The autonomous valet parking (AVP) system, which combines valet parking with an autonomous vehicle, is a technology that performs parking by moving the vehicle automatically to a parking space and moving it to a specific location when a user calls after parking. In general, the system controls a vehicle in the driving and parking situation without human manipulation.

There are several methods for implementing an autonomous valet parking system. Figure 1 illustrates the process of a general autonomous valet parking system. The system begins when the user executes it in the parking lot. Then, the search driving process is performed. The goal of this process is to find a parking space while autonomous driving in a parking lot. For this purpose, this process requires localization, collision avoidance, and parking space detection techniques.

If parking space is detected in search driving process, autonomous parking process is performed. In this process, the vehicle attempts to park in the detected parking space. For this, it is necessary to generate a parking-path considering various constraints such as the maximum turning radius, steering speed of the vehicle, obstacles, and the type of parking space.

Return driving process, which is the final process of the system, is performed when the user calls a vehicle after parking. This process is to move the vehicle to a place where the user can get on the vehicle again. This is implemented in a way that tracks paths used in previous processes. Therefore, this process requires path tracking technique.

If all of the above processes operate properly, people can escape various parking problem. For example, people may not experience major problems such as lack of parking lots, waste of fuel, and car accidents in the parking lot. For this

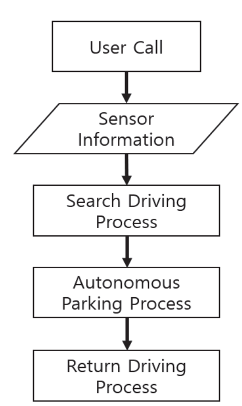

Figure 1. Process flow of the autonomous valet parking system.

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reason, the demand of autonomous valet parking system has been increasing daily (Thompson, 2016), and many companies and laboratories are entering the market to solve this problem.

Currently, Mercedes-Benz and Bosch and LG have established parking infrastructure for autonomous valet parking system (Lee, 2020; Kim, 2021). NVIDIA is developing an autonomous driving and detection method for parking spaces in a parking lot (Cvijetic, 2019). BMW is preparing to apply an autonomous parking module, which is part of an autonomous valet parking system, to its vehicles (Rosamond, 2021). In addition, studies in this field, such as research on autonomous parking using only cameras attached to vehicles (Jo *et al*., 2022), the development of reinforcement-based autonomous parking systems and learning simulators (Suhr and Jung, 2021; Um *et al*., 2020) are being actively conducted.

This paper provides the development status of autonomous valet parking systems. It is organized as follows. Section 2 describes the standardization trends and the performance evaluation criteria of an autonomous valet parking system. Section 3 introduces the newly developed techniques for each process of an autonomous valet parking system. Section 4 explains the limitations of the introduced technologies and the problems that must be solved in this field. Finally, Section 5 presents the conclusion of the study.

2. STANDARDIZATION TREND OF AUTONOMOUS VALET PARKING SYSTEM

2.1. Standardization Trend

As mentioned earlier, the autonomous valet parking system is one of the technologies currently receiving considerable attention. As autonomous valet parking is being developed in many countries and companies, the importance of technical standardization has emerged. As shown in Figure 2, technical standards for autonomous valet parking are being implemented in various organizations. The technical standardizations include geographic information, outdoor positioning, indoor space positioning, parking standards, and vehicle communication standards. Geographic information and positioning standards establish principles for the name, definition, and format of geographic information in outdoor spaces. Such standards include ISO 14825 Geographic Data Files, ISO 17572 Location Referencing, and ISO TC204 17438.

Standardization of information in indoor spaces is also underway, and representative standards include the ISO TC211 and OGC indoor GML. Because there is a difference in the amount and quality of information obtained outdoors and indoors, standardization proceeded differently according to each environment.

The parking standard, like ISO/DIS 16787 APS, proposes the types of information required for parking and defines the names of technologies that control vehicles. It defines the functions required to implement assisted parking system (APS) technology. APS is a system that provides images of parking spaces and trajectories. It also performs the steering control function of a vehicle.

Finally, standards related to vehicle communication include the European Commission for Mobility and Transport in Europe and the Commission delegated regulation (EU) 13.3.2019 proposed by the National Highway Traffic Safety Administration in the United States. Table 1 lists the data provided by the standards.

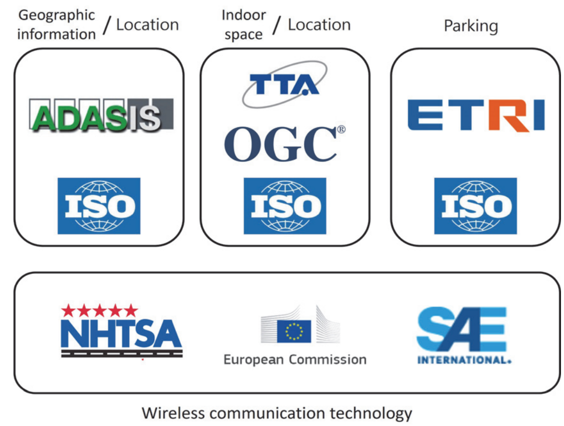

Figure 2. Organizations for standardization associated with the autonomous valet parking system.

Table 1. Standardization name and details of the autonomous valet parking system.

International standard name	Details
ISO 14825 Geographic data files	Compatibility of geographic information data used as map data of navigation
ISO 17572 Location referencing	A standard that defines location reference to find a specific location on different maps
ISO TC204 17438	A standard plan focused on outdoor spaces such as the composition of navigation data and real-time transmission of traffic information
ISO TC211	A standard that defines data types and service interfaces for location-based services in indoor spaces
OGC indoor GML	3D Map modeling standard
ISO/DIS 16787 APS	Functional standards such as providing parking space images and parking trajectories for light vehicles (pickup truck, minivan, two-wheeled vehicle).

2.2. Evaluation Method of the System

In addition to the technical definition of the autonomous valet parking system, there is also agreement on the evaluation method. The evaluation targets of the autonomous valet parking system are divided into autonomous driving and autonomous parking.

The evaluation of autonomous driving follows the 'autonomous driving technology stage' defined by the Society of Automotive Engineers (SAE). This stage is currently being used as an industry standard and is subdivided into six stages, from level 0 to level 5. This is classified according to the level of technology, subject of control, and ability to drive. ISO/WD 34501 and ISO/WD 34502 standardization discussions are underway to develop an evaluation process suitable for these stages. Currently, ISO/WD 34501 standardizes the terms and definitions for test scenarios applicable to level 3 systems. There are examples of an autonomous driving test scenario in the ISO/WD 34501 standard. ISO/WD 34502 defines the guidelines and safety evaluation processes for test scenarios. By using these standards, internationally reliable tests can be applied to autonomous driving systems.

Discussions on international standards for evaluating autonomous parking areas have just begun. Therefore, the level of technology is currently measured according to developer evaluation criteria. For example, Volkswagen worked with governments in Europe to establish a traffic situation scenario system called automated driving applications and technologies for intelligent vehicles (AdaptiVE). Using this, the company evaluates the capabilities of the autonomous parking system for each specific situation (Kelsch *et al*., 2017).

Table 2 presents an example of an autonomous parking scenario in AdaptiVE. This scenario was divided according to the performance level. AdaptiVE includes scenarios for evaluating both autonomous driving and parking and uses the autonomous driving technology stages defined by SAE to indicate the level of autonomous parking. In AdaptiVe, Level 2 is referred to as the parking assistant system, which helps people to park more easily. For example, there are obstacle distance-warning systems and rear cameras. Autonomous parking can be performed from level 3, which means that autonomous parking is possible in specific situations. Examples of situations include parking in garages and towers. In Level 4, all scenarios mentioned in Level 3 can be performed. In addition, when encountering an obstacle, it is possible to return to the destination after stopping or avoiding it.

Table 2. Example of an autonomous parking assessment scenario.

Level	Scenario
Lv 2	Parking Assist System
Lv 3	- Garage parking - Parking at the parking tower - Street parking
Lv 4	Safe Stop System

3. AUTONOMOUS VALET PARKING SYSTEM PROCESS

3.1. Overview

As mentioned in Section 1, the autonomous valet parking system includes search driving process, autonomous parking process, and return driving process. This section introduces developed techniques to perform each process.

3.2. Search Driving Process

When the system begins, the vehicle attempts the search driving process to find parking space. In this case, localization, collision avoidance, and parking space detection techniques are required. Localization is a technique to estimate the current location of a vehicle, which is necessary for efficient and accurate driving. To perform localization, it is needed to obtain information such as the location of the object around the vehicle and the location of the parking space. Various sensors and communication equipment may be used for it (Lou *et al*., 2020; Ma *et al*., 2021; Kanan and Arbess, 2020). For example, There is the system that uses satellite navigation technology with GPS and IMU sensors to confirm the speed and posture of the vehicle and correct the position estimation error (Amini *et al*., 2019).

In addition, there are sensors such as camera, lidar, and radar used for localization. The most common types of camera sensors are monocular, stereo, and fisheye cameras, which have different fields of view. Typically, autonomous vehicles are equipped with cameras with a field of view of 150 to 210 degrees. There are many lidar sensors with different fields of view. Lidar uses lasers to detect objects, and a single laser is called a channel. There are lidars with 16, 32, 64, and 128 channels, and the field of view varies depending on the number of channels. Lidar has a measurement range of about 200 meters and a vertical field of view of 30 to 50 degrees. Popular lidar sensors include Velodyne, Luminar iris, and Ouster. Radar sensors use short-range radar (SRR) and long-range radar (LRR) depending on the range required for an autonomous valet parking system. LRR sensors, such as the Continental ARS and Trimble CFX series, have a similar measurement range and vertical field of view to lidar. However, LRR has a horizontal field of view of 35 to 80 degrees, unlike lidar with a 360-degree field of view. These sensors are useful in places where satellite information is not available, such as indoor parking lots. Usually, these sensors are used in SLAM technology.

Table 3. Sensors used in autonomous valet parking systems.

Sensor		Measurement range	Horizontal FOV	Vertical FOV
Lidar	16, 32, 64, 128 channels	200 m	180° ~ 360°	30° ~ 50°
Camera	Monocular, stereo, fisheye lens	-	90° ~ 210°	90° ~ 180°
Radar	SRR	5 m	5° ~ 20°	10° ~ 35°
	LRR	200 m	35° ~ 80°	35° ~ 80°

SLAM is a technology that synthesizes information received from sensors to create a map and estimate the pose of the vehicle (Wang *et al*., 2018; Lee *et al*., 2015; Ying *et al*., 2021; Kumar *et al*., 2020; Qin *et al*., 2020). There are two main algorithms for SLAM: the direct method and the feature-based method. The direct method is to estimate the sensor pose by tracking the intensity of data that changes as the sensor moves. It is called that because it uses the raw data to directly estimate the pose of the sensor. However, SLAM using the direct method is vulnerable to changes in illumination. SLAM using the direct method may have good accuracy in pose estimation, but it will not be able to perform re-localization, which is the function of estimating the current sensor position from the created map. This is because the matching accuracy between old map data and new input data is low due to brightness differences. For this reason, SLAM is mostly developed using feature-based methods instead of direct methods.

To estimate a pose using a feature-based method, first, the feature points of the surrounding objects must be obtained from sensor information. After projecting the feature points received from the same object onto two different sensor coordinate systems, the position of the object can be estimated by calculating the geometric relationship of the projected points. This can be done using epipolar geometry, and the position difference between the two sensors can be obtained using this relationship. Epipolar geometry is the geometry of the points projected into the sensor coordinate systems. These projected points are created from a point in three-dimensional space.

Figure 3 shows that point X is projected onto x_1 in image A and x_2 in image B. Points e_1, e_2 are called epipoles, which are the intersections of the line connecting the origin points O and O' of the two sensors and coordinate planes. The lines L_1 and L_2 are called epipolar lines, which connect projected points and epipoles. A point x_1 on L_1 is unique even if the depth and the distance to the origin O and X change. However, the position of x_2 corresponding to x_1 changes according to the depth value. All points X with different depth values exist on the ray connecting the origins O and X, and the straight line L_2 is a projection of the ray onto image B. That is, point x_2 corresponding to x_1 exists on L_2 and this epipolar line is unique. As shown in Equation (1), the transformation matrix representing the relationship between point x_1 and the epipolar line corresponding to x_1 is the essential matrix E.

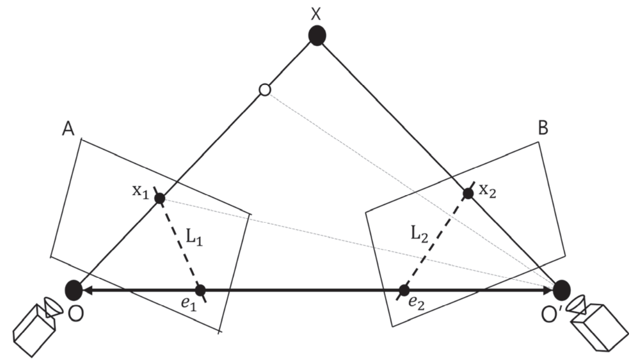

Figure 3. Projection of a three-dimensional point.

$$Ex_1 = L_2 \tag{1}$$

The essential matrix E represents the transformation relationship between the normalized image planes. Since the actual projection points are located in the pixel coordinate system, the fundamental matrix F, including the intrinsic camera parameters, should be used to represent the transformation relationship of the points in the pixel coordinate system, not the normalized coordinate system. If the camera intrinsic parameters of images A and B are K_A and K_B respectively, the relationship between the essential matrix and the fundamental matrix is as shown in Equation (2).

$$F = ({K_B}^T)^{-1} E {K_A}^{-1} \tag{2}$$

The fundamental matrix satisfies the following relationship with the two points x_1 and x_2 as shown in Equation (3).

$$[a_1\ b_1\ 1]\ F\ [a_2\ b_2\ 1] = 0 \tag{3}$$

In Equation (3), the left matrix is a homogeneous coordinate at point x_1, and the right matrix is a homogeneous coordinate at point x_2. F represents a fundamental matrix with dimensions of 3 × 3. This fundamental matrix represents the translation and rotation transformation between two pixel planes. If a fundamental matrix is obtained, it is possible to estimate the positions of origin points O and O'.

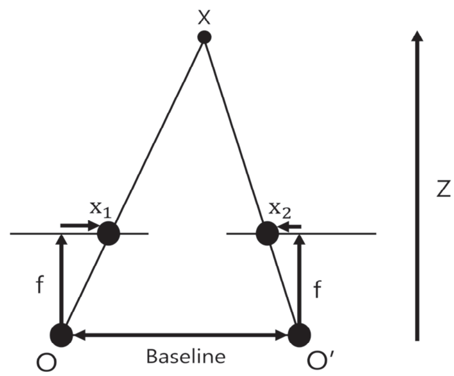

Figure 4. Disparity of projected points.

When the same object X is measured at two sensor positions O and O', the results are projected onto different pixel coordinate systems. In other words, points x_1 and point x_2 are projected to different coordinates in the left and right pixel coordinate systems, and this difference is used to calculate the depth information of object X. This difference is called disparity, which refers to the difference in positions between two different points projected from the same point. In Figure 4, $|x_1 \; \text{-} x_2|$ is a disparity. As shown in Figure 4, the disparity between x_1 and x_2 varies depending on the location of point X. The distance between the object and the sensor can be calculated from the disparity. Equation (4) shows the relationship between disparity and distance.

$$Disparity = |x1 - x2| = \frac{Baseline * f}{Z}. \qquad (4)$$

The disparity is inversely proportional to Z, the distance to the three-dimensional point X, and is proportional to the baseline and focal length of the sensor. Baseline is the difference between the positions of the two origin points O and O'. Therefore, the distance between the object and sensor can be obtained using the focal length, baseline, and disparity of the point pairs obtained through feature matching. The three-dimensional coordinates of the object can be estimated when the depth is calculated. A map is generated by synthesizing the three-dimensional coordinate information of the object. The map containing information on the environment surrounding the sensor is the final output of SLAM technology.

The images in Figure 5 are the examples of SLAM map with camera and lidar sensor information. Table 4 shows the relative pose error (RPE) measurement results of the introduced SLAMs. RPE is mainly used for driving accuracy evaluation and is a type of method to calculate the error between ground truth and predicted value. It shows the RPE of SLAMs that use lidar, camera, and fusion of multiple sensors. Sensor fusion SLAMs include V-LOAM, which combines camera and lidar, and Radar SLAM, which combines camera and radar.

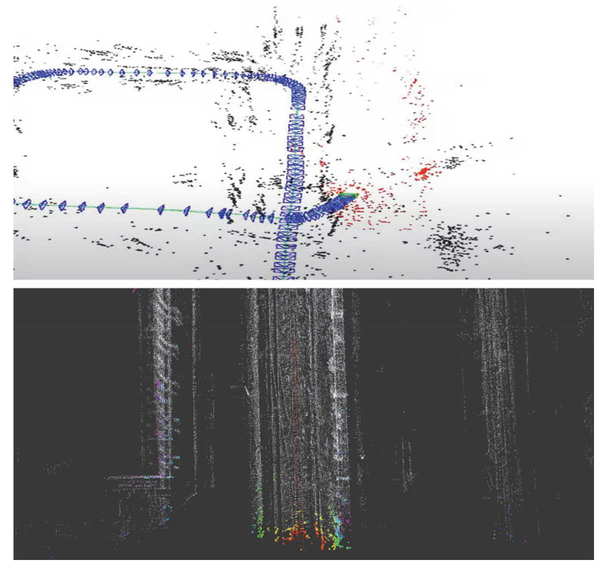

Figure 5. Examples of camera SLAM and lidar SLAM.

Table 4. Relative pose error measurement results on the KITTI Dataset.

		RPE (Translation)	RPE (Rotation)
Lidar SLAM	LOAM	0.44 m	0.05°/m
	A-LOAM	0.37 m	0.03°/m
Direct SLAM	LSD-VO	1.14 m	0.40°/m
	Stereo DSO	0.84 m	0.36°/m
Feature based SLAM	ORB-SLAM	0.7 m	0.53°/m
	ORB-SLAM3	0.66 m	0.37°/m
Sensor fusion SLAM	V-LOAM	0.21 m	0.11°/m
	Radar SLAM	0.55 m	0.50°/m

Search driving process is performed in the parking lot, and there are many objects in such place. Therefore, technique to avoid obstacles is essential for search driving process. The following sensors are used to prevent collision: (1) ultrasonic sensor, (2) shortwave radar sensor, (3) lidar sensor, and (4) camera sensor. In general, an ultrasonic sensor that emits a signal in a specific frequency band is used to transmit the distance information between features in the surrounding environment and the sensors. Figure 6 shows the results of the acquisition of objects information using an ultrasonic sensor (Sang, 2019). It is displayed in color, where the object is located. Similarly, radar and lidar sensors are also used to measure distance from objects to help warn of collision risks (Wang *et al*., 2021; Fernandes *et al*., 2021).

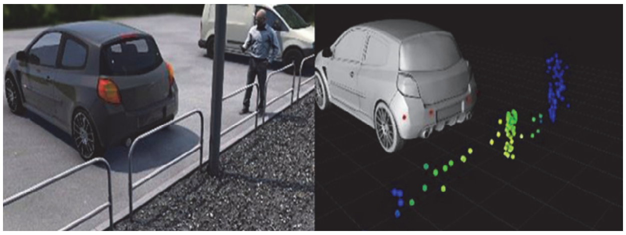

Figure 6. Object detection using three-dimensional ultrasonic sensors.

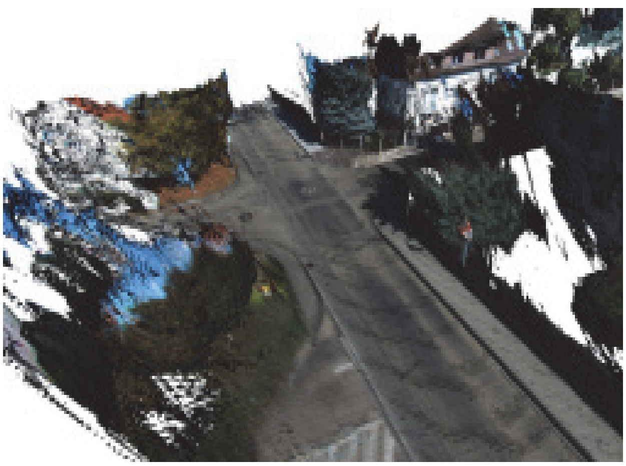

Figure 7. Three-dimensional map created using deep learning.

Camera sensor information is also used to estimate the distance from objects through image processing. For example, there is a image processing technique to generate a 3D map that includes objects (Barsan *et al*., 2018). The 3D map shown in Figure 7 includes the surrounding environment, object location, and sensor location information. There are also deep learning methods that combines cognitive technique, such as semantic segmentation (El Madawi *et al*., 2019), depth estimation (Kumar *et al*., 2018), and motion estimation (Siam *et al*., 2018). Semantic segmentation is a technique for classifying specific objects in an image. Figure 8 shows the results of classifying vehicles, people, and surrounding environments from the images. The objects classified by these techniques were used to depth estimation and motion estimation. Depth estimation and motion estimation are methods of calculating the distance using the difference in the position of the same object in two consecutive images.

Parking space detection is continuously performed during search driving process. This has been implemented using traditional computer vision, deep learning and hybrid approach with both methods combined. Computer vision is mostly a method for specifying and recognizing the shape of a parking space, such as line detection (Suhr and Jung, 2018; Xiang *et al*., 2021) and feature point detection (Hamada *et al*., 2015). As shown in Figure 9, parking spaces that should be recognized vary in shape and size, depending on the purpose. Therefore, methods using only computer vision technologies for parking space recognition should implement different techniques for each type of parking space.

Figure 8. Classification of objects by semantic segmentation.

Figure 9. Example of various parking spaces.

Deep learning has also been used to recognize parking spaces. This method primarily uses convolutional neural networks (CNN) (Gkolias and Vlahogianni, 2018; Gamal *et al*., 2020). It involves learning about various parking spaces using a CNN and performing parking space detection based on this. A CNN is a neural network model that performs a preprocessing operation called convolution, which is often used when processing image or video data. Convolutional filters can be used to build up a feature layer that preserves the spatial/local information of the input data. Figure 10 shows a representative CNN structure used for parking space detection. The Convolutional Layer learns the features of the input image, and the feature data is passed through the Fully connected Layer to produce an output. Since this is a supervised learning process, the output is determined by the labeled values in the training data.

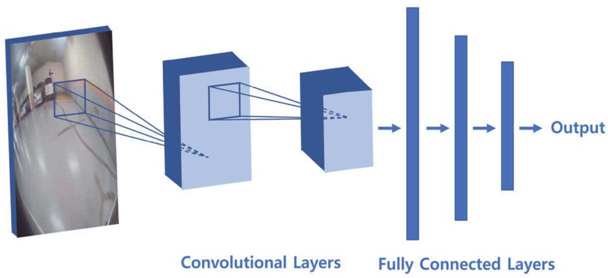

Figure 10. Basic CNN structure for parking space detection.

There are studies that detect parking spaces in this way (Patel and Meduri, 2020; Song *et al*., 2021). These studies used the R-CNN model, which is a variant of the CNN. Originally, R-CNN is a model for classifying and localizing objects. The model consists of a region proposal to find the location of an object and a region classification to classify the object. For parking detection, R-CNN can be used to identify the location of a parking space in an image and determine whether the parking space is empty or not. Specifically, a region proposal process is performed to estimate the region in the image where the parking space could be located. Region Classification determines whether an object exists in the found parking space. Through these two processes, the network model can find the location of empty parking spaces.

There are studies that have used deeper network models to improve the accuracy of parking space navigation (Dhuri *et al*., 2021; Singh and Christoforou, 2021). These studies perform parking space detection based on the VGG-16 model and ResNet-34, a type of CNN. The VGG-16 model consists of 13 convolutional layers and 3 fully connected layers. The ResNet-34 model is a deeper structure, with 34 layers. Although these network models were published a few years ago, their reliability has been recognized and they are used as a fundamental component of research on parking space detection using deep learning. The introduced studies also use a modified model based on these models.

Deep learning technology shows a higher recognition rate and strength than the computer vision method. However, the better the size and quality of input image, the higher the computational cost.

Recently, after estimating the approximate location of a parking space using the computer vision method, a method of applying deep learning techniques only around the estimated location has been studied (Wu *et al*., 2020; Suhr and Jung, 2021). For example, it first finds the area where parking lines intersects using a line detection method. Second, the identified area is used as the input image of the neural network to check whether the area is a parking space. If so, the type of parking space is checked. This method reduces the size of the image entering the neural network. Thus, this has high performance while keeping the calculation cost low.

3.3. Autonomous Parking Process

When the vehicle finds the parking space and reaches it, an autonomous parking process is performed. In general, the path generation methods are used to do autonomous parking. Parking-path generation is to determine how to move the vehicle by considering its direction and speed.

Parking-path generation is implemented by using algorithm-based methods and reinforcement learning. The algorithm-based methods have been used mainly from the past to the present. In addition, reinforcement learning for parking-path generation has recently emerged (Suhr and Jung, 2023).

The algorithm-based methods involve calculating a path considering the location and shape of the parking space and the current location of the vehicle. In order to calculate a suitable parking-path, formulas such as the Ackermann-Jantoud tupe (Zhao *et al*., 2013), optimal control problem (Zips *et al*., 2016), grid-based path planning method (He and Li, 2021; Xiong *et al*., 2021), and rapidly exploring random tree * (Gammell *et al*., 2014) are needed. These formular calculate parking-path by considering the minimum turning radius and position of the vehicle.

Table 5. Types of networks used in the introduced studies.

Field of study	Backbone network	Structure	List of studies
Segmentation	UNet	23-fully convolutional layers	El Madawai *et al*., 2019; Kumar *et al*., 2018; Siam *et al*., 2018
Parking lot detection	VGG-16	16-layers (13 conv, 3 FC)	Dhuri *et al*., 2021
	ResNet	34-layers (33 conv, 1 FC)	Singh and Christoforou, 2021
	Fast R-CNN	Region proposal + VGG-16	Patel and Meduri, 2020; Song *et al*., 2021

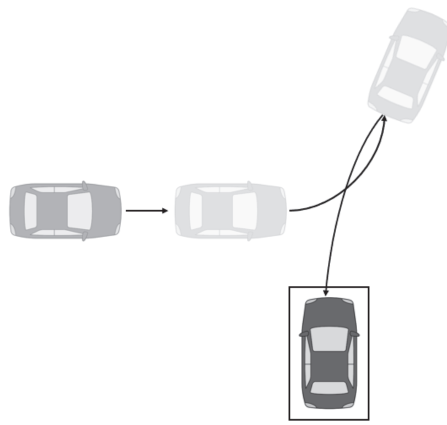

Figure 11. Reverse parking process.

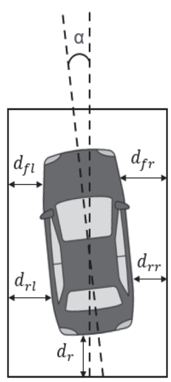

Figure 12. Measurement of parking accuracy.

The reinforcement learning method generates an optimal path for the autonomous parking process in the simulator. Usually, reinforcement learning for parking-path generation is performed using a simulator (Du *et al*., 2020; Özeloğlu *et al*., 2022; Rafiei *et al*., 2022). In the simulator, the vehicle learns a general parking process, as shown in Figure 11. The learning method is to repeat path generation and evaluation until the optimal path with highest parking accuracy is obtained. Parking accuracy can be measured using compensation conditions and Figure 12 shows the example of compensation conditions. d_{fl}, d_{fr}, d_{rl}, d_{rr}, and d_r represent the relative distance of the vehicle from the parking line, and α refers to the steering angle of the vehicle.

3.4. Return Driving Process

After autonomous parking is complete, the vehicle waits in the parking space until the user calls it. When the user calls the vehicle again, it moves to a specific location where the user can be picked up. For this mechanism in return driving process, path tracking technique is required.

In path tracking technique, there are a method of tracking a traveled path (Zhang, 2021; Chen *et al*., 2023) and a method of tracking the modified path (Xiong, 2022). The first tracking method is also called memory parking, and it is a method of storing and tracking a path that has traveled to a parking space. Second one is a method of tracking the path after adding or modifying a route from the parking space to the user selected location. The modified path is generated by considering the current posture of the vehicle.

All these methods have something in common in that they use similar vehicle control algorithms (Chen *et al*., 2020; Qiu *et al*., 2021). For path tracking, a control command for moving the vehicle along the generated path is sent, considering conditions, such as the current position and steering angle of the vehicle. The control command transmits a value that adjusts the speed and steering angle of the vehicle. Equation (5) shows the formula for calculating the steering angle to transfer the control command.

$$\tan\theta = \frac{\tan\theta_1 + \tan\theta_2}{2} = \frac{LR}{R^2 - \frac{W^2}{4}} \cong \frac{L}{R} \tag{5}$$

L is the distance between the axles of the vehicle, W is the distance between the wheels, and R is the radius of rotation to move to the destination. The steering angle of the left wheel of the vehicle is denoted by θ_1, while that of the right wheel is denoted by θ_2. The steering angles of the left and right wheels are expressed as shown in Equations (6) and (7), respectively:

$$\tan\ \theta_1 = \frac{L}{R + \frac{W}{2}} \tag{6}$$

$$\tan\ \theta_2 = \frac{L}{R - \frac{W}{2}} \tag{7}$$

The steering angle of each wheel varied depending on the length between the axles of the vehicle. Therefore, to minimize this difference, the final steering angle was calculated using the average of the two steering angles ($\tan\ \theta_1$, $\tan\ \theta_2$). This value was transmitted as a control command for path tracking.

4. CHALLENGES IN AN AUTONOMOUS VALET PARKING SYSTEM

This section introduces the research challenges that need to be addressed to complete an autonomous valet parking system. To date, many investments and developments have been made to implement autonomous valet parking systems. Consequently, it has reached a level at which it could be demonstrated in a specific environment. However, there are still issues that prevent commercialization, such as safety and cost. The following are the open problems of an autonomous valet parking system.

First of all, the system requires high costs for infrastructure construction. There are no production lines dedicated to infrastructure. In addition, the specifications of the communication equipment used to build the infrastructure and the sensors attached to the vehicle have not been standardized. Currently, infrastructure is being built based on its own production system. If this situation persists, autonomous valet parking systems completed in different places will not be easily compatible with different environments. This, in turn, will cause a waste of production and research costs. To solve this problem, the ISO/TC 204 department, an organization under the ISO, is developing the ISO/DIS 23374 standard. This standard not only organizes the required performance of sensors to be installed in the infrastructure for uniform equipment production but also defines the communication rules and functions of various communication equipment.

In addition, the risk of security breach is an important issue. Several sensors attempt to communicate with vehicles in infrastructure facilities for autonomous valet parking. When multiple communication devices and vehicles in a building exchange information, a high level of communication security is required. Currently, a vehicle communication method that combines blockchain technology is being developed for communication security (Yang *et al*., 2021).

Last but not least, there is a problem in determining the pick-up and drop-off points. Autonomous valet parking is a system that starts after the driver disembarks. In addition, the end of the system includes a function for moving the vehicle to a specific location so that the driver can return. Therefore, it is essential to determine where the driver will get off and get on. To make this decision, traffic flow, location where the driver wants to get on, and past traffic situation information must be considered.

5. CONCLUSION

This paper summarizes the standardization trend of the autonomous valet parking system and the process of the system and introduces the techniques used in each process. An autonomous valet parking system consists of search driving process, autonomous parking process, and return driving process. Although the autonomous valet parking system still has several issues to be solved, such as cost and sensor communication security, many development organizations are working together to solve each problem.

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